Satellite Scheduling Problems: a Survey of Applications in Earth and Outer Space Observation

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Abstract

With the growing interest in leveraging space technologies to provide both knowledge and services, the need for efficient space mission management also increases. Among all the related problems, the scheduling of tasks performed by observation satellites is not only crucial for the astrophysical community, but it also poses challenging optimization problems, which have been studied for nearly 30 years. The aim of this survey is to provide a comprehensive overview of Satellite Scheduling Problems (SSPs), with a particular focus on applications. First, we propose a novel literature classification of SSPs based on the main variants that have been defined over the years. We address both imaging and communication tasks in the context of Earth-centered missions and, for the first time, of outer space missions. Then, for each class of problems we provide a review of the main contributions available in the literature, offering insights about solution methodologies. Finally, we outline some promising future research directions.

Keywords: Satellite Scheduling Problems; Space missions; Earth Observation Satellites; Imaging Scheduling; Communication Scheduling

1 Introduction

Space missions have attracted significant public attention since the 1960s, and especially in recent years, as a means to explore and improve our knowledge of the Earth and the outer space, with a focus on the Moon and Mars. Surprisingly, what was once deemed unlikely, such as space tourism, has now become a realistic endeavor. Motivated by the numerous benefits that the human presence in the Solar System may yield (see the Global Exploration Roadmap, 2018), several stakeholders, both public and private, are participating in the development of new missions, making contributions both strategic and technical. Consequently, the space economy has emerged as a prominent component of political strategies.

As defined by the Organization for Economic Cooperation and Development (OECD), the space economy encompasses a wide range of activities and resource utilizations that generate value and benefits for humanity while exploring, researching, understanding, managing, and harnessing space (OECD 2019, 2022). While the space economy's societal impact is often associated with Earth satellites, its concept can extend to planetary missions as well. Venturing beyond Earth's confines not only provides us with valuable insights into the Solar System, but also sheds light on the birth and evolution of our own planet.

Investment in the space economy has become increasingly common and encouraged. However, alongside advancements in technology and ground infrastructure to handle airborne resources like satellites or spacecraft, and in the exploitation of missions' resulting data, there arises a pressing need for effective resource management. First of all, planning a space mission requires the coordination and work of several teams that try to balance the interest of many stakeholders (Coffin 1995). Moreover, space missions face the challenge of operating with limited resources (mainly memory and power) to achieve scientific goals and justify the substantial investments required to initiate them. In addition, planning space missions is operationally complex. First, it involves the coordination of several research teams that aim to exploit specific instruments. Second, the daily management is complicated by the fact that there are significant time delays (ranging from minutes to hours) in the transmission of commands, actual execution, and reporting of outcomes. Consequently, mission operations are often planned months in advance, through a series of refinements and trade-offs to meet mission goals within constraints on power, data rate, data volume, and time. All these factors call for optimization strategies to be implemented in order to minimize risks and costs both before and during the mission.

In light of these considerations, significant efforts have been devoted in recent years to the optimization of scheduling operations in space missions, particularly in the context of satellites management. Among all the optimization problems related to it, Satellite Scheduling Problems (SSPs) mainly concern the scheduling of operational tasks that have to be performed by a single or by multiple observation satellites (i.e., satellites equipped with cameras able to observe the surface of a planet). Their objective is to obtain a feasible schedule that maximizes some objective function while respecting all the physical and operational constraints. SSPs can be classified into two main categories. The first one involves the scheduling of scientific tasks that can be performed by the camera(s) installed onboard a satellite. Particularly, we refer to the so-called *imaging* or *remote sensing* tasks, which concern the *observation* of ground targets. The second one involves the communication tasks between satellites and ground stations, for the uploading of commands as well as the downloading of data. SSPs also include several variants that relate to specific constraints of the problem and diverse applications.

The study of satellite scheduling dates back to the late 1960s, and first focused on addressing communication issues in military (Ahara and Rossbach 1967) and civilian contexts (Inukai 1979). These seminal works dealt with the problem of scheduling the transmission of data through satellite antennas, to meet the increasing volume of long-distance TV, radio and telephone communications (Prins 1994). Here, the satellite does not perform any activity autonomously, but receives and transmits data between ground stations (Bourret et al. 1989, Ribeiro et al. 1989, Granz and Gao 1992). Since then, there has been a growing interest in the scheduling of satellites' tasks, including imaging, data transfer, and communication. Figure 1 shows the results of an analysis performed on Scopus, in which we looked for the documents where the following keywords were used to identify the subject of the study, the kind of optimization problem, the type of task, and the methodology, respectively: "satellite", "scheduling|planning|management", "collection|acquisition|image|imaging|observation" - "transmission|downlink|communication", "optimization|heuristic". This analysis confirms the increasing trend, which is strongly reflected in the number of papers published per year, especially in the last decade, with a rapid growth since 2018.

One of the first studies dealing with the imaging SSP was the one of Bensana et al. (1996). The authors described the daily management of an Earth Observation Satellite (EOS) and made a comparison between several solution methods, both exact and approximate. The 2003 ROADEF (French Operations Research & Decision Support Society) Challenge organized jointly with the French National Center for Space Studies (CNES) further sparked interest in SSPs (see `https://challenge.roadef.org/2003/en/`). The challenge was about the scheduling of imaging tasks on an EOS, in a simplified setting. The winner of the challenge developed an algorithm based on simulated annealing for solving the scheduling problem (Kuipers 2003), while the second prize winner proposed an algorithm based on tabu search (Cordeau and Laporte 2005).

After the ROADEF Challenge, several variants of the problem arose, to cope with the ad-

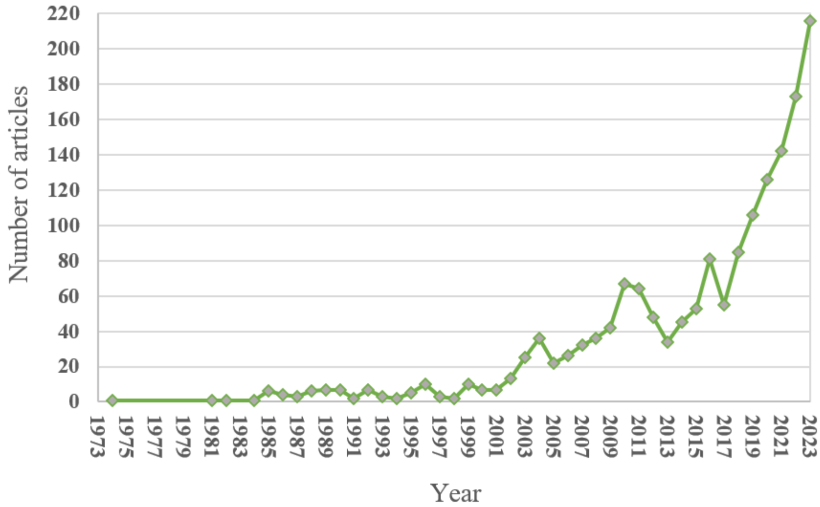

Figure 1: Number of published articles per year (Scopus)

vancement of technology and the growing popularity of satellite missions, mainly orbiting around the Earth. These advancements involve, among others, the exploitation of multiple satellites systems, and the shared utilization of a satellite. In addition, some research has been directed towards outer space missions, which have received more and more attention in the last decades. One of the authors of the present article is currently working on the Mars Express mission and has extensive experience in the actual planning and operations of space experiments (Orosei et al. 2018).

While a considerable amount of literature exists regarding the scheduling of tasks for Earth observing satellites, few studies have been conducted on extraterrestrial missions. The abundance of literature on EOS is justified by the prominent role that this kind of technology has in our everyday life, serving various purposes such as monitoring natural phenomena, weather forecasting, and telecommunications. This survey aims to comprehensively review the state of the art in SSPs in both Earth and outer space missions for imaging and communication SSPs, and to point out potential areas for future research. To provide a clear and useful overview, we adopted a perspective focused on the diverse applications of the problem, examining most relevant case studies found in the literature and describing exact and heuristic optimization methods developed for the solution of the covered variants of the SSPs.

The remainder of this article is organized as follows: Section 2 introduces a literature classification to highlight the different types of SSPs, thus clarifying the structure of the survey. Section 3 provides an overview of books and surveys related to the topic. Section 4 describes SSPs applied to EOSs and presents solution methods proposed by various authors. Specifically, it reviews imaging SSPs and its multiple variants, communication SSPs, and integrated SSPs. Section 5 discusses the scheduling problems in outer space missions. Finally, Section 6 draws some conclusions and outlines potential future research directions. A list of all the acronyms used in this survey is available in the Appendix.

2 Literature Classification

The SSP has been addressed from different perspectives and in different variants. In this survey we propose a novel classification based on problem characteristics as well as satellite and mission characteristics. A schematic representation of the classification performed is shown in Figure 2. As outlined above, we extended our review to Outer Space (OS) missions other than Earth Observation (EO) missions. In both cases the SSP has been increasingly studied, with a higher growth rate and magnitude for EO.

The SSPs can be classified into three main categories depending on the field of action. The Imaging Scheduling deals with the selection and scheduling of imaging tasks, commissioned by customers to be performed by the satellite in order to maximise user satisfaction. For the imaging SSP applied to EO, which has been widely studied over the years, we further identified several subcategories extending the standard problem to consider additional features to the application domain. Specifically, relevant variants addressed in the literature are the following:

- Inclusion of large areas as observation targets.
- Use of realistic time-dependent representations of profits and transition time.
- Consideration of policies for the sharing of a satellite among different users.
- Occurrence of emergency tasks that generate the need for dynamic replanning.
- Study of the imaging scheduling in the presence of clouds.

The Communication Scheduling addresses the problem of scheduling the communications between the satellites and the ground stations, by selecting the best available communication windows. Finally, the Integrated Scheduling combines imaging and communication scheduling, since they are strictly related.

SSP Literature Classification		*Imaging Scheduling*		*Communication Scheduling*		*Integrated Scheduling*	
		EO	*OS*	*EO*	*OS*	*EO*	*OS*
Satellite Technology	*Conventional Satellite*	✓	✓	✓	✓	✓	✓
	Agile Satellite	✓		✓		✓	
System Composition	*Single Satellite*	✓	✓	✓	✓	✓	✓
	Multiple Satellites	✓		✓		✓	
Decision Making	*Centralized*	✓	✓	✓	✓	✓	✓
	Autonomous	✓		✓		✓	

Figure 2: Literature Classification

The technology underlying satellite operativity is in constant evolution. We can mainly classify them into Conventional Satellite (CS) and Agile Satellite (AS). A CS has only a degree of freedom for imaging (roll) and a fixed viewing direction, therefore it can only observe the target during a fixed Visible Time Window (VTW), i.e., its observation Time Window (TW) coincides with the target VTW. On the contrary, an AS has three degrees of freedom (roll, pitch, and yaw), allowing manoeuvrability during and between image acquisitions (Lemaître et al. 2002). Consequently, the direction and starting time of an observation are free and the target VTW for an AS is longer than the corresponding observation TW, due to the satellite's ability to look ahead and look back (Figure 3). Moreover, the AS can possibly execute two or more observation tasks within the VTW, as long as all operational constraints are satisfied (Wang et al. 2020). Figure 3 shows the difference between the observation capacity of a CS and an AS. Both satellites have a fixed-duration observation TW (white rectangle) to observe a target (gray rectangle). The CS can only observe the target when it is exactly above it, as its camera has a fixed viewing direction. The AS, on the other hand, can change its field of view, so that it can take advantage of a longer VTW (black rectangle) and decide to place the observation TW before arriving above the target, looking forward, or after, looking backward.

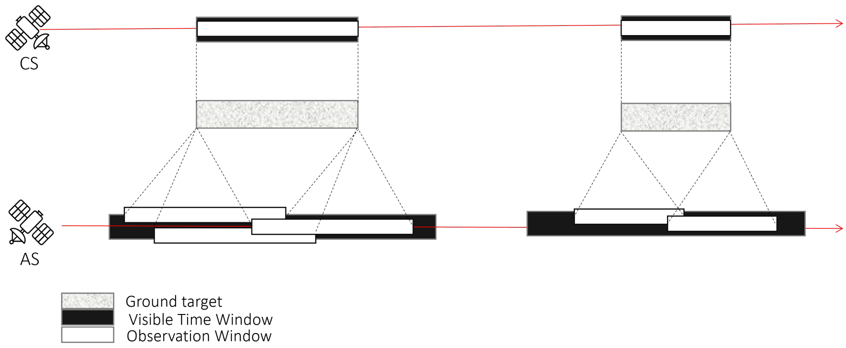

Figure 3: Difference between the observation capacity of a CS (above) and an AS (below)

A particular type of agile satellite is the video satellite, capable of staring at targets for longer observation times (Cui et al. 2018). Furthermore, a new generation of AS, called super agile satellites, has been recently introduced. This kind of satellite can perform imaging of ground targets during attitude maneuvering, allowing to perform non-along track observations (Lu et al. 2021). Therefore, super-agile satellites do not require multiple observations for imaging target sequences that are not parallel to satellite track or non-linear area, such as coastline and borderlines (Wang et al. 2020). Clearly, along with the improvement of the observation capability of an AS and the resulting increased efficiency of the imaging scheduling, the complexity of the agile SSP, in comparison with the conventional SSP, increases too.

Regarding the satellite system composition, studies on SSPs address both single satellites and constellations of satellites. This choice has an impact on the methods proposed, since the scheduling of multiple satellites is more complicated. When scheduling a fleet or constellation of satellites, one has more resources in terms of agents, memory, and power and more tasks can be performed at the same time. As a consequence of this flexibility, the scheduling process has many more decision variables.

Finally, the decision making process can be centralized in a ground station, corresponding to the management center of the satellite, or delegated to the satellites themselves that autonomously generate the plans, through software installed onboard. Since the autonomous scheduling has different characteristics and solution methods compared to ground center scheduling, we do not treat this problem in this survey.

To the best of our knowledge, we are the first to perform a comprehensive literature classification focused on the application of the SSPs. As can be seen in the following section, existing surveys on the SSPs adopt a methodology perspective and do not provide the reader with a complete overview of the numerous subproblems existing in the SSPs, especially in the field of imaging SSP.

3 Books and Surveys

Several books have been published that explore optimization in space-related problems. Ciriani et al. (2003) discuss optimization problems in the space and air industry sectors. They mainly refer to spacecraft design, trajectory optimization, and satellite management for the space industry, and to airline and airport management for the air industry. Within the same book, Gabrel and Murat (2003) present a chapter that focuses on the EOS mission planning and introduces the Spot5 mission case study. This work will be further described in the next sections. The book series by Fasano and Pintér (2013, 2019, 2023) presents advanced case studies and challenges in space engineering, documenting advancements over the years. In the first chapter of Fasano and Pintér (2013), the authors review optimization applications in space engineering. They categorized the problems into ten classes, among which they describe planning and scheduling, observation data handling and remote monitoring, and cargo loading and unloading. In the second volume, Mitrovic-Minic et al. (2019) present a framework consisting of a pre-processing tool and an optimizer for planning and scheduling multiple missions. Chen et al. (2023) recently provided an overview of the key technologies and the research status of task planning for EOSs. They introduce the centralized and distributed EOSs task scheduling models, algorithms under deterministic conditions, and dynamic scenarios of EOSs task rescheduling methods. Finally, they describe the architecture of typical satellite task scheduling and planning systems.

Regarding SSPs, several surveys have been conducted, focusing on specific aspects or problem variants:

- Wang et al. (2020) summarize current research on the imaging scheduling problem applied to agile EOS. They discuss several formulations, both simple and advanced, to handle various profit definitions, multiobjective functions, and autonomous models. They also review solution methodologies, including exact methods, heuristics, metaheuristics, and machine learning techniques.
- Xhafa and Ip (2019) survey SSPs primarily in relation to communication tasks, covering problem variants and satellite deployment systems. They then extend their previous work in Ip et al. (2022), deepening the description of the optimization algorithms for the solution of the communication SSPs.
- Zhang et al. (2021) discuss the theoretical foundations and applications of the imaging SSP. They also propose a classification of the problems and review model building approaches and solution techniques.
- Wu et al. (2022) focus on autonomous SSPs, i.e., when task scheduling is performed onboard the satellite, considering both imaging and communication tasks. They explore different modeling methods and response/rolling strategies for autonomous planning. Additionally, they survey heuristic, metaheuristic and machine learning approaches. They emphasize multiple-satellite case studies as for communication architecture and synchronization.
- Li et al. (2023) review the research on the satellite range scheduling problem, which aims to schedule general communications between satellites and ground stations (including maneuvering, command uploading and data downloading). They analyze mathematical formulations of the problem and then classify and summarize the common solution methods, their characteristics, and application scenarios.

In comparison to previous related work, we make three primary contributions: (i) we address both imaging and communication SSPs, providing a comprehensive overview for researchers studying these problems; (ii) we survey several variants of SSPs and present them with an application perspective, thus distinguishing our approach from existing surveys that primarily focus on the solution methods; (iii) we include works that address SSPs for outer space missions.

This article does not cover optimization problems related to satellites other than the planning and management of their activities. For other problems, we refer the interested reader to Hu et al. (2018) for trajectory optimization, to Cerf (2013) and Barea et al. (2020) for active debris removal, to Sun and Teng (2003) for satellite layout optimization (i.e., optimal placement of equipment in a satellite module), and to Wang et al. (2021) for constellation design (i.e., optimal selection of orbits and number of satellites for a new constellation). Similarly, solution techniques for SSPs that fall outside the realm of Operations Research, such as machine learning (Herrmann and Schaub 2023) and agent modeling (Schetter et al. 2003), are not included in this survey.

4 Earth Observation Missions

Earth observation missions play an increasingly important role in the space economy and are essential for the understanding of the Earth and its environment, as EOSs are the major platform for space image acquisition. An EOS can perform various tasks such as disaster surveillance, military oversight, and environmental monitoring. The images acquired by satellites are valuable not only in territorial studies and related activities (e.g., agriculture or fishing), but also in regional planning, education, and intelligence (Zhao et al. 2022). Therefore, EOSs' management is a topic of great interest in many scientific disciplines and in the context of Operations Research. The management of an EOS concerns the generation of activity plans and communications plans, in order to achieve the scientific goals and fulfill the stakeholders' needs. An activity plan is necessary to decide which task (observation) to perform and when, during the planning horizon. The communication plan is essential since a contact between satellites and ground stations is allowed only in particular TWs and in some cases could not overlap with operational windows of the satellites.

Earth observation is enabled by the presence and frequent upgrade of satellites orbiting around the Earth, which are launched and then managed by different research institutes, that often collaborate and share satellites. The first artificial satellite orbiting the Earth was Sputnik 1, launched by the Soviet Union on 4 October 1957: scientists used it to study the ionosphere by radio signals (Cracknell and Varotsos 2007). In the field of observation satellites, the first photo of Earth from a satellite was taken by Explorer 6, launched by the National Aeronautics and Space Administration (NASA)'s Jet Propulsion Laboratory, on 14 August 1959 (Uri 2020). In 1972 the United States started the Landsat program, the largest program for the acquisition of images of Earth from space (Wulder et al. 2019) and, finally, the first real-time satellite image was acquired by the United States's KH-11 satellite system in 1977 (Krebs). According to the *Index of Objects Launched into Outer Space*, maintained by the United Nations Office for Outer Space Affairs and to the Union of Concerned Scientists, there were 11,330 individual satellites orbiting the Earth at the end of June 2023, but only 70% of them were active. Among these, about 1200 satellites are devoted to Earth observation, mainly controlled by American companies (Planet Labs, Spire Global) or Chinese and Russian Ministries of Defence. The greatest part (almost 5000) are instead used for communication and were mostly launched by SpaceX (Starlink constellation). Earth observation is attracting considerable attention and providing increasing opportunities for the development of new services. As a result, in the following years many more EOSs are expected to be launched. An example of this trend is observable in the European Space Agency (ESA)'s program in Earth observation from 2010 to 2030 (Figure 4).

Figure 4: Developed Earth observation missions (ESA 2023)

Some real EOS or constellations of EOSs have been studied within the literature that addresses the EOS scheduling problem. Authors dealing with specific satellites delve into their specific attributes and subsequently devise tailored solutions for the SSP. Satellites usually considered in Operations Research are:

- SPOT5 - *Satellite pour l'Observation de la Terre* (Bensana et al. 1996, Vasquez and Hao

2001, Gabrel and Vanderpooten 2002, Gabrel and Murat 2003, Mansour and Dessouky 2010, Ribeiro et al. 2010): was a commercial EOS from the French Space Agency, active from May 2002 to March 2015.

- KOMPSAT-2 - *Korean Multi-purpose Satellite 2* (Jang et al. 2013): is an Earth-imaging/ environmental Korean satellite, launched on 28 July 2006.
- FORMOSAT-2/ROCSAT-2 - *Republic of China Satellite-2* (Lin et al. 2005, Liao and Yang 2007): is a decommissioned EOS operated by the National Space Organization of Taiwan, active from May 2004 to August 2016.
- COSMO-SkyMed - *COnstellation of small Satellites for the Mediterranean basin Observation* (Bianchessi and Righini 2008): is an Italian Earth-imaging constellation of four identical satellites, launched between 2007 and 2010.
- PLEIADES (Lemaître et al. 2002, Bianchessi et al. 2007): is an environment-focused constellation of two satellites, from the French CNES, launched in 2011 and 2012.
- RADARSAT-2 (Karapetyan et al. 2015): is a Canadian Space Agency (CSA) EOS, launched on 14 December 2007.

In the remainder of this section, we will present a review of works focused on scheduling imaging tasks, communication tasks, or a combination of both in Earth observation missions. We will classify the imaging scheduling problem into several sub-problems, to specify different applications and particular problem constraints.

4.1 Imaging Scheduling in EO

The imaging scheduling problem applied to satellites orbiting around the Earth has been intensively studied in the literature. In the simplest version of the problem, a set of requests has to be selected and scheduled on a satellite or constellation of satellites in order to maximize the observation profit, while satisfying a set of complex operational constraints. Each satellite can have different characteristics in terms of storage capacity, energy consumption, and maneuverability. Each request has its weight or priority and concerns some specified area on the Earth's surface. The requests are collected from customers by the ground center that operates the satellite and correspond to the input of the scheduling problem. Generally, the number of requests is very large and not all the requests can be fulfilled given the limited satellite capacity and the operational constraints. Hence, the imaging scheduling problem is an oversubscribed problem, i.e., the amount of requests largely exceeds the amount of observations that a satellite system can provide.

Users' requests can be of two types: mono or stereo. For the mono type, each request is observed only once, whereas for stereo requests, each target must be acquired twice in the same direction but from different angles. Furthermore, an observation request can have one out of two shapes: spot (i.e., a small circular area) or large polygonal area. Each observation request can be transformed into a set of strips that cover it (Figure 5). A spot target can be covered by a single strip, while a polygonal area may require several strips to be completely imaged (see Section 4.1.3).

The constraints included in the imaging SSP are mainly temporal constraints and onboard resources limitations, both energy and memory. Moreover, due to the satellite moving in its orbit, target points or areas can be observed only in limited TWs. Furthermore, in other specific download windows the spacecraft can communicate with the ground stations, download the data collected and hence empty its memory. Some examples of typical constraints are:

- The satellite has a daily image acquisition time limit.
- Orbits have a maximum number of observations that can be scheduled.

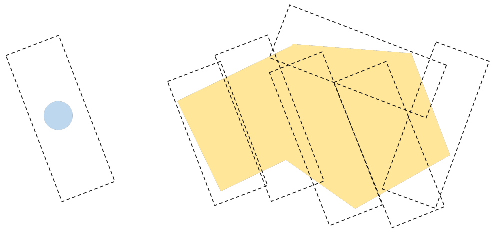

Figure 5: Examples of spot (on the left) and polygonal area (on the right) target

- The storage capacity onboard the satellite is limited.
- The satellite has limited energy to perform imaging and maneuvering.
- The satellite performs only an observation at a time.
- A pair of observations can be scheduled only if the setup time requirement between them is satisfied.
- An observation can be scheduled if its weather conditions satisfy some given requirements.
- A minimum transition time for achieving the correct position has to be considered between each pair of consecutive observation activities of the same resource.

The profit function reflects several criteria aggregating more or less explicitly commercial, strategic or technical aspects. The simplest profit function maximizes the number of requests satisfied by the schedule. In more advanced objective functions, each request is weighted by its priority, reflecting client importance or demand urgency. Finally, different works introduced multi-objective problems, to consider at the same time several goals together with profit maximization, such as the maximization of fairness of resource sharing and load balance, or the minimization of energy costs and failure rate.

4.1.1 Conventional Satellite with no additional features

The first advancements in satellite technology were made by conventional satellites, which then became the initial focus for the Operations Research community. The Conventional Satellite scheduling problem, when examined in its basic form without additional features, stands as the simplest version within the SSP domain. This version focuses only on fulfilling spot target requests, with the satellite having a single opportunity to acquire them during its pass over the designated area in a single orbit.

Many articles have been published on the Conventional SSP without additional features, both in early and later years. To help the reader navigate this section, Table 1 provides an overview of the references that are discussed here, along with their main characteristics. Particular emphasis is put on test cases, which include many real-world satellites.

Early works. The imaging SSP was addressed for the first time in relation to the daily scheduling of a single conventional EOS, in which each imaging request has a unique VTW. In this framework, great attention was devoted to the multiple-camera satellite Spot5, which hosts three cameras that can observe at most one target at a time and may not be used together. In the imaging SSP applied on Spot5, as firstly described in Bensana et al. (1996), a set of mono and stereo imaging requests is provided with different weights. Notably, in this problem an imaging request coincides with the *shot* that can cover it (i.e., the photograph lasting as its VTW). Each mono request can be fulfilled by any of the three cameras, while stereo requests need both the front and the rear one. The problem aims to select a maximum-weight subset of observations to be performed, while meeting three hard constraints: a minimum transition time between two observations on the same camera, a limitation of the instantaneous flow of data, and a finite satellite storage capacity. Bensana et al. (1996) compared exact and approximate approaches to solve 20 instances of the Spot5 problem provided by CNES (see Bensana et al. 1999), in both one-orbit or multi-orbit scenarios. The two sets of instances range from 67 to 364 requests

Table 1: Summary - Conventional Satellites with no additional features

Reference	System Composition	Multiple Objectives	Methodology Exact	Methodology Heuristic	Test Cases
Bensana et al. (1996)	SS		✓	✓	Spot5
Vasquez and Hao (2001)	SS			✓	Spot5
Gabrel and Vanderpooten (2002)	SS	✓	✓		Random Instances
Mansour and Dessouky (2010)	SS	✓		✓	Spot5
Ribeiro et al. (2010)	SS		✓		Spot5
Wu et al. (2013)	MS			✓	JB-3A, JB-3C, CBERS-1, CBERS-2
Xiaolu et al. (2014)	MS			✓	Random Instances
Wu et al. (2017)	MS			✓	JB-3A, JB-3C, CBERS-1, CBERS-2
Chen et al. (2018)	MS			✓	Spot5, MTI, ORBVIEW-3, IKONOS-2, EO-1
Chen et al. (2019)	MS		✓		HJ-1A, HJ-1B, HJ-1C
Luo (2020)	SS			✓	Spot5, ZY-3, GF-1
Wu et al. (2022)	MS			✓	Random Instances
Wang et al. (2023)	MS		✓		Random Instances

Abbreviations: Single Satellite (SS), Multiple Satellites (MS)

and from 209 to 1057 requests, respectively. In particular, they test a Depth First Branch-and-Bound (B&B), and a Russian Dolls search (a B&B algorithm on nested subproblems, in which the results of each search is used in the following one, Verfaillie et al. 1996) within a Constraint Satisfaction Programming (CSP) framework and a Best First B&B applied to an Integer Linear Programming (ILP) formulation. These exact methods are compared with a greedy algorithm and a tabu search. The Russian Dolls search proves to be the best exact approach for the one-orbit instances, which include less than 400 variables. On the other hand, for the multiple-orbit scenario it fails to find good solutions within the time limit, while tabu search always finds the best solution. Shortly after, Vasquez and Hao (2001) translated Bensana et al. (1996)'s ILP formulation into a knapsack formulation with conflict constraints and proposed a new tabu search algorithm to solve the Spot5 imaging SSP. Their algorithm improves the best known solutions by Bensana et al. (1996) for the multi-orbit instances, but without near-optimality guarantees.

In the following years, several attempts were made to generate tight upper bounds for the single and multi-orbit instances of the problem. Gabrel and Murat (2003) proposed a decomposition approach, where a sub-problem is assigned to each camera onboard the satellite. The sub-problems are then modeled with a vertex-path formulation and solved by a longest path algorithm, while the whole problem concerning the compatibility of sub-problem solutions is handled through column generation. This approach provided good upper bounds for the single-orbit instances. Later, Vasquez and Hao (2003) employed a partition-based approach following the *divide and conquer* principle, in which several sub-problems containing a subset of variables are solved exactly and their optimal values are summed up to get the final bound. They outperform the bounds of Gabrel and Murat (2003) for the one-orbit instances. Moreover, new bounds are presented for the multi-orbit set, which improve the classical ones obtained from the linear relaxation or logical constraints relaxation in the knapsack formulation.

In contrast to previous works, Gabrel and Vanderpooten (2002) addressed the daily scheduling problem of a one-camera satellite, regarding it as the selection of a *shot* sequence, where each shot can fulfill one or more imaging requests. Not all shots can be taken due to the problem's feasibility constraints, and some shots have higher priority related to strategic importance. Multiple criteria are introduced to evaluate a sequence: number of imaging requests satisfied and total priority of the shots performed (to be maximized), and satellite utilization (to be minimized). To solve the problem, a feasibility graph is built to generate all the feasible shot sequences, and an adapted shortest-path algorithm is employed to extract the efficient ones. Finally, a multiple criteria interactive procedure allows to adapt the importance of each criterion and to select the most satisfactory sequence.

Later works. Some years after the first studies on the Spot 5 problem, Ribeiro et al. (2010)

strengthened Vasquez and Hao (2001)'s formulation with valid inequalities arising in node packing and 3-regular independence system polyhedra and improved both computational times and optimality gaps. This new formulation allowed the CPLEX general-purpose solver to finally solve to optimality all the multi-orbit instances. Later on, some slight variations of the Spot5 problem were studied. Mansour and Dessouky (2010) proposed a multi-criteria genetic algorithm for the bi-objective Spot5 problem, in which a new not-binary genome representation is adopted. The objective function maximizes the total profit and the number or requests satisfied, while penalizing genome's infeasibility due to the observation conflicts and memory constraints. Luo (2020) extended the model of Vasquez and Hao (2001) for the Spot5 scheduling problem to cover cases with N on-board cameras, and proposed a hybrid artificial bee colony algorithm to solve the problem. Their algorithm achieves smaller solution gaps than Vasquez and Hao (2001)'s tabu search algorithm on both Spot5 instance sets and a new test set randomly generated from the operational parameters of the Chinese satellites ZY-3 and GF-1.

In recent years, several studies have been published on advanced pre-processing techniques to reduce the complexity of the problem. Different works introduce task merging strategies in the SSP, noting that if two or more targets are geographically adjacent, they might be covered by one observation strip. Consequently, task merging allows to fulfill more requests while saving the satellite's energy. However, merging is not always feasible as it depends on technical constraints, such as storage capacity, available energy, and transition time required between the positions of tasks. Wu et al. (2013) studied the multi-satellite SSP and proposed a two-phase scheduling method, composed by a cluster-task phase and a scheduling phase. In the former, a graph is established, representing the imaging requests and whether or not they meet the merging feasibility constraints. The task clustering is then performed with an improved minimum clique partition algorithm. In the latter, a hybrid ant colony optimization generates the solution to the scheduling problem. The authors prove the effectiveness of the algorithm on two reference scenarios containing the orbits of two and four Chinese satellites, respectively. Moreover, they demonstrate the utility of the task-clustering mechanism when solving large scale instances of the problem (up to 834 targets and 2516 VTWs). Later, Xiaolu et al. (2014) and Wu et al. (2017) proposed dynamic task clustering approaches within a metaheuristic framework. Xiaolu et al. (2014) presented a multi-EOS scheduling iterative approach composed by task assignment and task merging. The task assignment is performed by an adaptive ant colony optimization algorithm that selects a TW for each task and assigns them to a satellite. Then, in the second phase, a dynamic programming algorithm finds the best solution for each satellite, i.e., an observation plan including information on how tasks should be merged (and observed) to maximize the profit. In Wu et al. (2017) an adaptive simulated annealing algorithm is employed to generate satellite schedules, while the dynamic task clustering strategy is embedded into the neighbourhood search process. The proposed approach outperforms Wu et al. (2013)'s static one. Particularly, two scenarios with different target distributions are tested and the results show that task merging has a larger impact on the profit-energy ratio for large-scale and densely-distributed instances.

Some pre-scheduling approaches were developed in the following years. Chen et al. (2018) addressed the multi-SSP and analyzed several conflict indicators of VTWs and requests, based, for instance, on the number of conflicting requests in a VTW or the number of VTWs for each request. The indicators are then employed in two greedy heuristics and an improved differential evolution algorithm. Starting from the study of Chen et al. (2018), Chen et al. (2019) utilized the conflict indicators in a pre-processing strategy to decrease the number of TWs, thus reducing the size of the problem. They formulated the problem with a Mixed Integer Linear Programming (MILP) model, in which constraints are derived from an analysis of the interdependence between feasible time intervals. Wang et al. (2023) improved Chen et al. (2019)'s study with a bidirectional rolling horizon pre-processing, which pre-schedules more tasks, and with an in-depth analysis to strengthen the MILP formulation. With the improved pre-processing strategy and formulation, instances with up to 800 observation requests and 20 satellites can be optimally solved within

20 minutes. In addressing the EOS scheduling problem, they link it to the unrelated parallel machine scheduling with multiple TWs.

Finally, a decomposition method was proposed by Wu et al. (2022). They adopt a divide-and-conquer framework to solve the large-scale multi-satellite observation scheduling problem, in which the orbits of satellites are treated as the resources providing imaging services. The authors propose a method that combines exact and metaheuristic approaches in two iterative phases: a task-orbit allocation phase, performed by an algorithm based on ant colony optimization and tabu search, and a task scheduling phase, in which a linear model for every single orbit is solved via B&B. They efficiently solve instances up to 1600 tasks.

4.1.2 Agile Satellites with no additional features

Agile satellites represent the majority of active satellites in the Earth's orbit. For this reason, the latest research on SSPs concerns them for the most part and a great effort has been made to include some advanced and realistic features in the various studies, as described in the following sections. Nevertheless, the study of the simplest agile SSP dates back to the late 20th century when the first flexible-moving satellites emerged.

Early works. To the best of our knowledge, the first work dealing with single-agile SSP was carried out by Gabrel et al. (1997), who proposed a graph model applicable to both the single- and multiple-orbit imaging SSP. The study explores the acquisition of images from various orbits (with diverse camera rolling angles), and starting at different times (with distinct pitching angles). The proposed model employs a time discretization strategy to identify all the possible observations for each request, so the quality of the solution (a feasible observation sequence with a maximum number of requests fulfilled) depends on the chosen discretization. Therefore, to assess the efficacy of their graph-based solution approach, the authors conduct a comparative analysis against two alternative approaches that utilize a continuous set of observations. Some years later, Globus et al. (2004) addressed the imaging SSP for multiple EOSs with flexible nadir-pointing capability (i.e., able to observe in different directions from the one orthogonal to the surface) and multi-day horizon. The study conducts a comprehensive comparison of thirteen permutation-based scheduling algorithms, encompassing variants of genetic algorithm, hill climbing, simulated annealing, random search, and squeaky wheel optimization (an iterative greedy heuristic based on priorities, Joslin and Clements 1999). They test the algorithms on ten instances with up to 6114 observation targets. The findings suggest that strategies characterized by an initial wide exploration followed by a more narrow search, such as simulated annealing, appeared best suited for this problem.

Later works. Further works on Agile SSP without additional features were published in the last decade. Xu et al. (2016) investigated a multi-agile scheduling problem, and proposed an ILP formulation. They developed two priority-based indicators to evaluate benefits and opportunity costs of different positioning of the observations in a feasible sequence. The indicators are then employed in two constructive algorithms and an ant colony optimization approach. The latter outperforms the exact solution by the ILP solved by CPLEX for instances involving more than 50 requests, whereas CPLEX fails to produce a feasible solution for instances with 200 tasks. To reduce the dimension of the solution space and the calculation cost, Zhao et al. (2020) proposed a pre-processing method based on task clustering for dense point targets in a single agile SSP. Then, the authors adopt a double-layered tabu algorithm that generates the local observation path within the cluster regions (inner layer) and the global target observation path including all clusters (outer layer).

Recent publications have emerged also in response to the new technological advances, particularly in the development of video and super-agile satellites. Cui et al. (2018) investigated the scheduling problem of multi-target fixed-duration staring imaging for a single video satellite, with a planning horizon shorter than one orbit period. Both video staring imaging and photo staring imaging are considered, with time requirements of 5 s and 0.5 s, respectively. The authors formulate a continuous time model and propose a modified ant colony optimization algorithm with tabu lists to solve the problem. To design their test case, they employ the real parameters of the Tiantuo-2 satellite. Differently, in Chang et al. (2020) the final image duration is set as a variable of the problem. The authors propose a mission planning model for an optical video satellite and a dedicated method to calculate the minimum image duration of each observation, considering task priority and ground target congestion. A greedy heuristic is developed to generate a feasible solution, supported by heuristic deductions. As for super-agile satellites, Lu et al. (2021) proposed a scheduling method to observe multiple targets within a single pass exploiting satellite's ability. The authors combine multiple point targets into imaging strips through a clustering and decomposition approach, and establish a bi-objective mathematical model aiming at maximizing the mission coverage benefit and minimizing the mission completion time. Finally, an improved particle swarm optimization algorithm is employed to solve the problem. The computational tests outline the benefit of this approach compared to methods that consider independent point targets or fixed positions of the satellite camera.

4.1.3 Large Area Target

Customer requests submitted to a satellite or a constellation of satellites can be spot or area targets. Dealing with area targets involves the consideration of additional aspects compared to spot targets. Indeed, a large area target cannot be imaged in a unique observation, and splitting and acquisition strategies should be developed. Consequently, an area target can be translated into a set of strips that cover it and must be acquired in order to fully observe it. An area target is conventionally decomposed into parallel strips. However, when multiple-satellites or single-satellite multiple-orbit scenarios are considered, an area target can be covered with the aid of multiple nonparallel strips (Figure 6). The strip-decomposition leads to an increase in the complexity and size of the problem, especially when it comes to multiple-satellite systems, when, however, better coverage of the targets can be achieved.

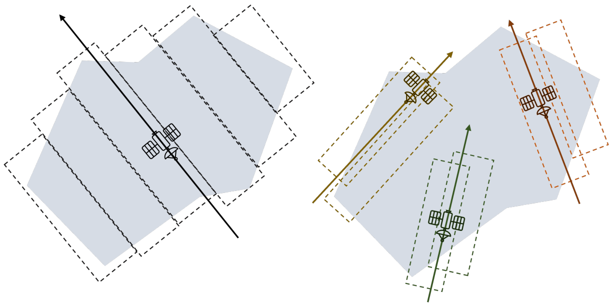

Figure 6: Difference between parallel acquisitions in a single-satellite single-orbit environment (on the left) and nonparallel acquisitions in a multi-satellite or single-satellite multi-orbit environment (on the right)

The study of SSPs with large area targets has received great attention over the years, as it represents a very realistic scenario in Earth observation. Table 2 provides an overview of the many references reported in this section and their main characteristics. For each reference, its test case is outlined, including both real-world satellites or specific target areas.

Partial coverage. Several authors allow the rewarding of the partial acquisition of an area target and compute the resulting profit depending on the percentage of the coverage. Lemaître et al. (2002) describe the problem of selecting and scheduling observations of an agile EOS during a single orbit, considering both spot and area targets, the latter ranging from 20 to 100 km in length. They cut the area target into contiguous and parallel strips of equal width and propose a convex objective function to maximize the sum of partial rewards obtained from each

Table 2: Summary - Large Area Target

Reference	System Composition	Multiple Objectives	Methodology Exact	Methodology Heuristic	Test Cases
Lemaître et al. (2002)	SS		✓	✓	ROADEF 2003
Cordeau and Laporte (2005)	SS			✓	ROADEF 2003
Habet et al. (2010)	SS			✓	ROADEF 2003
Jang et al. (2013)	SS		✓	✓	KOMPSAT-2
Perea et al. (2015)	MS			✓	Extremadura, Andalusia, Cadiz*
Niu et al. (2018)	MS	✓		✓	2008 Wenchuan earthquake*
Barkaoui and Berger (2019)	MS			✓	CBERS-2, IKONOS-2, Spot5
Berger et al. (2020)	MS		✓		CBERS-2. IKONOS-2, Spot5
Wu et al. (2019)	MS	✓		✓	L-band InSAR satellite
Xu et al. (2019)	MS			✓	African Savannah, Amazon Forest, Southern China*
Zhu et al. (2019)	MS			✓	FengYun, YaoGan, and ZiYuan
Zhibo et al. (2021)	MS			✓	Nanhai, Southeast China*
Gu et al. (2022)	MS			✓	20 Chinese satellites
Zheng et al. (2023)	MS			✓	Gabon, Belarus*, L-SAR 01A, L-SAR 01B, GAOFEN 3

* specific area target

Abbreviations: Single Satellite (SS), Multiple Satellites (MS)

request. The gain percentage associated with a partial acquisition of a polygon is computed with a piecewise linear function associating to the 40% and 70% of the acquisition the 10% and 40% of the revenue, respectively. They compare four different approaches for the solution of the problem: a greedy algorithm, a dynamic programming algorithm, a constraint programming approach and a local search algorithm. The same profit function was later adopted also by several authors, as Benoist and Rottembourg (2004), Cordeau and Laporte (2005), Habet et al. (2010), Xu et al. (2019), Zhu et al. (2019), Zheng et al. (2023).

The problem addressed by Lemaître et al. (2002) became the subject of the ROADEF Challenge 2003 (Verfaillie et al. 2002) and has therefore been much studied in subsequent years. Cordeau and Laporte (2005) won the second prize in the Challenge by means of a tabu search heuristic previously developed for the vehicle routing problem with TWs. The algorithm allows the exploration of infeasible solutions during the search, penalizing them with a self-adjusting parameter. Good upper bounds for the solution of the ROADEF instances were provided by Benoist and Rottembourg (2004) by enriching the linear model of the problem with valid inequalities and exploiting a Russian Dolls approach. The bounds, which were the best known for the problem, reach an average gap of 12.2% with respect to the best known solutions. Some years later, Habet et al. (2010) proposed a tabu search algorithm to solve the ROADEF problem. To improve the search in case of moves leading to the same gain value, a second tabu search algorithm is used, which minimizes the sum of the transition durations between two image acquisitions. Through the developed approach, they obtained the best known solutions for 15 of the 20 instances provided by the Challenge, and found a better one for four of them.

Other applications of the imaging SSP with area targets have been studied in the last years. In these works the profit gathered from each target covered by the schedule depends on the percentage with which it is covered (i.e., the size of the acquired area respect to the complete area). Niu et al. (2018) consider the multi-SSP of large areal tasks for rapid response to natural disaster. They design a strip-decomposition method considering a slewing angle step, and a multi-objective model to optimize coverage rate, imaging completion time, average spatial resolution and slewing angle. They present a real disaster scenario (2008 Wenchuan earthquake) and two specific sub-scenarios. The multi-objective Non-dominated Sorting Genetic Algorithm (NSGA)-II (Deb et al. 2002) is applied to efficiently solve the problem. In Barkaoui and Berger (2019) the multi-conventional satellite imaging scheduling problem with area targets is compared to the vehicle routing problem with TWs and then solved via a hybrid genetic algorithm. In this study, each area target is partitioned into multiple parallel strips and then in additional segments. The authors considered a non-deterministic setting, in which the expected profit of the schedule depends on observation outcome uncertainty, defined by a probability value, and the proportion of the area targets acquired. Later, Berger et al. (2020) studied the effect of covering the area target with observations performed in different directions (i.e., from different orbits, thus acquiring non-parallel strips). To handle the possible overlapping, minimal covering constraints are introduced in the formulation. The authors develop a new CPLEX-based problem solver (QUEST) for the resulting quadratically constrained problem, in which Lagrangian relaxation is exploited to get upper bounds and then a Branch-and-Cut (B&C) algorithm is run to achieve a high quality integer solution. Finally, Gu et al. (2022) proposed an accurate coverage calculation in which large area target are defined as spherical polygons of the Earth and a polygon clipping technique (Vatti 1992) allows the consideration of the overlapping of different observation strips on the same target. They prove that the proposed approach can calculate the coverage accurately within less time than calculation methods based on grid points (described in the following paragraph). The studied scheduling problem, which aims to maximize the total area of the observed regions, is solved through a particle swarm optimization algorithm with an individual reconstruction method to deal with infeasible solutions.

Space discretization. In addition to strips-decomposition, space discretization is a widely used approach to deal with the acquisition of area targets. Indeed, this technique largely simplifies the computation of the coverage rate when considering multi-satellite or multi-orbit scenarios, which would generate cases of overlap of the observation strips. Jang et al. (2013) study an image collection planning problem for KOMPSAT-2, a Korean satellite. They discretize each area target in square regions (scenes) and generate feasible observation segments by grouping adjoining scenes. The problem is formally stated with an ILP model that chooses non-overlapping segments in order to maximize the total profit in a multi-orbit long-term planning environment (31-days). They adopt a Lagrangian relaxation and subgradient methods to obtain upper bounds of the objective function, and a deletion and insertion greedy heuristic to restore the feasibility of the Lagrangian solution. This approach outperforms the CPLEX solver applied to the ILP problem for instances with more than 100 area targets.

A point-discretization was later introduced by Xu et al. (2019), who studied the coverage of very large area in a multi-SSP. Specifically, they propose a set covering model and a three-phase solving framework, composed by a discretization phase to convert the area target into a set of equidistant points, a target strips-decomposition phase, and a scheduling phase through a genetic algorithm. The strip coverage is computed as the number of points covered by selected strips and the reward function deducts overlapping points from the profit. They test their approach on the coverage of three high vegetation-covered areas: African Savannah, Amazon Forest and Southern China.

Grid-discretization was employed in the same year by Zhu et al. (2019) and Wu et al. (2019). In Zhu et al. (2019) many square cells generate candidate strips according to satellite imaging opportunities. A three-phase solution method is here developed and compared to the classical two-phase one (discretization and scheduling). In the proposed approach a cover optimization phase is performed by a dynamic greedy algorithm, which identifies the strips that can cover each area target, looking for the strip that covers the most uncovered cells for each imaging opportunity. Then, a tabu search algorithm selects the strips to generate the final plan, among the ones chosen in the previous step. Wu et al. (2019) study the imaging SSP for China's L-band satellite formation, in which each target can be requested multiple times. The targets are classified according to their size (spot or area) and the number of observations requested, and three different objective functions are defined according to each class of targets. The region targets are decomposed into grids, which define meta-tasks, and an improved NSGA-III algorithm (Deb and Jain 2014) is employed for the solution of the optimization problem. Recently, Zhibo et al. (2021) dealt with a multi-SSP with area targets and addressed the case in which the time duration of a candidate strip exceeds the maximal working duration of the camera. They introduce an excursion parameter $\Delta\lambda_t$ to divide the infeasible strips into a set of feasible strips, starting in successive time instants. Furthermore, the discretization parameter $\Delta\lambda_\gamma$ is introduced to divide the consistent range of rolling angles into a set of discrete values, thus allowing side-overlapping strips. They present a non linear model and a genetic algorithm in which an individual reconfiguration method corrects infeasible solutions and a grid-discretization of the area targets is performed to evaluate the fitness function. Two scenarios are finally tested, involving the region of Nanhai and Southeast China.

Regional mapping. Some authors address the imaging SSP for the coverage of a unique large area target. Perea et al. (2015) study a scheduling problem for the coverage of an area by multi-EOS by modelling it as a set covering problem. Here, the intersection of all possible acquisition strips and the area target generates a series of sub-regions that must be covered within a planning horizon, while minimizing the acquisition costs. A heuristic algorithm based on the Greedy Randomised Adaptive Search Procedure (GRASP) is proposed and compared with the ILP formulation. The computational tests are performed over three Spanish targets with different extensions (Extremadura, Andalusia, and Cadiz). The ILP could not find a solution for the medium and large size instances, while for the small size ones the average computational times of the heuristic were inferior by two orders of magnitude. Differently, in Zheng et al. (2023) only part of the target area could be captured by the satellites during the given schedule time horizon (1-day). Therefore, the objective function aims to maximize the total profit of the observation schedule, calculated with a piecewise linear function (Lemaître et al. 2002). The authors propose a three-phase method composed of grid space construction to translate an irregular area into a rectangular-system, candidate strip generation allowing for non-parallel strips, and strip selection performed by a tabu search algorithm with variable neighborhoods. They test their approach on two regions having different sizes, shapes and latitudes (Belarus and Gabon) and prove the efficiency of their approach compared to parallel-strips decomposition ones.

4.1.4 Time-dependent Profits and Transition Time

Several authors have introduced in their works a more realistic representation of the problem's characteristics. In particular, they focus on the description of profit or quality functions, and transition time between two targets. Indeed, while most research assumes they are constant to simplify the formulation and the solution of the problem, these attributes are strongly time-dependent. Table 3 summarizes the articles discussed in this section and their specific test cases. As can be seen, the study of this variant is quite recent, except for some references in the early 2000s, and mainly focuses on AS-01, the first agile satellite of China.

Table 3: Summary - Time-dependent Profits and Transition Time

Reference	System Composition	Multiple Objectives	Methodology		Test Cases
			Exact	Heuristic	
Wolfe and Sorensen (2000)	SS			✓	Random Instances
Lin et al. (2005)	SS	✓		✓	ROCSAT-II
Li et al. (2017)	SS			✓	Random Instances
Liu et al. (2017)	SS			✓	AS-01
He et al. (2018)	MS			✓	AS-01
Li et al. (2018)	MS	✓		✓	HJ-1A, HJ-1B
Peng et al. (2019)	SS			✓	AS-01
Xie et al. (2019)	SS			✓	AS-01
Peng et al. (2020)	MS			✓	AS-01
Peng et al. (2020)	SS		✓		AS-01
Wei et al. (2021)	SS	✓		✓	AS-01

Abbreviations: Single Satellite (SS), Multiple Satellites (MS)

Time-dependent profits. Time-dependent profits are usually introduced in SSP studies to address the need to obtain high quality data from observations. This strongly depends on the timing and the relative position between the satellite and the target. A typical assumption is that the best quality is obtained when the observation TW is set at the middle of the VTW, since the satellite is perfectly above the target. However, the preferences can be more complicated due to orbital dynamics, the nature of the specific target, or environmental factors. Some examples of profit functions are represented in Figure 7, where the real profit collected by an observation is a different percentage of the original value p, depending on the relative position of the observation TW respect to the VTW.

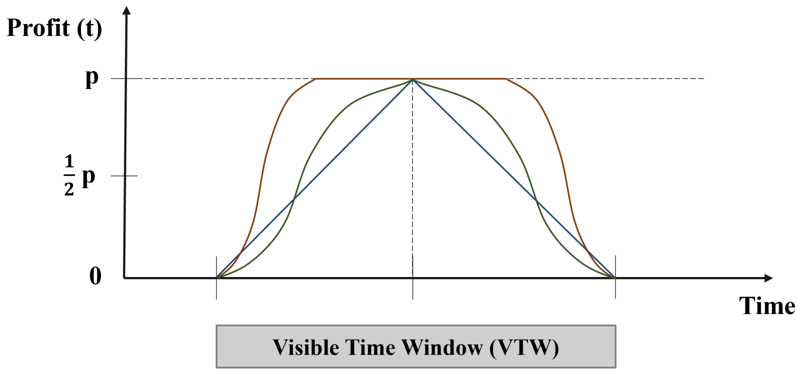

Figure 7: Examples of time-dependent profit functions

Wolfe and Sorensen (2000) were the first to consider time-dependent profits applied to a single-agile SSP. In their study, task preference is specified by a suitability function defined within the feasible TW. The authors propose two constructive heuristics, based on priorities and look-ahead function, respectively, and a genetic algorithm that allows to skip tasks or to place them at their worst position in the TW. A similar suitability function is adopted also by Lin et al. (2005), who address the daily imaging scheduling problem for a low-orbit EOS, ROCSAT-II, in which a request is composed by multiple tasks. The objective function evaluates task completion and setup costs, as well as the total suitability of all tasks performed. The problem is solved through a Lagrangian relaxation of the MILP formulation, enriched with a feasibility adjustment heuristic algorithm. They finally adapt Vasquez and Hao (2001)'s tabu search algorithm to their problem and show that the Lagrangian-relaxation approach is superior to the tabu search one in both solution quality and computation time. In Li et al. (2017) the revenue from a request is a piecewise linear function of its tardiness and earliness (with reference to its due date), following the *just-in-time* philosophy. The authors formulate this problem with a MILP model and develop a novel hybrid differential evolution algorithm to solve it, testing instances up to 100 requests. Finally, Li et al. (2018) proposed a five-objective MILP formulation for the multi-agile SSP, including profit, observation task number, image quality, resource balance and observation timeliness. In their study, the image quality depends on the distance and angle from the camera to the target, where the best value is obtained in the middle of the VTW. They propose and compare three different preference-based multi-objective evolutionary algorithms to solve the problem and an interactive framework for the decision maker to adjust preferences during the search.

Time-dependent transition time. Time-dependency in transition time computation arises from the dynamic nature of the minimum transition time required by a maneuver between the conclusion of an observation and the start of the following one. Indeed, it strongly depends on the precise time at which the transition begins, which influences the relative position of two observations and the maneuver speed needed by the camera to observe them. The typical way to represent the transition time t_{ij} between two consecutive observations i and j is through a piecewise linear function depending on Θ_{ij}, i.e., the angle to transit between the targets covered by i and j, and different angular velocities v depending on the angles, as follows:

$$t_{ij} = \begin{cases} a + \Theta_{ij}/v_1 & \text{if } \Theta_{ij} \leq \alpha \\ b + \Theta_{ij}/v_2 & \text{if } \alpha < \Theta_{ij} \leq \beta \\ \ldots \\ n + \Theta_{ij}/v_n & \text{if } \Theta_{ij} > \omega. \end{cases}$$

Peng et al. (2020) prove that the time-dependent transition time satisfies both the FIFO and the triangle inequality rules. The authors propose a greedy randomized iterated local search for the agile SSP with time-dependent transition time and constants profits. Their algorithm outperforms both Liu et al. (2017) and He et al. (2018) for the single and multiple SSP, respectively. Later on, Wei et al. (2021) studied the single agile EOS scheduling problem and proposed a multi-objective memetic approach with the consideration of time-dependent transition time, combined with problem-specific crossover, mutation, and local search operators inspired by Peng et al. (2020). They consider two objectives: the failure rate and the load balance degree.

Time-dependent profits and transition time. Most studies introduce both time-dependent transition times and profits in the problem. Liu et al. (2017) refer to single-agile EOS scheduling applied to the particular case of the Chinese AS-01 satellite, including time-dependent transition times and quality. The real image quality of each request is assessed on a ten-level scale, and is computed as a function of the time at which the observation is performed. In this problem, the quality is one of the user's requirements so it figures as a problem constraint, while the goal is the maximization of the priorities. Due to time-dependencies, the problem is quite complex to solve exactly, hence the authors propose a two-phase procedure to solve small-size instances with a CSP model. They further develop an Adaptive Large Neighborhood Search (ALNS), in which a number of simple destroy and repair operators compete to modify the current solution. To deal with the expensive computation of transition time they define two time slacks to compute the maximum time by which each observation can be moved in its VTW without causing the schedule to become infeasible. In follow-up work, He et al. (2018) extended the ALNS algorithm to the multiple-satellite case. Specifically, they introduce a heuristic task assignment mechanism to assign requests to different satellites. The multi-satellite problem is thus decomposed into several single-satellite subproblems, which are solved by ALNS. Moreover, the assignment mechanism will reassign tasks to different satellites if the solution of the subproblems has not improved for a number of destroy-repair iterations. Xie et al. (2019) adopt similar functions to describe time-dependent transition times and observation quality (here seen as a profit in the objective function) in the multiple-agile EOS scheduling problem. They propose a heuristic algorithm based on a temporal conflict network, which characterizes the overlaps of the VTWs of the target points through the edges and their weights. The computational analysis shows that when the problem size is large (over 300 requests), their algorithm outperforms that of He et al. (2018). Later on, Peng et al. (2019) solved the agile EOS scheduling problem with both time-dependent transition times and time-dependent profits, modelling it as an Orienteering Problem. They proposed a bidirectional dynamic programming based iterated local search algorithm, and define auxiliary features to simplify the feasibility check on transition time and the computation of accumulated profit during the search. Their approach is compared with Liu et al. (2017) and improves the performance of ALNS by 20.33% in the no-time-dependent profit version. Further improvements were obtained in a later work (Peng et al. 2020) with an exact approach, which adapts the bidirectional dynamic programming with decremental state space relaxation proposed by Righini and Salani (2009) to tackle the single-orbit scheduling for an agile EOS with time-dependent transition times and profits.

4.1.5 Satellite Sharing

Due to their cost, space projects, such as Earth observation missions, are often co-funded by several agents. The shared-resources EOSs must be managed to satisfy physical constraints (hard constraints), but also efficiency and fairness ones (soft constraints). Indeed, each agent has its own requests, with specific priorities and due dates, and could have different rights on the exploitation of the resources.

Usually, this problem is faced by stating a multiple-objective model, including both profit and fairness maximization. These two objectives may be at odds with each other: generally, an allocation cannot be efficient (Pareto-optimal) and perfectly equitable at the same time. Lemaître et al. (2003) describe four different centralized arbitration procedures to solve the bi-objective multi-agent allocation problem in the context of EOS mission management, based on different ways of taking into account the efficiency and equity trade-off. In particular, they define an individual utility $u_i(x)$ and a collective utility $u_c(x)$, that measure the satisfaction level of the arbitrator concerning the solution x. Finally, they introduce a variant of the problem that considers task priorities defined by agents and users' rights on resource exploitation. Later, Bianchessi et al. (2007) addressed the case of the PLEIADES system, co-funded by multiple users, in which they aim at maximizing the weighted sum of the normalized utilities associated with the different users of the system. They propose a tabu search heuristic and an upper bounding procedure based on column generation to evaluate the quality of the solutions. Their approach is tested on representative benchmark instances provided by the French CNES. Each set considers two satellites performing 12 or 13 orbits in a 24-hour time horizon, and four users.

Further contributions emerged from Tangpattanakul et al. (2012, 2015). Tangpattanakul et al. (2012) propose a Biased Random-Key Genetic Algorithm (BRKGA), along with two alternative methods for the selection of the elite set of solutions in the algorithm, based on NSGA-II and an indicator-based evolutionary algorithm. In their research, the fairness is considered by minimizing the maximum profit difference between each pair of users. The methods are evaluated on realistic instances derived from the 2003 ROADEF Challenge modified for four users requirements. Tangpattanakul et al. (2015) propose an indicator-based multi-objective local search which proved to be statistically better than their previous BRKGA.

4.1.6 Emergency Tasks and Dynamic Replanning

When dealing with the management of a satellite and the scheduling of its imaging tasks, there may be a need to perform a replanning in response to unforeseen events, such as the presence of emergency tasks. This situation is very common for disaster monitoring and the resulting optimization problem could become very complex. Indeed, emergency tasks could introduce conflicts in the existing schedule with the other tasks, that consequently must be removed. Additionally, they may have different urgency levels and priorities that depend on several factors. Various methods have been proposed to compute the priority of emergency tasks. Cui and Zhang (2019) propose a calculation model of emergency mission priority for the multi-satellite mission scheduling based on seven impact factors, including urgency degree, conflict degree, target visibility and mission revenue. Then, they employ a hybrid genetic tabu search algorithm and heuristic factors to solve the scheduling problem. Wu et al. (2019) decompose the task priority into four parts: target, imaging task, TT&C (track, telemetry, and control) requirement, and data transmission requirement. They extensively describe the computation strategy for each part and then apply the priority model to dynamical assign priorities during the rolling rescheduling of the emergency tasks, performed via genetic algorithms.

Solving the SSP oriented to emergency tasks involves either generating a completely new plan, or adapting the existing one. Wu et al. (2012) take the first approach via a hybrid ant colony optimization algorithm. The authors set the execution of feasible emergency tasks as a hard constraint and common tasks are then scheduled on the remaining observation resources.

Although creating an updated schedule guarantees the best solution, it is less preferable due to higher solving time and adaptation effort. Hence, to dynamically adjust the oldest plan and reduce the problem complexity, several authors adopt rolling-horizon policies, with event trigger (Haiquan et al. 2019), period trigger (Wu et al. 2019) or mixed trigger mode (Qiu et al. 2013). This approach dynamically schedules tasks into smaller TWs. A great number of dynamic heuristic methods proposed in the literature aim, instead, to insert new tasks into an existing schedule, utilizing strategies like direct insertion, insertion by shifting or deleting, also considering the minimization of the perturbation of the existing scheme (Wang et al. 2014; Wang et al. 2015; Haiquan et al. 2019). Wang et al. (2014) study the single SSP and propose two heuristic factors to evaluate the congestion degree of a TW and the overlapping degree of a task when inserting a new one. Wang et al. (2015) introduce in their solution approach a task-merging algorithm: if two or more targets are geographically adjacent, they tune the slewing angle and the observation duration of the sensor to enable an observation strip to cover them all. In particular, they try to merge an emergency task with an existing one. Haiquan et al. (2019) consider a multi-satellite scheduling problem with additional constraints on instruction transmission, satellite storage and data transmission.

A replanning process may be necessary even when a fault occurs in the satellite. Zhu et al. (2015) propose a dynamic fault-tolerant scheduling model, defining backup tasks for each primary task. Their algorithm also includes overlapping of backup tasks and a task merging mechanism. In Zhai et al. (2015) the robustness against unforeseeable events is associated with the number of tasks that can be rearranged in another time slot. The authors propose a NSGA-II to generate the initial schedule, and a heuristic algorithm with a task merging strategy to adapt the solution. Finally, Li and Li (2019) addressed the agile EOS proactive scheduling problem and include robustness against satellite failure or emergency task insertion by maximizing the slack time between two consecutive tasks, which is able to absorb some level of uncertainties without rescheduling. They solve the resulting bi-objective problem via a differential evolution algorithm with binary encoding representation of candidate solutions.

4.1.7 Cloud Coverage

The presence of clouds is one of the major causes of observation failure and the primal source of uncertainty when scheduling observations (Han et al. 2022). Cloud coverage not only substantially degrades imaging quality but also consumes resources, including the observation TW, satellite storage capacity, and energy. Such resource consumption consequently diminishes observation opportunities for other targets, underscoring the pivotal role of cloud forecasting in effective mission planning for EOSs. This problem is particularly critical for optical sensors in EOSs, which are unable to penetrate cloud cover.

Some early works deal with cloud coverage in a deterministic way. In Lin et al. (2005) cloud-covered TWs are computed from the weather forecast data of Center Weather Bureau. Consequently, cloud-free images for ROCSAT-II can be obtained preventing the observations within these windows (see Section 4.1.4 for further details). In the following years, however, the imaging SSP with cloud coverage was primarily studied as a stochastic problem. One of the first works dealing with uncertainties from weather condition was the one of Liao and Yang (2007), that, unlike following works, considers the probability of rain to formulate the success rate of a job at each time period. The authors cast the scheduling problem of FORMOSA-2 as a stochastic integer programming problem, employing a rolling horizon strategy that leverages Lagrangian relaxation and a heuristic algorithm for feasibility adjustment.

Later on, to address this variant of the imaging SSP researchers usually included some new parameters in their models representing cloud coverage. Most studies simplified it into two conditions: complete cloud occlusion and no cloud occlusion. Wang et al. (2016) embrace the uncertainty of cloud coverage by modeling cloud blocks as stochastic events, denoted by 0-1 stochastic variables and a probability value. They formulate the multi-satellite scheduling problem through a Chance Constraint Programming (CCP) model imposing a certain confidence level on the profit of the observations. The problem is then solved via a sample approximation method and a B&C algorithm, based on lazy constraint generation. Two years later, Wang et al. (2018) suggested to schedule each task in multiple orbits to increase the probability of successful observation. They proposed an exact algorithm in which each sub-problem is solved by path programming and three heuristics to solve the large-scale problems. A real-world case of disaster monitoring is provided, and all the proposed methodologies outperformed on average the current schedule. Moreover, the exact algorithm proves to be more efficient and more robust than the Liao and Yang (2007) algorithm, which schedules each task to at most one orbit. Wang et al. (2020) formulate a multiple EOS scheduling model considering the impact of clouds and propose a Branch-and-Price (B&P) algorithm based on a Dantzig–Wolfe decomposition. Furthermore, they discuss the impact of clouds on successful observations from different orbits in the case of joint probabilities (i.e., when probabilities of cloud coverage for each target are not considered different and independent), and establish a sample average approximation model.

Recent works allow for partial coverage considerations. In Wang et al. (2019) the limits of considering 0-1 observation profits under the impact of cloud coverage, which does not represent reality, is overcome. Here, a range for the actual observation profit is defined by the nominal and deviation values. The nominal value denotes the expectation observation profit which is determined by the original mission profit and the predicted situation of cloud coverage. The deviation value represents the deviation of actual profit compared to the nominal value, which depends on the accuracy of cloud coverage prediction. The authors establish a linearized robust scheduling model, with a budget for the deviations allowed, and propose a column-generation-based heuristic, which is hybridized with simulated annealing in Wang et al. (2021). Differently, Valicka et al. (2019) introduce two-stage and three-stage stochastic MILP models for the multi-SSP in which a set of scenarios is considered with different fraction of cloud coverage over the target. The profit for each scenario is an inverse function of cloud cover. In their stochastic approach, the scheduling is first produced over the complete set of scenarios representing cloud cover uncertainty, considering the related probability. Then, the realized profit is computed only after the uncertainty is solved and the scenario is realized. The stochastic models outperform the deterministic model applied to the expected cloud coverage scenario for both small and large scenario sets. Gu et al. (2022) propose a dynamic replanning scheme for multiple EOSs based on cloud forecasting. The approach involves a proactive scheduling based on a CCP model, in which the cloud occlusion is first formulated as a 0-1 stochastic event. To simplify the calculation of probability in CCP, a Monte Carlo simulation is adopted to create a set of sample scenarios. Then, a rolling horizon-based replanning algorithm considers cloud forecasting via a predictive recurrent neural network, which allows to consider partial coverage profit, and combines a rapid insertion method and an interval shrinking-based moving strategy. Finally, in Han et al. (2022) the authors started from the CCP model of Gu et al. (2022) and proposed an improved simulated annealing-based heuristic combining a fast insertion strategy for large-scale observation missions.

4.2 Communication Scheduling in EO

The communication between a satellite and a ground station is a fundamental activity for the daily management of a satellite. Indeed, satellites need to contact the ground stations for manoeuvrability instructions, status control, and uplinking of commands. Moreover, for the imaging satellites the downlink communication is fundamental to continue their activity. In the communication SSP the resource set of satellites need to connect with the ground station resources. To do so, only determined TWs are available, during which, generally, each satellite can communicate with a unique ground station and vice versa. The communication problem consists in associating with each satellite-ground station pair a TW to perform their task. Since the dimension of satellite constellations is increasing due to higher need for flexibility and robustness, while ground station networks are hardly expanded, the problem is harder to solve for the real case scenarios (Marinelli et al. 2011). The scheduling of all types of communication tasks, for a generic satellite, is addressed as Satellite Range Scheduling Problem (SRSP). The SRSP includes data downlink. Hence, in the following paragraph we will describe the main works published on SRSP. Then, we will delve into the download scheduling problem related to imaging satellites.

Satellite Range Scheduling Problem. The first formal analysis of SRSP was presented by Barbulescu et al. (2004) in the context of air force satellite control network (communication satellites). Then, Marinelli et al. (2011) proposed a time indexed ILP formulation aimed at maximizing the number of tasks completed on time. They employ a Lagrangian heuristic to solve the problem and test it on GALILEO constellation, a global satellite positioning and navigation system. To deal with the complexity of the problem, Luo et al. (2017) propose a pre-scheduling technique based on the analysis of flexibility of a request (i.e., the difficulty of its scheduling) and conflicts between satellites requests. Then, a rescheduling approach based on conflict resolution tries to insert unscheduled requests into the existing plan. Differently, Brown et al. (2018) assume the point of view of the ground stations and try to minimize the number of time periods that satellites are not tracked, considering their priority, in view of a fair allocation of tracking time. They propose a population-based local search including a conflict resolution approach and a track period extension to maximize the utilization of the ground stations, bounded through a Lagrangian relaxation of the MILP model. Du et al. (2019) address a multi-objective SRSP aiming at the minimization of failure rate and maximization of the load balance of ground stations. They propose a multi-objective evolutionary algorithm combined with a tabu search-based local search, to generate a memetic approach. They prove this combination improves the performance of several multi-objective approaches, such as NSGA-II. Finally, to simplify the problem Liu et al. (2019) considered as the resource set only the critical resources, i.e., ground stations requested by more than one satellite simultaneously. Therefore, they optimally assign non-critical resources during a space-reduction phase, and then solve the scheduling problem for the critical resources via a dynamic approach.

Download Scheduling Problem. The generation of effective download schedules is very important since image downlink often becomes the bottleneck in the efficiency of the whole system. Indeed, satellites have finite storage capacity and need to empty their memory before continuing to collect data. To do this, they dispose of a set of TWs available for the transmission of data to the Earth. Data transmission can follow two protocols: real-time transmission, requiring the satellite being within an available VTW while undertaking observation tasks, and record playback, that consists in storing data before transmission to the Earth.

The objective of the optimization problem is to maximize the global profit or quantity of the transmitted data, while respecting the process constraints. Additionally, some authors aim at minimizing the total tardiness, i.e., the total delay of all observing data from observation to transmission. Karapetyan et al. (2015) considered the optimization of the data transmission tardiness in the downlink scheduling problem for Canada's Earth observing satellite, RADARSAT-2, and proposed a schedule generation procedure that schedules urgent and regular requests in two consecutive steps, respecting task priorities. The authors compare the performance of four standard metaheuristics: GRASP, ejection chain, simulated annealing and tabu search.

In the same year, Spangelo et al. (2015) study the single-satellite multiple-ground stations download scheduling problem. They take into consideration the dynamics of energy consumption and data storage and propose a MILP model of the problem for linear dynamics. An iterative algorithm based on the MILP representation is then developed to solve the non-linear dynamics case. Later, Chen et al. (2020) included the consideration of data topics in the problem. A data topic is required by a particular user and contains a set of observation data units provided by different satellites. Every observation data topic has completeness and timeliness requirements, which are evaluated in the objective function thanks to specific reward functions. The full amount of reward is assigned only if all of the observation data belonging to one topic have been transmitted to the ground station before the expected time, otherwise the value of the observation data will be decaying sharply. To solve the problem, the authors proposed a hybrid scheduling algorithm, combining particle swarm optimization and a genetic algorithm. Liu et al. (2022) address the multi-satellite downlink scheduling problem considering waiting time through the minimization of latency costs. They propose a simulated annealing algorithm with a tabu list to assign the download requests to ground stations, and then solve the single station scheduling problem via greedy approaches based on arrival time considerations.

The previous works assume prior knowledge of the exact amount of new data generated by observations and stored. In new satellites systems, the execution of sophisticated compression algorithms makes the volume of data generated uncertain, since it depends on the imaged ground area and on the conditions over them. To cope with this problem, the maximum volumes could be assumed for all the tasks, leading to under-utilisation of resources. Maillard et al. (2016) presented an approach in which download scheduling is made on the ground via a squeaky wheel optimization algorithm, considering maximum volumes only for high-priority observations and expected volumes for low-priority ones. Then, a schedule adaptation is performed onboard, when most of the volumes are known, via repair heuristic procedures. This approach improves the performance of the pure ground scheduling and reduces the computational effort of a pure online scheduling.

Modern satellites dispose of a new capability for transmitting data in a more efficient way. Indeed, an original image can be split in several segments that can be transmitted independently and without following the capturing order. Chang et al. (2023) deal with this new aspect of the satellite image data download scheduling problem, and propose a bi-objective memetic algorithm to minimize transmission failure rate and improve the service-balance degree.

4.3 Integrated Scheduling in EO

The integrated scheduling problem considers at the same time imaging and download tasks scheduling. Indeed, the result of imaging scheduling has an effect on data transmission scheduling, since the download volume depends on the size of collected images, and data transmission scheduling influences the imaging scheduling and the available storage capacity in return. Therefore, simultaneous planning of imaging and communication tasks enables the generation of efficient schedules, providing an all-around perspective. An integrated approach is particularly necessary in the recent years, as the number of imaging requests is increasing.

Various authors address a real case study and solve the problem with heuristic methods. Bianchessi and Righini (2008) describe the optimization problem and all operational constraints related to the COSMO-SkyMed project for the observation of the Earth through a constellation of satellites. The aim of the scheduling problem is to synchronize the acquisition and the download operations in order to maximize the number of images taken and transmitted, in a long (16-days) and middle (4-days) horizon. Large area requests are taken into account but partial acquisition is not rewarded. They present a greedy constructive algorithm, enriched with look-ahead and backtracking capabilities. Later, Wang et al. (2011) studied the bi-objective integrated scheduling of Huanjing constellation (HJ-1A and HJ-1B), in which both the summed rewards for spot targets and the proportional reward for area targets must be maximized. They improve the performance of the algorithm of Bianchessi and Righini (2008) with a priority-based heuristic, and insert a check for conflict-avoidance and a download-as-needed policy. The article of Augenstein et al. (2016) presents a MILP model for a large constellation of EOSs, Terra Bella, to maximize the number of collected images while minimizing the undownlinked data onboard the satellites. To solve the problem the authors propose a sequential scheduler, with successive scheduling of downlinks and image collections, supported by a dynamic programming heuristic. Recently, Monmousseau (2021) presented a MILP model for the integrated SSP of Planet's Dove constellation, composed by thirty satellites. They compare the performance of the B&B algorithm used for MILP against the software used by Planet to process the available data, which exploits a simulated annealing algorithm to find a good solution. As expected, the MILP model performs better than Planet's software, providing solutions with higher utility value and lower consumption of the satellites' power.

Several other works have been published over the years, introducing new constraints into the problem or different solution approaches. Cho et al. (2018) propose a two-step MILP formulation to first solve the data download time intervals allocation problem, and then the imaging scheduling problem, by introducing the result of the previous step as a constraint. In their study the precedence condition between tasks is considered. An exact solution method was later presented by Hu et al. (2019), who developed a B&P algorithm for a multi-satellite integrated SSP. They divide the overall scheduling horizon into several time periods and then decompose the problem into a master problem and multiple pricing problems via Dantzig and Wolfe decomposition. They embed the column generation process into a B&B framework and then develop a heuristic to prune tree branches earlier. Waiming et al. (2019) propose a MILP model using a directed acyclic graph for determining candidate solution options. To solve the problem, they develop a two-phase genetic annealing method, where the genetic algorithm is used to explore new solutions and the simulated annealing algorithm improves global searching. Differently, Chang et al. (2021) aim to optimize the loss rate of data capturing and the energy consumption of multiple satellites within three different scenarios: separated scheduling of imaging and download, compromised scheduling (i.e., the imaging scheduling includes transmission constraints), and coordinated integrated scheduling. They design an adaptive bi-objective memetic algorithm, which integrates ALNS and NSGA-II, and compare its performance on the different frameworks. Finally, the transmission mode (real-time and record playback) was included for the first time by Zhang and Xing (2022) as a variable in the formulation of the integrated SSP. They propose an improved genetic algorithm with a novel idea of encoding and decoding, to match the specific request with the corresponding satellite-ground resources.

5 Outer Space Missions

The quest for knowledge about the universe has prompted humanity to develop technologies capable of exploring other planets, a crucial endeavor for understanding Earth's origins and predicting its future. Two key technologies, rovers and orbiters, play essential roles in this exploration. Rovers investigate planetary surfaces and materials, while orbiters (i.e., satellites) host several instruments onboard, among which cameras to perform observations from above. The images acquired are transmitted to ground centers for analysis, contributing to our understanding of celestial bodies and to the improvement of future missions.

Over the years, numerous missions have been planned to explore the Solar System. The first satellite to achieve a heliocentric orbit was the Soviet Luna 1 in 1959. In the same year, the probe Luna 3 acquired the first picture of the far side of the Moon. In 2003, the European Space Agency started a lunar mission mainly aimed at taking three-dimensional X-ray and infrared imagery of the lunar surface. Subsequently, several missions focused on the exploration of the Moon, as it is the closest celestial body to Earth, and Mars, considered the planet most similar to ours. At present, seven orbiters are surveying the red planet: Mars Odyssey, Mars Express, Mars Reconnaissance, MAVEN, Trace Gas, Hope Mars, and Tianwen-1. They are managed by different space agencies and contribute to the collection of information about Mars. Some other missions also focused on Venus, Jupiter, Saturn, and Mercury (see `https://www.planetary.org/space-missions` for a complete overview). Space missions are continuously developed and launched. NASA's exploration road-map sets future goals until 2033 and includes mission towards the Moon, Jupiter, Mars, Venus, and Titan (Williams 2024). Similarly, ESA is planning several future missions, as reported in Figure 8.

Planning the schedules of extraterrestrial orbiters is an even more challenging task than that

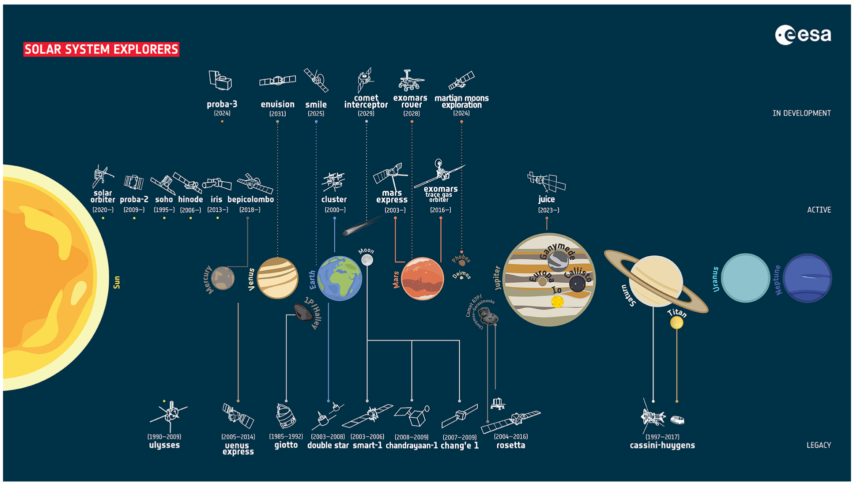

Figure 8: Solar System Explorers: Legacy, Active, and in Development (ESA 2023)

of EOS. Surprisingly, the study of extraterrestrial artificial satellites in the field of Operations Research is limited, with many current planning and scheduling procedures relying on common-sense or heuristic reasoning. While EOS studies provide some insights, they are not entirely applicable to space missions due to the vast differences in context. Outer space satellite scheduling necessitates long-term planning, as opposed to the daily planning of EOS. Additionally, it must account for various external conditions and limitations, such as available activity time and resources. Moreover, outer space spacecraft were launched years ago, using technology that may not be fully optimized, carrying inherent limitations.

All the studies in the field of outer space SSP refer to active or planned missions. The main application found in the literature is the Mars Express mission, launched in 2003 with the aim of observing the entire surface at high and super resolution, and also determining the structure of the sub-surface and the composition of the atmosphere (Orosei et al. 2015). In particular, many studies address the Mars Express mission in the field of Communication SSP (see Section 5.2). Moreover, some of the authors of this survey are currently working to an Imaging SSP applied to the radar sounder MARSIS (Mars Advanced Radar for Subsurface and Ionosphere Sounding), onboard the Mars Express orbiter (Delorme et al. 2024).

To the best of our knowledge, the pioneering introduction of an automatic planner and scheduler for mission management occurred in 1999, when NASA activated the Remote Agent Experiment (RAX) on the Deep Space One mission. The RAX Planner/Scheduler facilitated high-level goal-oriented commanding of the spacecraft, utilizing heuristic procedures to generate plans (Jónsson et al. 2000). This software demonstrated its capability to construct concurrent plans with over a hundred tasks, including thrust activities, communication, and imaging tasks. The software operated by taking a candidate plan as input and recursively extending it, considering the task to be scheduled and the associated constraints. Following this milestone, dedicated systems were subsequently developed to address the diverse scheduling needs of space missions, encompassing both early-stage mission scheduling and detailed planning of imaging and communication tasks. Most of these software tools integrate heuristic procedures with correction and visualization tools. Implementation of these software tools varied, with some deployed onboard the spacecraft itself and others residing in ground control centers for remote management. For the sake of coherence, only the latter will be mentioned below, with reference to the research work applied to them.

In the remaining part of this section, we will delve into a review of works centered around scheduling imaging tasks, communication tasks, or a combination of both in outer space context.

5.1 Imaging Scheduling in OS

The image selection and scheduling problem in the outer space field mainly refers to the coverage of large area targets (i.e., part or all of the surface of a planet). As in the Earth observation imaging SSP, the target is visible only in specific VTWs and the viewing ability of the camera allows to observe only a limited region below the satellite. Moreover, the satellite has very limited storage capacity, due to fewer possibilities to download data to ground stations. Hence, the imaging SSP in OS aims to optimally plan the acquisition tasks of a satellite for each orbit, usually in a long-time horizon, to maximize the coverage rate while respecting the resource capacity.

This problem has been addressed by Knight and Chien (2006) using squeaky wheel optimization. They introduced CLASP, a scheduler system that employs a gridded representation of regions and generates strips to represent observation opportunities. CLASP was utilized to evaluate maximum coverage for the first five flybys of Europa Clipper mission and the ten closest flybys for each target body of the JUpiter ICy moons Explorer (JUICE) by Troesch et al. (2017), and it was also prototyped as a tool for early-stage mission planning of the Mars Odyssey THEMIS instrument by Mclaren et al. (2011). In a recent study, Maillard et al. (2021) presented five new greedy algorithms to enhance the quality of schedules generated within CLASP's core.

In 2020, Paterna et al. (2020) approached the imaging scheduling problem as a multi-objective optimization problem and employed genetic algorithms to solve it. The proposed technique consists of two main stages: segmentation and selection. The inputs to the system include the total scheduling interval, and a description of the spacecraft's trajectory during its orbit around the target celestial body. The segmentation stage divides the time horizon into shorter acquisition intervals, using either a time-based or a target-based criterion. The output of the segmentation stage comprises a set of acquisition segments, characterized by metrics such as surface coverage, power consumption, and memory usage. These metrics are then utilized in the selection phase, where they are combined into suitable cost or fitness functions to evaluate the quality of the acquisition schedule. In this phase, the authors employed NSGA-II, a multi-objective variant of genetic algorithms. To demonstrate the effectiveness of their approach, they applied it to the operations of a radar sounder onboard JUICE during the phase called GCO-500 lasting 130 days.

5.2 Communication Scheduling in OS

The communication SSP in OS has received more attention than the imaging SSP, and has been mainly referred to Mars Express mission. The primary communication issue discussed in the literature is known as the Mars Express Memory Dumping Problem (MEX-MDP). In this scenario, the objective is to create a set of commands for downlinking data generated by the payload and stored in the onboard memory to Earth, while accounting for constraints such as limited onboard memory, a restricted number of downlink sessions, and varying data transmission rates during communication TWs. The plans need to be robust and minimize data loss due to memory overwriting or communication issues.

Oddi et al. (2002) extensively described MEX-MDP with preemption allowed and provided its formal mathematical representation. They proposed a two-level greedy heuristic guided by either packet store priority or data volume, along with a tabu search procedure. They tested their approaches on a set of instances generated from few realistic initial data and classified in four levels of complexity. The instances contain a number of observation requests ranging from 12 to 96, corresponding to three days of satellite works. In subsequent years, the authors proposed improvements to the solution methods, introducing iterative random sampling (Oddi et al. 2005), which increased the performances up to 70% over the greedy heuristic for the hard instances, and a max-flow formulation (Oddi and Policella 2007) solved using the Edmond-Karp implementation of the Ford-Fulkerson method. They also developed an iterative level procedure to enhance solution robustness by considering the utilization of onboard memory. This approach is implemented within the MEXAR2 tool, currently used by the planning team of Mars Express. Righini and Tresoldi (2009) developed a linear programming model for MEX-MDP and provided rules for producing balanced solutions. In the extended problem, they incorporated four objective functions: the minimization of data losses, residual data, and number of dump operations, and the maximization of the schedule's robustness. The first two objectives are hierarchically prioritized, while a multi-objective analysis is performed for the latter two. They tested their algorithms on real data from which they generated 23 instances with planning horizons ranging from 3 to 28 days. Their approach reduced both the number of transmissions and the saturation level compared to plans generated by MEXAR2 for all instances and also reduced the computational time by up to 98%.

A generalization of MEX-MDP is the overlapping memory dumping problem, where data collection and downlink activities can occur concurrently. This problem was discussed in relation to the Rosetta comet rendezvous mission conducted by ESA. For Rosetta operations, the behavior of each downlink can be controlled by setting priorities or limiting duration. Rabideau et al. (2017) described two heuristics implemented in the DALLOC tool, which utilizes buffer volume profiles to assign priorities to data buffer emptying, and compare them to a maximum flow solution adapted from Oddi and Policella (2007). They tested their heuristics on real mission data instances of about three months and a half, with 324 downlink TWs and over 40,000 data production events, and proved they can provide faster and more robust solutions compared to the max-flow approach, which in return performs better with nonoverlapping downlinks. Hébrard et al. (2022) subsequently proposed an improvement to the best heuristic implemented by Rabideau et al. (2017), employing a randomized repair strategy and testing it on a large synthetic data set.

Similar to the downlink, the uplink scheduling problem aims to generate a feasible schedule for transmitting telecommands from the ground segment to the space segment. Due to the considerable distance between Mars and the Earth, the solution needs to be robust as repair operations can be time-consuming or even impossible. Robustness can be enhanced, for example, by requiring confirmation or retaining a backup window whenever feasible. Cesta et al. (2008) developed a two-step greedy algorithm within the RAXEM tool used for the Mars Express mission. In this algorithm, files are sorted based on the execution time of their first telecommand. Thanks to the developed software, the work-hours involved in planning the uplink for a week has been reduced by a factor of 4-6 on average. Donati et al. (2011) developed a greedy algorithm enriched with look-ahead and backtracking capabilities. This algorithm aims to find an ideal solution initially, and if not possible, it adjusts by making compromises. In addition to maximizing the number of telecommands transmitted and ensuring robustness, the scheduling algorithm can be configured with different settings to optimize secondary aspects. The authors compared their solutions with those generated by RAXEM to evaluate their effectiveness on a not tightly constrained set of eleven instances coming from real data, with a number of uplink files ranging from 25 to 114, containing from 220 to 270 telecommands each. Their algorithms resulted in solutions as robust as RAXEM's, but faster for most instances.

5.3 Integrated Scheduling in OS

The literature on SSPs in outer space also includes attempts to address the integrated scheduling problem, which involves the simultaneous consideration of imaging and communication tasks. In 2012 a challenge was published for the International Competition on Knowledge Engineering for Planning and Scheduling by Fratini and Policella (2012), focusing on the Mars Express domain. The challenge aimed to determine a set of slewing actions that would generate time slots for the spacecraft's main activities (observation, communication, and maintenance). Furthermore, it involved creating commands for downlinking data to Earth and uploading command files for the chosen experiment from Earth to the satellite. The problem's input comprised a set of files providing information on the observations to be performed, as well as additional details regarding the spacecraft's orbits and the availability of ground stations for communication. One of the solutions, proposed by Kolombo et al. (2013), employed a simple method based on the incremental addition of operations to a partial schedule, with adjustments made to the time allocation of already scheduled operations to fit the newly added ones. The algorithm prioritized scheduling imaging and maintenance requests using a depth-first search approach, followed by scheduling the related communication actions.

As part of a general effort promoted by ESA to support the integrated mission planning by means of software tools, a planning system was developed for the long-term planning of Mars Express mission, MrSPOCK (Cesta et al. 2011). The long term plan level involves decisions about slot assignments for the main activities of the spacecraft (i.e., science, communication, and maintenance) such that all the operative constraints are satisfied. MrSPOCK exploits a genetic algorithm led by a multi-objective function.

6 Conclusions and Future Research Directions

The efficient management of space missions is a critical challenge for the astrophysics community, given the limited resources available and the many physical and environmental constraints. Within this challenge, Satellite Scheduling Problems (SSPs) have emerged as a prominent and extensively studied class of optimization problems in the field of Operations Research, focusing on the optimal planning of tasks executed by observation satellites. While Earth observation systems have received considerable attention, with milestones set by the Spot5 problem and the ROADEF Challenge 2003, outer space satellites have been comparatively less studied.

This survey extensively reviews over a hundred papers mostly spanning the last three decades, offering a comprehensive outlook on both Earth observation and outer space missions. Recognizing the diverse variants encompassed by the SSP and its varied application contexts, an application-centric perspective is adopted, thus facilitating the navigation of this expansive field for new researchers. We provided a detailed classification of the literature based on three primary problem classes: Imaging, Communication, and Integrated. Within each problem class, we have delineated the principal contributions and techniques developed over the years to cope with the difficulty of the problem. Our analysis reveals a prevalence of heuristic or hybrid methodologies, with a scarcity of exact approaches. Notably, numerous studies based their investigations on real-world test cases and data involving both existing satellites and targets, emphasizing the practical relevance of the research.

In the area of Earth observation studies, imaging and communication scheduling are well-established research fields, which have been addressed in different variants and through several approaches. When studied separately, both imaging and communication SSP make simplified assumptions on their counterpart. However, the integration of imaging and communication decisions is relevant for real applications and the development of effective algorithms to face the integrated SSP should be a focus in future research. Other interesting research directions may include multi-objective optimization, investigating techniques that balance conflicting objectives, such as maximizing observation coverage, minimizing costs, and optimizing energy consumption. Multi-objective optimization can provide a more comprehensive understanding of trade-offs and enable decision-makers to choose satisfying solutions. Pursuing the same idea, more attention should be devoted to the fair allocation of resources between the several users of the satellites. Indeed, the sharing of a satellite, or an instrument onboard it, is a very common practice and the fairness in the planning process is a realistic constraint (and objective), which can preclude the feasibility of a classic maximum-profit schedule. Nevertheless, despite its relevance, few works have studied this optimization problem in the SSP domain so far. Finally, addressing the dynamism of the SSP and the fault tolerance of satellite scheduling systems emerges as a critical focal point for improvement. Future research should aim to develop improved algorithms capable of dynamic adjustment in response to unforeseen events or changes in mission requirements, as well as to unexpected disruptions, mitigating the impact of failures.

Turning our attention to outer space missions, the research landscape presents significant opportunities for the development of novel methodologies, as little research has been applied to this domain. Moreover, several space missions are currently active (see, e.g., Mars Express, Chicarro et al. 2004), just started (see, e.g., JUICE launched on 14 April 2023, Grasset et al. 2013), or are planned for the coming years (see, e.g., Uranus Orbiter planned to be launched in the late 2030s, Girija 2023), providing an interesting and wide range of application scenarios. New methodologies can enhance existing scheduling software, which often rely on basic heuristic strategies or provide only visual support for human decision-making processes. Specifically, applying insights from Earth observation to outer space missions, particularly in addressing challenges such as environmental impacts and coverage of large areas, represents a promising avenue for future research.

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Appendix. Acronyms

ALNS	Adaptive Large Neighborhood Search
AS	Agile Satellite
B&B	Branch-and-Bound
B&C	Branch-and-Cut
B&P	Branch-and-Price
BRKGA	Biased Random-Key Genetic Algorithm
CCP	Chance Constraint Programming
CNES	National Center for Space Studies
CS	Conventional Satellite
CSP	Constraint Satisfaction Programming
EO	Earth Observation
EOS	Earth Observation Satellite
ESA	European Space Agency
GRASP	Greedy Randomised Adaptive Search Procedure
ILP	Integer Linear Programming
JUICE	JUpiter ICy moons Explorer
MARSIS	Mars Advanced Radar for Subsurface and Ionosphere Sounding
MEX-MDP	Mars Express Memory Dumping Problem
MILP	Mixed Integer Linear Programming
MS	Multiple Satellites
NASA	National Aeronautics and Space Administration
NSGA	Non-dominated Sorting Genetic Algorithm
OECD	Organization for Economic Cooperation and Development
OS	Outer Space
RAX	Remote Agent Experiment
ROADEF	French Operations Research & Decision Support Society
SS	Single Satellite
SSP	Satellite Scheduling Problem
TW	Time Window
VTW	Visible Time Window

References

[1] C Ahara and J Rossbach. The scheduling problem in satellite communications systems. *IEEE Transactions on Communication Technology*, 15(3):364–371, 1967.

[2] S Augenstein, A Estanislao, E Guere, and S Blaes. Optimal scheduling of a constellation of Earth-imaging satellites, for maximal data throughput and efficient human management. In *International Conference on Automated Planning and Scheduling*, volume 26, pages 345–352, London, UK, 2016.

[3] L Barbulescu, JP Watson, LD Whitley, and AE Howe. Scheduling space–ground communications for the air force satellite control network. *Journal of Scheduling*, 7:7–34, 2004.

[4] A Barea, H Urrutxua, and L Cadarso. Large-scale object selection and trajectory planning for multi-target space debris removal missions. *Acta Astronautica*, 170:289–301, 2020.

[5] M Barkaoui and J Berger. A new hybrid genetic algorithm for the collection scheduling problem for a satellite constellation. *Journal of the Operational Research Society*, 71(9): 1390–1410, 2019.

[6] T Benoist and B Rottembourg. Upper bounds for revenue maximization in a satellite scheduling problem. *4OR*, 2(3):235–249, 2004.

[7] E Bensana, G Verfaillie, JC Agnese, N Bataille, and D Blumstein. Exact & inexact methods for daily management of Earth observation satellite. In *Space Mission Operations and Ground Data Systems-SpaceOps' 96*, volume 394, page 507, Munich, Germany, 1996.

[8] E Bensana, M Lemaitre, and G Verfaillie. Earth observation satellite management. *Constraints*, 4(3):293–299, 1999.

[9] J Berger, N Lo, and M Barkaoui. QUEST-A new quadratic decision model for the multi-satellite scheduling problem. *Computers & Operations Research*, 115:104822, 2020.

[10] N Bianchessi and G Righini. Planning and scheduling algorithms for the COSMO-SkyMed constellation. *Aerospace Science and Technology*, 12(7):535–544, 2008.

[11] N Bianchessi, JF Cordeau, J Desrosiers, G Laporte, and V Raymond. A heuristic for the multi-satellite, multi-orbit and multi-user management of Earth observation satellites. *European Journal of Operational Research*, 177(2):750–762, 2007.

[12] P Bourret, S Goodall, and M Samuelides. Optimal scheduling by competitive activation: application to the satellite antennae scheduling problem. In *International 1989 Joint Conference on Neural Networks*, volume 1, pages 565–572, Washington DC, USA, 1989.

[13] N Brown, B Arguello, L Nozick, and N Xu. A heuristic approach to satellite range scheduling with bounds using lagrangian relaxation. *IEEE Systems Journal*, 12(4):3828–3836, 2018.

[14] M Cerf. Multiple space debris collecting mission-debris selection and trajectory optimization. *Journal of Optimization Theory and Applications*, 156(3):761–796, 2013.

[15] A Cesta, G Cortellessa, M Denis, A Donati, S Fratini, A Oddi, N Policella, E Rabenau, and J Schulster. RAXEM–a support tool to plan uplink activities for Mars Express–a timeline based approch. In *Proceedings of the 9th International Symposium on Artificial Intelligence, Robotics and Automation in Space*, Hollywood, USA, 2008.

[16] A Cesta, G Cortellessa, S Fratini, and A Oddi. MrSPOCK—steps in developing an end-to-end space application. *Computational Intelligence*, 27(1):83–102, 2011.

[17] 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*, 66(11):2597–2609, 2020.

[18] Z Chang, Z Zhou, L Xing, and F Yao. Integrated scheduling problem for Earth observation satellites based on three modeling frameworks: an adaptive bi-objective memetic algorithm. *Memetic Computing*, 13(2):203–226, 2021.

[19] Z Chang, AP Punnen, Z Zhou, and S Cheng. Solving dynamic satellite image data downlink scheduling problem via an adaptive bi-objective optimization algorithm. *Computers & Operations Research*, 160:106388, 2023.

[20] H Chen, B Zhai, J Wu, C Du, and J Li. A satellite observation data transmission scheduling algorithm oriented to data topics. *International Journal of Aerospace Engineering*, 2020: 2180674, 2020.

[21] H Chen, S Peng, C Du, and J Li. *Earth Observation Satellites: Task Planning and Scheduling*. Springer, Singapore, 2023.

[22] X Chen, G Reinelt, G Dai, and M Wang. Priority-based and conflict-avoidance heuristics for multi-satellite scheduling. *Applied Soft Computing*, 69:177–191, 2018.

[23] X Chen, G Reinelt, G Dai, and A Spitz. A mixed integer linear programming model for multi-satellite scheduling. *European Journal of Operational Research*, 275(2):694–707, 2019.

[24] A Chicarro, P Martin, and R Trautner. The Mars Express mission: an overview. In A Wilson, editor, *Mars Express: the scientific payload*, volume 1240, pages 3–13. ESA Publications Division, 2004.

[25] D Cho, J Kim, H Choi, and J Ahn. Optimization-based scheduling method for agile Earth-observing satellite constellation. *Journal of Aerospace Information Systems*, 15(11): 611–626, 2018.

[26] TA Ciriani, G Fasano, S Gliozzi, and R Tadei. *Operations Research in Space and Air*, volume 79 of *Applied Optimization*. Springer, New York, 2003.

[27] RC Coffin. Discovery planetary mission operations concepts. *Acta Astronautica*, 35:493–500, 1995.

[28] JF Cordeau and G Laporte. Maximizing the value of an Earth observation satellite orbit. *Journal of the Operational Research Society*, 56(8):962–968, 2005.

[29] AP Cracknell and CA Varotsos. Fifty years after the first artificial satellite: from Sputnik 1 to ENVISAT. *International Journal of Remote Sensing*, 28(10):2071–2072, 2007.

[30] J Cui and X Zhang. Application of a multi-satellite dynamic mission scheduling model based on mission priority in emergency response. *Sensors*, 19(6):1430, 2019.

[31] K Cui, J Xiang, and Y Zhang. Mission planning optimization of video satellite for ground multi-object staring imaging. *Advances in Space Research*, 61(6):1476–1489, 2018.

[32] K Deb and H Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation*, 18(4):577–601, 2014.

[33] K Deb, A Pratap, S Agarwal, and T Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.

[34] M Delorme, B Ferrari, M Iori, M Lippi, and R Orosei. MARSIS observation scheduling problem: a two-stage approach combining machine learning and optimization. Technical report, University of Modena and Reggio Emilia, 2024.

[35] A Donati, N Policella, E Rabenau, G Righini, and E Tresoldi. An automatic planning and scheduling system for the Mars Express uplink scheduling problem. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 41(6):942–954, 2011.

[36] Y Du, L Xing, J Zhang, Y Chen, and Y He. MOEA based memetic algorithms for multi-objective satellite range scheduling problem. *Swarm and Evolutionary Computation*, 50: 100576, 2019.

[37] ESA. Developed Earth observation missions. Available at: https://www.esa.int/ESA_Multimedia/Images/2019/05/ESA-developed_Earth_observation_missions, 2023. Last Accessed: 8 February 2024.

[38] ESA. ESA's science fleet of Solar System explorers. Available at: https://www.esa.int/ESA_Multimedia/Images/2019/02/ESA_s_science_fleet_of_Solar_System_explorers, 2023. Last Accessed: 8 February 2024.

[39] G Fasano and JD Pintér. *Modeling and Optimization in Space Engineering*, volume 73 of *Springer Optimization and Its Applications (SOIA)*. Springer, New York, 2013.

[40] G Fasano and JD Pintér. *Modeling and Optimization in Space Engineering: State of the Art and New Challenges*, volume 144 of *Springer Optimization and Its Applications (SOIA)*. Springer, Switzerland, 2019.

[41] G Fasano and JD Pintér. *Modeling and Optimization in Space Engineering: New Concepts and Approaches*, volume 200 of *Springer Optimization and Its Applications (SOIA)*. Springer, Switzerland, 2023.

[42] S Fratini and N Policella. ICKEPS 2012 challenge domain: Planning operations on the Mars Express mission. In *22nd International Conference on Automated Planning and Scheduling (ICAPS)*, Sao Paulo, Brazil, 2012.

[43] V Gabrel and C Murat. Mathematical programming for Earth observation satellite mission planning. In TA Ciriani, G Fasano, S Gliozzi, and R Tadei, editors, *Operations Research in Space and Air*, pages 103–122. Springer, 2003.

[44] 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(3):533–542, 2002.

[45] V Gabrel, A Moulet, C Murat, and VT Paschos. A new single model and derived algorithms for the satellite shot planning problem using graph theory concepts. *Annals of Operations Research*, 69:115–134, 1997.

[46] AP Girija. A flagship-class Uranus orbiter and probe mission concept using aerocapture. *Acta Astronautica*, 202:104–118, 2023.

[47] A Globus, J Crawford, J Lohn, and A Pryor. A comparison of techniques for scheduling Earth observing satellites. In *AAAI Conference on Artificial Intelligence*, pages 836–843, 2004.

[48] A Granz and Y Gao. SS/TDMA scheduling for satellite clusters. *IEEE Transactions on Communications*, 40(3):597–603, 1992.

[49] O Grasset, MK Dougherty, A Coustenis, EJ Bunce, C Erd, D Titov, M Blanc, A Coates, P Drossart, LN Fletcher, et al. JUpiter ICy moons Explorer (JUICE): An ESA mission to orbit Ganymede and to characterise the Jupiter system. *Planetary and Space Science*, 78: 1–21, 2013.

[50] International Space Exploration Coordination Group. The Global Exploration Roadmap. Available at: https://www.nasa.gov/wp-content/uploads/2015/01/ger_2018_small_mobile.pdf, 2018. Last Accessed: 8 February 2024.

[51] Y Gu, C Han, Y Chen, S Liu, and X Wang. Large region targets observation scheduling by multiple satellites using resampling particle swarm optimization. *IEEE Transactions on Aerospace and Electronic Systems*, 59(2):1800–1815, 2022.

[52] Y Gu, C Han, Y Chen, and WW Xing. Mission replanning for multiple agile Earth observation satellites based on cloud coverage forecasting. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 15:594–608, 2022.

[53] D Habet, M Vasquez, and Y Vimont. Bounding the optimum for the problem of scheduling the photographs of an agile Earth observing satellite. *Computational Optimization and Applications*, 47(2):307–333, 2010.

[54] S Haiquan, X Wei, H Xiaoxuan, and X Chongyan. Earth observation satellite scheduling for emergency tasks. *Journal of Systems Engineering and Electronics*, 30(5):931–945, 2019.

[55] C Han, Y Gu, G Wu, and X Wang. Simulated annealing-based heuristic for multiple agile satellites scheduling under cloud coverage uncertainty. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 53(5):2863–2874, 2022.

[56] L He, X Liu, G Laporte, Y Chen, and Y Chen. An improved adaptive large neighborhood search algorithm for multiple agile satellites scheduling. *Computers & Operations Research*, 100:12–25, 2018.

[57] E Hébrard, C Artigues, P Lopez, A Lusson, SA Chien, A Maillard, and GR Rabideau. An efficient approach to data transfer scheduling for long range space exploration. In *IJCAI-ECAI 2022, The 31st International Joint Conference on Artificial Intelligence*, pages 4635–4641, 2022.

[58] A Herrmann and H Schaub. Reinforcement learning for the agile Earth-observing satellite scheduling problem. *IEEE Transactions on Aerospace and Electronic Systems*, 59(5):5235–5247, 2023.

[59] Q Hu, J Xie, and X Liu. Trajectory optimization for accompanying satellite obstacle avoidance. *Aerospace Science and Technology*, 82:220–233, 2018.

[60] X Hu, W Zhu, B An, P Jin, and W Xia. A branch and price algorithm for EOS constellation imaging and downloading integrated scheduling problem. *Computers & Operations Research*, 104:74–89, 2019.

[61] T Inukai. An efficient SS/TDMA time slot assignment algorithm. *IEEE Transactions on Communications*, 27(10):1449–1455, 1979.

[62] AWH Ip, F Xhafa, J Dong, and M Gao. An overview of optimization and resolution methods in satellite scheduling and spacecraft operation: description, modeling, and application. *IoT and Spacecraft Informatics*, pages 157–217, 2022.

[63] J Jang, J Choi, HJ Bae, and IC Choi. Image collection planning for Korea multi-purpose SATellite-2. *European Journal of Operational Research*, 230(1):190–199, 2013.

[64] AK Jónsson, PH Morris, N Muscettola, K Rajan, and BD Smith. Planning in interplanetary space: Theory and practice. In *Proceedings of the Fifth International Conference on Artificial Intelligence Planning Systems*, pages 177–186, Breckenridge CO, USA, 2000.

[65] DE Joslin and DP Clements. Squeaky wheel optimization. *Journal of Artificial Intelligence Research*, 10:353–373, 1999.

[66] D Karapetyan, SM Minic, KT Malladi, and AP Punnen. Satellite downlink scheduling problem: A case study. *Omega*, 53:115–123, 2015.

[67] R Knight and S Chien. Producing large observation campaigns using compressed problem representations. In *International Workshop on Planning and Scheduling for Space (IWPSS)*, Space Telescope Science Institute, Maryland, USA, 2006.

[68] M Kolombo, M Pecka, and R Barták. An ad-hoc planner for the Mars Express mission. In *Proceedings of the 8th International Workshop on Planning and Scheduling for Space (IWPSS)*, California, USA, 2013.

[69] GD Krebs. KH-11 / Kennen / Crystal. Available at: https://space.skyrocket.de/doc_sdat/kh-11.htm. Last Accessed: 8 February 2024.

[70] EJ Kuipers. An algorithm for selecting and timetabling requests for an Earth observation satellite. *Bulletin de la Société Française de Recherche Opérationnelle et d'Aide à la Décision*, pages 7–10, 2003.

[71] M Lemaître, G Verfaillie, F Jouhaud, JM Lachiver, and N Bataille. Selecting and scheduling observations of agile satellites. *Aerospace Science and Technology*, 6(5):367–381, 2002.

[72] M Lemaître, G Verfaillie, H Fargier, J Lang, N Bataille, and JM Lachiver. Equitable allocation of Earth observing satellites resources. In *Proceedings of the 5th ONERA-DLR Aerospace Symposium*, Toulouse, France, 2003.

[73] G Li, C Chen, F Yao, R He, and Y Chen. Hybrid differential evolution optimisation for Earth observation satellite scheduling with time-dependent earliness-tardiness penalties. *Mathematical Problems in Engineering*, pages 1–10, 2017.

[74] L Li, H Chen, J Li, N Jing, and M Emmerich. Preference-based evolutionary many-objective optimization for agile satellite mission planning. *IEEE Access*, 6:40963–40978, 2018.

[75] S Li, Q Yu, and H Ding. Reviews and prospects in satellite range scheduling problem. *Autonomous Intelligent Systems*, 3(1):9, 2023.

[76] Z Li and X Li. A multi-objective binary-encoding differential evolution algorithm for proactive scheduling of agile Earth observation satellites. *Advances in Space Research*, 63 (10):3258–3269, 2019.

[77] DY Liao and YT Yang. Imaging order scheduling of an Earth observation satellite. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37 (5):794–802, 2007.

[78] W Lin, D Liao, C Liu, and Y Lee. Daily imaging scheduling of an Earth observation satellite. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 35(2):213–223, 2005.

[79] 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*, 86:41–53, 2017.

[80] Y Liu, S Zhang, and H Hu. A simulated annealing algorithm with tabu list for the multi-satellite downlink schedule problem considering waiting time. *Aerospace*, 9(5):235, 2022.

[81] Z Liu, Z Feng, and Z Ren. Route-reduction-based dynamic programming for large-scale satellite range scheduling problem. *Engineering Optimization*, 51(11):1944–1964, 2019.

[82] Z Lu, X Shen, D Li, Y Chen, and D Li. A mission planning modeling method of multi-point target imaging within a single pass for super-agile Earth observation satellite. *IEEE Systems Journal*, 16(2):1921–1932, 2021.

[83] K Luo. A hybrid binary artificial bee colony algorithm for the satellite photograph scheduling problem. *Engineering Optimization*, 52(8):1421–1440, 2020.

[84] K Luo, H Wang, Y Li, and Q Li. High-performance technique for satellite range scheduling. *Computers & Operations Research*, 85:12–21, 2017.

[85] A Maillard, G Verfaillie, C Pralet, J Jaubert, I Sebbag, F Fontanari, and J Lhermitte. Adaptable data download schedules for agile Earth-observing satellites. *Journal of Aerospace Information Systems*, 13(3):280–300, 2016.

[86] A Maillard, S Chien, and C Wells. Planning the coverage of solar system bodies under geometric constraints. *Journal of Aerospace Information Systems*, 18(5):289–306, 2021.

[87] MAA Mansour and MM Dessouky. A genetic algorithm approach for solving the daily photograph selection problem of the Spot5 satellite. *Computers & Industrial Engineering*, 58(3):509–520, 2010.

[88] F Marinelli, S Nocella, F Rossi, and S Smriglio. A lagrangian heuristic for satellite range scheduling with resource constraints. *Computers & Operations Research*, 38(11):1572–1583, 2011.

[89] D Mclaren, G Rabideau, S Chien, R Knight, S Anwar, G Mehall, and P Christensen. Scheduling results for the THEMIS observation scheduling tool. In *7th International Workshop on Planning and Scheduling for Space (IWPSS)*, Darmstadt, Germany, 2011.

[90] S Mitrovic-Minic, D Thomson, J Berger, and J Secker. Collection planning and scheduling for multiple heterogeneous satellite missions: Survey, optimization problem, and mathematical programming formulation. In *Modeling and Optimization in Space Engineering*, pages 271–305. Springer, 2019.

[91] P Monmousseau. Scheduling of a constellation of satellites: Creating a mixed-integer linear model. *Journal of Optimization Theory and Applications*, 191(2):846–873, 2021.

[92] X Niu, H Tang, and L Wu. Satellite scheduling of large areal tasks for rapid response to natural disaster using a multi-objective genetic algorithm. *International journal of disaster risk reduction*, 28:813–825, 2018.

[93] A Oddi and N Policella. Improving robustness of spacecraft downlink schedules. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37 (5):887–896, 2007.

[94] A Oddi, A Cesta, N Policella, and G Cortellessa. Scheduling downlink operations in Mars Express. In *Proceedings of the 3rd International NASA Workshop on Planning and Scheduling for Space*, Houston, Texas, 2002.

[95] A Oddi, N Policella, A Cesta, and G Cortellessa. Constraint-based random search for solving spacecraft downlink scheduling problems. In *Multidisciplinary Scheduling: Theory and Applications*, pages 133–160. Springer, 2005.

[96] OECD. *The Space economy in figures: how space contributes to the global economy*. OECD Publishing, Paris, 2019. Accessible at: https://www.oecd-ilibrary.org/content/publication/c5996201-en.

[97] OECD. *OECD Handbook on Measuring the Space Economy, 2nd Edition*. OECD Publishing, Paris, 2022. Accessible at: https://www.oecd-ilibrary.org/content/publication/8bfef437-en.

[98] R Orosei, RL Jordan, DD Morgan, M Cartacci, A Cicchetti, F Duru, DA Gurnett, E Heggy, DL Kirchner, R Noschese, et al. Mars advanced radar for subsurface and ionospheric sounding (MARSIS) after nine years of operation: A summary. *Planetary and Space Science*, 112:98–114, 2015.

[99] R Orosei, SE Lauro, E Pettinelli, A Cicchetti, M Coradini, B Cosciotti, F Di Paolo, E Flamini, E Mattei, M Pajola, et al. Radar evidence of subglacial liquid water on Mars. *Science*, 361(6401):490–493, 2018.

[100] S Paterna, M Santoni, and L Bruzzone. An approach based on multiobjective genetic algorithms to schedule observations in planetary remote sensing missions. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13:4714–4727, 2020.

[101] G Peng, R Dewil, C Verbeeck, A Gunawan, L Xing, and P Vansteenwegen. Agile Earth observation satellite scheduling: An orienteering problem with time-dependent profits and travel times. *Computers & Operations Research*, 111:84–98, 2019.

[102] G Peng, G Song, Y He, J Yu, S Xiang, L Xing, and P Vansteenwegen. Solving the agile Earth observation satellite scheduling problem with time-dependent transition times. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 52(3):1614–1625, 2020.

[103] G Peng, G Song, L Xing, A Gunawan, and P Vansteenwegen. An exact algorithm for agile Earth observation satellite scheduling with time-dependent profits. *Computers & Operations Research*, 120:104946, 2020.

[104] F Perea, R Vazquez, and J Galan-Viogue. Swath-acquisition planning in multiple-satellite missions: An exact and heuristic approach. *IEEE Transactions on Aerospace and Electronic Systems*, 51(3):1717–1725, 2015.

[105] C Prins. An overview of scheduling problems arising in satellite communications. *Journal of the Operational Research Society*, 45(6):611–623, 1994.

[106] D Qiu, C He, J Liu, and M Ma. A dynamic scheduling method of Earth-observing satellites by employing rolling horizon strategy. *The Scientific World Journal*, 2013:304047, 2013.

[107] G Rabideau, S Chien, M Galer, F Nespoli, and M Costa. Managing spacecraft memory buffers with concurrent data collection and downlink. *Journal of Aerospace Information Systems*, 14(12):637–651, 2017.

[108] CC Ribeiro, M Minoux, and MC Penna. An optimal column-generation-with-ranking algorithm for very large scale set partitioning problems in traffic assignment. *European Journal of Operational Research*, 41(2):232–239, 1989.

[109] GM Ribeiro, MF Constantino, and LAN Lorena. Strong formulation for the Spot5 daily photograph scheduling problem. *Journal of combinatorial optimization*, 20(4):385–398, 2010.

[110] G Righini and M Salani. Decremental state space relaxation strategies and initialization heuristics for solving the orienteering problem with time windows with dynamic programming. *Computers & Operations Research*, 36(4):1191–1203, 2009.

[111] G Righini and E Tresoldi. A mathematical programming solution to the Mars Express memory dumping problem. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 40(3):268–277, 2009.

[112] T Schetter, M Campbell, and D Surka. Multiple agent-based autonomy for satellite constellations. *Artificial Intelligence*, 145(1-2):147–180, 2003.

[113] S Spangelo, J Cutler, K Gilson, and A Cohn. Optimization-based scheduling for the single-satellite, multi-ground station communication problem. *Computers & Operations Research*, 57:1–16, 2015.

[114] ZG Sun and HF Teng. Optimal layout design of a satellite module. *Engineering Optimization*, 35(5):513–529, 2003.

[115] P Tangpattanakul, N Jozefowiez, and P Lopez. Multi-objective optimization for selecting and scheduling observations by agile Earth observing satellites. In *Proceedings of International Conference on Parallel Problem Solving from Nature*, pages 112–121, Taormina, Italy, 2012. Springer.

[116] P Tangpattanakul, N Jozefowiez, and P Lopez. A multi-objective local search heuristic for scheduling Earth observations taken by an agile satellite. *European Journal of Operational Research*, 245(2):542–554, 2015.

[117] M Troesch, S Chien, and E Ferguson. Using automated scheduling to assess coverage for europa clipper and jupiter icy moons explorer. In *International Workshop on Planning and Scheduling for Space (IWPSS)*, Pittsburgh, CA, USA, 2017.

[118] J Uri. 90 years of our changing views of Earth. Available at: https://www.nasa.gov/history/90-years-of-our-changing-views-of-earth/, 2020. Last Accessed: 8 February 2024.

[119] CG Valicka, D Garcia, A Staid, JP Watson, G Hackebeil, S Rathinam, and L Ntaimo. Mixed-integer programming models for optimal constellation scheduling given cloud cover uncertainty. *European Journal of Operational Research*, 275(2):431–445, 2019.

[120] M Vasquez and JK Hao. A "logic-constrained" knapsack formulation and a tabu algorithm for the daily photograph scheduling of an Earth observation satellite. *Computational optimization and applications*, 20(2):137–157, 2001.

[121] M Vasquez and JK Hao. Upper bounds for the Spot5 daily photograph scheduling problem. *Journal of Combinatorial Optimization*, 7(1):87–103, 2003.

[122] BR Vatti. A generic solution to polygon clipping. *Communications of the ACM*, 35(7):56–63, 1992.

[123] G Verfaillie, M Lemaître, and T Schiex. Russian doll search for solving constraint optimization problems. volume 1, pages 181–187, Portland, Oregon, 1996.

[124] G Verfaillie, M Lemaître, N Bataille, and JM Lachiver. Management of the mission of Earth observation satellites Challenge description. *Technical report*, 2002.

[125] Z Waiming, H Xiaoxuan, X Wei, and J Peng. A two-phase genetic annealing method for integrated Earth observation satellite scheduling problems. *Soft Computing*, 23(1):181–196, 2019.

[126] J Wang, X Zhu, LT Yang, J Zhu, and M Ma. Towards dynamic real-time scheduling for multiple Earth observation satellites. *Journal of Computer and System Sciences*, 81(1): 110–124, 2015.

[127] J Wang, E Demeulemeester, and D Qiu. A pure proactive scheduling algorithm for multiple Earth observation satellites under uncertainties of clouds. *Computers & Operations Research*, 74:1–13, 2016.

[128] J Wang, E Demeulemeester, X Hu, D Qiu, and J Liu. Exact and heuristic scheduling algorithms for multiple Earth observation satellites under uncertainties of clouds. *IEEE Systems Journal*, 13(3):3556–3567, 2018.

[129] J Wang, E Demeulemeester, X Hu, and G Wu. Expectation and SAA models and algorithms for scheduling of multiple Earth observation satellites under the impact of clouds. *IEEE Systems Journal*, 14(4):5451–5462, 2020.

[130] J Wang, G Song, Z Liang, E Demeulemeester, X Hu, and J Liu. Unrelated parallel machine scheduling with multiple time windows: An application to Earth observation satellite scheduling. *Computers & Operations Research*, 149:106010, 2023.

[131] M Wang, G Dai, and M Vasile. Heuristic scheduling algorithm oriented dynamic tasks for imaging satellites. *Mathematical Problems in Engineering*, 2014:234928, 2014.

[132] 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*, 61(2):322–335, 2011.

[133] X Wang, G Song, R Leus, and C Han. Robust Earth observation satellite scheduling with uncertainty of cloud coverage. *IEEE Transactions on Aerospace and Electronic Systems*, 56(3):2450–2461, 2019.

[134] 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*, 15(3): 3881–3892, 2020.

[135] X Wang, Y Gu, G Wu, and JR Woodward. Robust scheduling for multiple agile Earth observation satellites under cloud coverage uncertainty. *Computers & Industrial Engineering*, 156:107292, 2021.

[136] X Wang, H Zhang, S Bai, and Y Yue. Design of agile satellite constellation based on hybrid-resampling particle swarm optimization method. *Acta Astronautica*, 178:595–605, 2021.

[137] L Wei, L Xing, Q Wan, Y Song, and Y Chen. A multi-objective memetic approach for time-dependent agile Earth observation satellite scheduling problem. *Computers & Industrial Engineering*, 159:107530, 2021.

[138] D Williams. Upcoming planetary events and missions. Available at: https://nssdc.gsfc.nasa.gov/planetary/upcoming.html, 2024. Last Accessed: 8 February 2024.

[139] WJ Wolfe and SE Sorensen. Three scheduling algorithms applied to the Earth observing systems domain. *Management Science*, 46(1):148–166, 2000.

[140] G Wu, M Ma, J Zhu, and D Qiu. Multi-satellite observation integrated scheduling method oriented to emergency tasks and common tasks. *Journal of Systems Engineering and Electronics*, 23(5):723–733, 2012.

[141] G Wu, J Liu, M Ma, and D Qiu. A two-phase scheduling method with the consideration of task clustering for Earth observing satellites. *Computers & Operations Research*, 40(7): 1884–1894, 2013.

[142] G Wu, H Wang, W Pedrycz, H Li, and L Wang. Satellite observation scheduling with a novel adaptive simulated annealing algorithm and a dynamic task clustering strategy. *Computers & Industrial Engineering*, 113:576–588, 2017.

[143] G Wu, Q Luo, X Du, Y Chen, PN Suganthan, and X Wang. Ensemble of meta-heuristic and exact algorithm based on the divide and conquer framework for multi-satellite observation scheduling. *IEEE Transactions on Aerospace and Electronic Systems*, 58(5):4396–4408, 2022.

[144] J Wu, J Zhang, J Yang, and L Xing. Research on task priority model and algorithm for satellite scheduling problem. *IEEE Access*, 7:103031–103046, 2019.

[145] J Wu, Y Chen, Y He, L Xing, and Y Hu. Survey on autonomous task scheduling technology for Earth observation satellites. *Journal of Systems Engineering and Electronics*, 33(6): 1176–1189, 2022.

[146] K Wu, D Zhang, Z Chen, J Chen, and X Shao. Multi-type multi-objective imaging scheduling method based on improved nsga-iii for satellite formation system. *Advances in Space Research*, 63(8):2551–2565, 2019.

[147] MA Wulder et al. Current status of Landsat program, science, and applications. *Remote sensing of environment*, 225:127–147, 2019.

[148] F Xhafa and AWH Ip. Optimisation problems and resolution methods in satellite scheduling and spacecraft operation: a survey. *Enterprise Information Systems*, 15(8):1022–1045, 2019.

[149] L Xiaolu, B Baocun, C Yingwu, and Y Feng. Multi satellites scheduling algorithm based on task merging mechanism. *Applied Mathematics and Computation*, 230:687–700, 2014.

[150] P Xie, H Wang, Y Chen, and P Wang. A heuristic algorithm based on temporal conflict network for agile Earth observing satellite scheduling problem. *IEEE Access*, 7:61024–61033, 2019.

[151] R Xu, H Chen, X Liang, and H Wang. Priority-based constructive algorithms for scheduling agile Earth observation satellites with total priority maximization. *Expert Systems with Applications*, 51:195–206, 2016.

[152] Y Xu, X Liu, R He, and Y Chen. Multi-satellite scheduling framework and algorithm for very large area observation. *Acta Astronautica*, 167:93–107, 2019.

[153] X Zhai, X Niu, H Tang, L Wu, and Y Shen. Robust satellite scheduling approach for dynamic emergency tasks. *Mathematical Problems in Engineering*, 2015:1–20, 2015.

[154] G Zhang, X Li, G Hu, Z Zhang, J An, and W Man. Mission planning issues of imaging satellites: Summary, discussion, and prospects. *International Journal of Aerospace Engineering*, 2021:7819105, 2021.

[155] J Zhang and L Xing. An improved genetic algorithm for the integrated satellite imaging and data transmission scheduling problem. *Computers & Operations Research*, 139:105626, 2022.

[156] Q Zhao, L Yu, Z Du, D Peng, P Hao, Y Zhang, and P Gong. An overview of the applications of Earth observation satellite data: impacts and future trends. *Remote Sensing*, 14(8):1863, 2022.

[157] Y Zhao, B Du, and S Li. Agile satellite mission planning via task clustering and double-layer tabu algorithm. *Computer Modeling in Engineering & Sciences*, 122(1):235–257, 2020.

[158] Q Zheng, H Yue, D Liu, and X Jia. A scheduling method of using multiple sar satellites to observe a large area. *Sensors*, 23(6):3353, 2023.

[159] E Zhibo, R Shi, L Gan, H Baoyin, and J Li. Multi-satellites imaging scheduling using individual reconfiguration based integer coding genetic algorithm. *Acta Astronautica*, 178: 645–657, 2021.

[160] W Zhu, X Hu, W Xia, and H Sun. A three-phase solution method for the scheduling problem of using Earth observation satellites to observe polygon requests. *Computers & Industrial Engineering*, 130:97–107, 2019.

[161] X Zhu, J Wang, X Qin, J Wang, Z Liu, and E Demeulemeester. Fault-tolerant scheduling for real-time tasks on multiple Earth-observation satellites. *IEEE Transactions on Parallel and Distributed Systems*, 26(11):3012–3026, 2015.