Deterministic and Probabilistic Decision Models for GSaaS-based Satellite Communication Resource Management

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Abstract

Our research addresses the complex task of scheduling data downloads from satellite constellations to a network of ground stations, considering the diminishing value of data over time and the need for complete datasets. The paper presents two novel models for communication slot allocation: a deterministic model that provides a robust framework for resource management, and a probabilistic model that accounts for the inherent uncertainties in satellite communication scheduling. Through these comprehensive models, we aim to optimize communication schedules for numerous satellite constellations, taking into account diverse access conditions and operational constraints of various ground station networks. Our findings contribute significantly to the field, offering a pathway to enhanced resource management and data exchange efficiency in the evolving landscape of EO satellite communications.

1 Introduction

Conventionally, Earth Observation (EO) space missions possess individualized resources. Each mission is equipped with a satellite constellation, ground stations, and a command center for satellite communication, uploading observation blueprints, and downloading collected data. In recent years, the development of third-party communication stations adopting the Ground Station as a Service (GSaaS) model has been observed (Carcaillon and Bancquart 2020; Nguyen 2012). This approach allows customers to reserve communication resources from ground segment service providers rather than constructing their own facilities. These service providers offer on-demand data communication, download, and processing services for customer satellites on a pay-per-use basis. The primary clientele of GSaaS comprises operators of Low Earth Orbit (LEO) satellites, with or without their own ground stations. For those who do have their own infrastructure, the main goal of integrating GSaaS is to enhance the frequency of communication with their satellites. To facilitate coordination among disparate EO missions, a multi-agent federation layer has been proposed in the DOMINO-E project (DOMINO-E Consortium 2024; Farges et al. 2024). This layer, illustrated in Figure 1, aims to streamline client access to multiple satellite constellations and communication sites for the assembly and retrieval of extensive acquisition data in less time than traditional, uncoordinated methods.

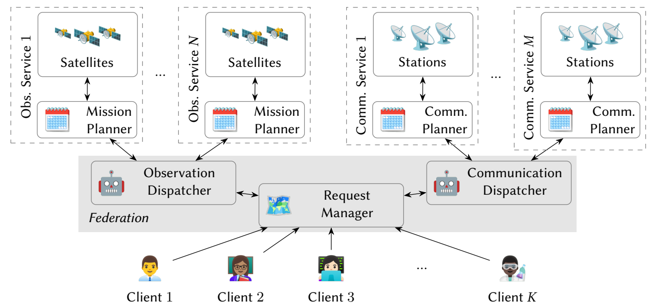

Figure 1: The DOMINO-E architecture calls different systems as services, optimizing combined requests from multiple clients to multiple systems in a transparent way (Farges et al. 2024).

The communication dispatcher, coined Satellite Communication and Resource Management System (SCRMS), is central to the federation layer, orchestrating communications for N satellites across multiple ground stations, each with its own antenna. SCRMS integrates both member-owned stations and external GSaaS services, adapting to diverse operational needs by leveraging satellite orbit data and station visibility information. It efficiently handles communication scheduling through a three-part functional framework: identifying potential contacts; selecting optimal ones based on mission requirements; and booking these slots with attention to GSaaS protocols and potential rejections. This methodology ensures effective resource management amidst the complexities of satellite constellations and ground station variability, optimizing data exchange across the network.

The task of orchestrating data downloads from a constellation's satellites to an allocated network of ground stations has been extensively addressed in existing literature. For example, (Chen et al. 2020) employs evolutionary algorithms to refine scheduling models for observation topics where the value of data diminishes rapidly if the dataset is incomplete by a specified deadline. Another instance involves the ap-

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plication of a greedy algorithm aimed at maximizing the total volume of data transmitted to Earth (Castaing 2014). On NASA's Deep Space Network (DSN) (Johnston 2020), the communication scheduling is performed by a 3-stages algorithm, composed by a min-conflict hill climbing algorithm performed after a greedy initial assignment and with a final deconflict and repair, while taking into account user's preferences (importance ranking) over their own missions. On the ground station front, research continues to evolve; Monte Carlo simulations have been utilized to evaluate the potential saturation of an individual ground station in response to burgeoning downlink data demands and an escalating number of conflicting satellite passes as the constellation size increases (Writt 2018). An automated tool leveraging Integer Linear Programming (ILP) has been developed to resolve scheduling conflicts across multi-site ground networks that cater to a multitude of satellite operators (Vazquez, Perea, and Vioque 2014). Scheduling strategies that ensure an equitable distribution of redundant communication windows among various requests, coupled with data synchronization and error recovery protocols for satellite downlinks, have been shown to enhance the overall efficiency of ground station networks, as discussed in (Schmidt 2011).

Nevertheless, the emergence of multiple competing ground station networks such as AWS (Amazon Web Services 2023) and KSAT (KSAT 2023), driven by advancements in satellite technology, introduces a novel challenge: optimizing communication schedules for numerous satellite constellations utilizing diverse ground station networks with varying access conditions. Consequently, the focus of this study is to devise mathematical formulations that encapsulate both the constraints and criteria pertinent to the reservation of communication resources within these complex multi-network environments.

In this paper we propose the following contributions:

1. A *deterministic decision model* for assigning communication slots to satellites, balancing jamming impacts and reservation costs across various pricing schemes, including tiered models with free slots up to a threshold,
2. A *probabilistic decision model*, where the GSaaS providers may reject booking requests following a given probability,
3. A *comprehensive experimental assessment* via realistic simulations of multiple missions and ground stations over an extended period of 60 days, offering actionable insights.

The structure of this paper is outlined below. In Section 2, we lay out the fundamental concepts and terminologies. The subsequent Section 3 delves into a deterministic approach to modeling the communication slot allocation problem. Following that, Section 4 introduces a probabilistic framework for the same problem. To conclude, we present our final thoughts and observations in Section 6.

2 Core Concepts and Definitions

Satellites are spatial entities that need to communicate with other entities (terrestrial or spatial) for various reasons (data transfer, receiving instructions, etc.). In this work we consider the decision problem of booking communication windows with ground stations only. Each satellite has a set of potential contacts (L_i for satellite i). Each satellite has communication *needs* that must be satisfied. This corresponds to a minimum quantity of data that must be transferred for a given period of time (e.g. each day), and a given radio band (e.g. X or S). Satellites are the primary actors whose needs and communications must be managed optimally.

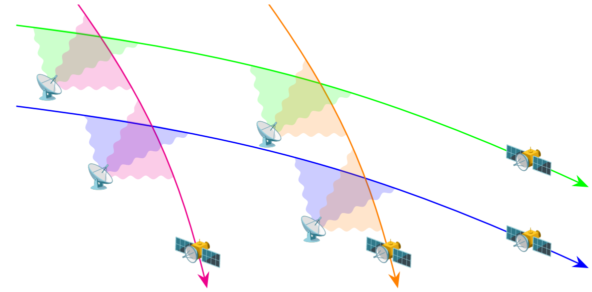


Figure 2: Four satellites, each one having potential contacts with two ground stations (Farges et al. 2024).

Contacts represent opportunities for communication between a satellite and a ground station, as illustrated in Figure 2. Each contact is defined by a time window (as thus a duration). Each contact can contribute to satisfying one or more needs of a satellite. Optimal selection of contacts is crucial for satisfying satellite needs while minimizing costs and conflicts.

Needs represent the requirements that satellites must see fulfilled, often related to communication. Several types of needs could be considered:

- *Routine needs*: standard and recurring needs of satellites, that can be managed relatively simply in terms of contact scheduling. We denote $\mathcal{RN}$ the set of routine needs.
- *Localized needs*: specific needs tied to particular observation areas and communication bands, which require finer planning due to their specific temporal and spatial constraints. We denote $\mathcal{LN}$ the set of localized needs.

A *cost model*, $cm \in CM$ the set of cost model, defines how expenses are calculated for using contacts. We consider several cost models:

- *Pay per Use*: cost is proportional to the duration of the used contact, which encourages optimizing contact duration to minimize costs. Their set is denoted PU.
- *Pay per Pass*: a fixed cost is charged for each contact, regardless of duration; thus, contact selection should be based on their value relative to the fixed cost. Their set is denoted PP.
- *Pay per Pass with Commitment*: combination of fixed costs for a guaranteed number of contacts and variable costs for additional contacts, which requires fine forecasting of needs to optimize the balance between commitments and flexibility. Their set is denoted PPC.

Conflicts between satellites to access nearby stations may generate radio-frequency *jamming*. This negative phenomena results from the simultaneous selection of certain contacts that can interfere with each other. Jamming is assessed by the magnitude of conflict between two specific contacts, which is a function of the duration of overlaps between communication windows. It must be minimized to ensure effective and reliable communications.

3 Deterministic Decision Problem

In this section we present a decision problem, where the reservation of a contact is always accepted by a GSaaS.

3.1 Model

Decision variables. The problem considers N satellites and each satellite i have L_i potential contacts and K_i needs. It consists in selecting some contacts in the set of potential contacts. The decision variable corresponding to selection of lth contact of satellite i is $x_{i,l} \in \{0, 1\}$ and the set of all decision variables is noted **x**. We denote the set $\{1, \ldots, \cdot\}$ by the notation $[\cdot]$.

Constraints. Contacts, when selected, contribute to fulfill satellite's needs: the set of needs being fulfilled in part by contact l of satellite i is $\mathcal{Z}_{i,l}$. This set may contain multiple routine needs if the ground station allows communication on multiple bands, as their communication can be simultaneous without jamming, but may also contain localized needs, the special needs having temporal and spacial constraints.

A localized need of satellite i, noted $k \in \mathcal{LN}_i$, is defined by three criteria: an observation area, a time window width Δ_k and a communication band. When the communication band is S, the need is used to upload the observation plan to the satellite before entering its observation area, therefore the need must be fulfilled beforehand. Therefore, the effective time window for fulfilling localized need k, is defined by $\left[\underline{t}_{i,k} - \Delta_k,\ \underline{t}_{i,k}\right]$ with $\underline{t}_{i,k}$ the time of entrance of satellite i in the observation area of localized need k. On the contrary, when the communication band is X, the need is used to download the measurements and must therefore be fulfilled after leaving the observation area. The effective time window is in that case is $\left[\bar{t}_{i,k},\ \bar{t}_{i,k} + \Delta_k\right]$ with $\bar{t}_{i,k}$ the time of exit of the satellite from the observation area. During the period of time considered for fulfilling the need the satellite can fly over the area several times, we note C_k the set of all the such time windows for the considered period. If and only if contact l intersects with C_k then $k \in \mathcal{Z}_{i,l}$.

We can then note that if a contact l with satellite i can contribute to fulfill $k \in \mathcal{LN}_i$ then it necessarily can also contribute to fulfill the routine need of the same band. Instead of complexifying the model to account for selecting the contact l in order to fulfill the localized need or the routine need, or some mixture of the two, we can take advantage of this necessary condition. Indeed, we can artificially increase the required duration $D_{i,k*}$ of the routine need $k* \in \mathcal{RN}_i$ sharing the same band as localized need $k \in \mathcal{RN}$ by $D_{i,k}$, and select contact l for fulfilling both needs. The only assumption required for this "trick" to fully operate is that at most one localized need per band can belong to $\mathcal{Z}_{i,l}$, otherwise their superposition requires the complexity of defining for which localized need we select contact l.

Contact l of satellite i has a duration $d_{i,l}$, the kth needed duration is $D_{i,k}$ and the fulfillment provided by contact l to the kth need is $d_{i,k,l}$. Satisfaction of needs leads to the constraints for $i \in [N]$ and $k \in [K_i]$:

$$\sum_{l \in [L_i] / k \in \mathcal{Z}_{i,l}} d_{i,k,l} x_{i,l} \geq D_{i,k} \tag{1}$$

Criteria Two criteria are considered. The first one is the total cost of selected contacts:

$$C = \sum_{i=1}^{N} \sum_{l=1}^{L_i} c_{i,l} x_{i,l} \tag{2}$$

where $c_{i,l}$ is the cost of contact l of satellite i. The value of this cost is defined by the *cost model* $cm \in CM$ of the contact, denoted $cm(i, l)$:

- Pay per Use, i.e. $cm(i, l) \in PU$: $c_{i,l} = c^t_{cm(i,l)} * d_{i,l}$, the cost is proportional to the communication duration $d_{i,l}$, with $c^t_{cm(i,l)}$ the cost per second of the cost model.
- Pay per Pass, i.e. $cm(i, l) \in PP$: $c_{i,l} = c^0_{cm(i,l)}$, the cost is fixed once the contact is selected, with $c^0_{cm(i,l)}$ the fixed cost of a contact of the cost model.
- Pay per Pass with Commitment, i.e. $cm(i, l) \in PPC$: $c_{i,l} = c^0_{cm(i,l)}$, like Pay per Pass contacts, but only if $Y_{cm(i,l)}$ contact already are booked, $c_{i,l} = 0$ otherwise. The contact is considered free until the number of committed contact $Y_{cm(i,l)}$ is reached.

We then obtain the detailed cost criteria:

$$\begin{aligned} C = \sum_{s \in PU} \sum_{\substack{l=1 \\ | s = cm(i,l)}}^{L_i} c^t_s d_{i,l} x_{i,l} + \sum_{s \in PP} \sum_{\substack{l=1 \\ | s = cm(i,l)}}^{L_i} c^0_s x_{i,l} \\ + \sum_{s \in PPC} c^0_s \max(0, \sum_{i=1}^{N} \sum_{\substack{l=1 \\ | s = cm(i,l)}}^{L_i} x_{i,l} - Y_s) \end{aligned} \tag{3}$$

The second criterion is the total amount of conflict and jamming:

$$J = \sum_{i=1}^{N-1} \sum_{l=1}^{L_i} \sum_{j=i+1}^{N} \sum_{m=1}^{L_j} b_{i,l,j,m} x_{i,l} x_{j,m} \tag{4}$$

where $b_{i,l,j,m}$ indicates the amount of conflict and jamming generated by simultaneous selection of contact l of satellite i and contact m of satellite j.

Strict order between solutions The criteria have to be considered in a lexicographic order. More precisely there is two booking strategies:

- The *Mini* booking strategy which considers cost more important than conflict and jamming, i.e. $C \gg J$;
- The *Secure* booking strategy which considers conflict and jamming more important than cost, i.e. $J \gg C$.

Whatever the strategy used, a preference relationship between admissible solutions, $>_{\text{pref}}$, is defined. For instance, for the Mini booking strategy we have:

- $C(\mathbf{x}) < C(\mathbf{y}) \implies \mathbf{x} >_{\text{pref}} \mathbf{y}$
- $C(\mathbf{x}) = C(\mathbf{y})$ and $J(\mathbf{x}) < J(\mathbf{y}) \implies \mathbf{x} >_{\text{pref}} \mathbf{y}$
- $C(\mathbf{x}) = C(\mathbf{y})$ and $J(\mathbf{x}) = J(\mathbf{y})$ and $\mathbf{x} \neq \mathbf{y} \implies \mathbf{x} >_{\text{pref}} \mathbf{y}$ on an heuristic basis

with for all other cases $\mathbf{y} >_{\text{pref}} \mathbf{x}$. The Secure booking strategy can be obtained by inverting C and J in the relations above. The heuristic basis for the choice of the preference relationship is induced by the way the Java TreeSet class detects duplicated elements needs a strict order between elements. The chosen heuristic is the value of the first different $x_{i,l}$ ordered by i and then by l.

3.2 Integer Linear Programming Approach

Integer Linear Programming (ILP) solvers are general purpose software that are able to solve optimization problems with a linear criterion and linear constraints. A famous example of such software is CPLEX[1]. The problem described by Equations (1), (3) and (4) is almost linear. Indeed, Equations (3) and (4) are not linear. The general idea for using a ILP approach is to linearize this equation.

Linearization of the conflict and jamming criterion. In order to linearize the conflict and jamming criterion, a new variable is introduced for each couple of contacts, contact l or satellite i and contact m of satellite j, that presents a non null $b_{i,l,j,m}$ parameter:

- $\forall i \in [N-1], \forall l \in [L_i], \forall j \in \{i+1, \ldots, N\}, \forall m \in [L_j]$ such that $b_{i,l,j,m} > 0$, the variable is $y_{i,l,j,m} \in \{0,1\}$.

This new variable stands for the product $x_{i,l}x_{j,m}$. The set of all those new decision variables is noted $\mathbf{y}$. Those new variables allow a rewriting of the conflict and jamming criterion in a linear form:

$$J = \sum_{i=1}^{N-1} \sum_{l=1}^{L_i} \sum_{j=i+1}^{N} \sum_{m \in [L_j]: b_{i,l,j,m} > 0} b_{i,l,j,m} y_{i,l,j,m} \tag{5}$$

However $y_{i,l,j,m}$ shall stick to $x_{i,l}x_{j,m}$ on $\{0,1\} \times \{0,1\}$. In order to have this property the following constraints are introduced:

$$\forall i \in [N-1], \forall l \in [L_i], \forall j \in \{i+1, \ldots N\},$$
$$\forall m \in [L_j] : b_{i,l,j,m} > 0$$
$$y_{i,l,j,m} \leq x_{i,l} \tag{6}$$
$$y_{i,l,j,m} \leq x_{j,m} \tag{7}$$
$$y_{i,l,j,m} \geq x_{i,l} + x_{j,m} - 1 \tag{8}$$

Equation (6) and Equation (7) ensure that if $x_{i,l}$ or $x_{j,m}$ is null $y_{i,l,j,m}$ is also null. In those three cases Equation (8) is verified. Equation (8) ensures that in the fourth case, i.e. if $x_{i,l} = x_{j,m} = 1$, $y_{i,l,j,m} = 1$. In this case Equation (6) and Equation (7) are verified. Finally, note that because the MILP solver is minimizing and $b_{i,l,j,m}$ are positive constraints corresponding to Equations (6) and (7) are not absolutely necessary.

[1]https://www.ibm.com/fr-fr/products/ilog-cplex-optimization-studio

Integration of cost models. The integration of the Pay per Use and Pay per Pass into the objective function is straightforward and does not require specific encoding for the ILP formulation. However, in order to take into account the Pay per Pass with Commitment services, two new variables for each service $s \in PPC$ for each considered period are introduced, f_s capturing the number of selected contacts within the range of the committed contacts Y_s and c_s capturing the number of selected contacts past the committed contacts, both positive or null. In order to obtain this partition of the total number of selected contacts, the following constraints are introduced:

$$\forall s \in PPC \; f_s + c_s = \sum_{i=1}^{N} \sum_{\substack{l=1 \\ |s=cm(i,l)}}^{L_i} x_{i,l} \tag{9}$$
$$\forall s \in PPC \; f_s \leq Y_s \tag{10}$$

The third term of Equation (3) can then be rewritten as $\sum_{s \in PPC} c_s^0 c_s$. Equation (9) ensure that the total number of selected contacts is split between the contacts within the already committed contacts and the contacts that will require an additional cost. Equation (10) ensure that the number of selected contacts as belonging to the free committed contacts do not exceed the service limit. As the MILP solver is performing a minimization of the costs, where only the c_s are present, they will take a non zero value only if the constraints in Equation (10) is saturated.

Problem provided to the solver. In consequence, the problem provided to the MILP solver has the following characteristics:

- Variables: $\mathbf{x}$, $\mathbf{y}$, $\mathbf{f}$ and $\mathbf{c}$
- Constraints: Equations (1), (6), (7), (8) (9) and (10).
- Criteria: Equations (3) and (5)

Note that is a bi-criteria problem, that can be either straightforwardly fed to some multi-objective MILP solver (e.g. CPLEX), or require chaining several solving iterations (one per objective) with some other solvers (e.g. OR Tools).

4 Probabilistic Decision Problem

In this section we present the extension of the former decision problem, with probabilities attached to the acceptance of slot reservations by the GSaaS providers.

4.1 Model

The main problem of the model presented in Section 3.1 is that the GSaaS network has the possibility to reject a booking request. This means that constraints and criteria should be assessed with respect to actual booking instead of selection. The actual booking for contact l of satellite i is a random variable, $z_{i,l}$ linked to $x_{i,l}$ by the relation :

$$z_{i,l} = \begin{cases} x_{i,l} & \text{with probability } p_{i,l} \\ 0 & \text{with probability } 1 - p_{i,l} \end{cases} \tag{11}$$

where $p_{i,l}$ is the probability of acceptance by the GSaaS network of the booking request related to contact l of satellite i.

Constraints. Respecting constraints in a probabilistic context is quite tricky. Indeed, taking the mathematical expectation of the left part of Equation (1) would lead to disrespect approximately half of the constraints while the user expectation is that :

$$P(\sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d_{i,k,l}z_{i,l} \geq D_{i,k}) \geq P_{\text{target}} \quad (12)$$

Where $P(.)$ denotes the probability and P_{target} a target probability for respecting constraints. A precise assessment of Equation (12) would need to consider 2^{L_i} cases with their associated probabilities. Instead, it is possible to use an approximation based on the central limit theorem, i.e. mean minus Q_{target} times the standard deviation larger than $D_{i,k}$, where $Q_{\text{target}} > 0$ is related to P_{target} through the property of the Normal law. Assuming independence of actual bookings, it lead to the constraint for each $i \in [N]$ and $k \in [K_i]$:

$$\sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d_{i,k,l}p_{i,l}x_{i,l} - Q_{\text{target}}(\sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d^2_{i,k,l}p_{i,l}x_{i,l}(1-p_{i,l}))^{\frac{1}{2}} \geq D_{i,k} \quad (13)$$

Note that, because $x_{i,l}$ is a Boolean variable, $p_{i,l}x_{i,l}(1 - p_{i,l}x_{i,l}) = p_{i,l}x_{i,l}(1-p_{i,l})$.

Criteria. The criteria of Equations (3) and (4) shall be written using $z_{i,l}$ instead of $x_{i,l}$ and are also random variables. The approach consists in optimizing the mathematical expectations, denoted by $\mathbb{E}[.]$, of the criteria:

$$\begin{aligned}\mathbb{E}[C] = &\sum_{s\in PU} \sum_{\substack{l=1\\|s=cm(i,l)}}^{L_i} c^t_s d_{i,l}p_{i,l}x_{i,l} \\ &+ \sum_{s\in PP} \sum_{\substack{l=1\\|s=cm(i,l)}}^{L_i} c^0_s p_{i,l}x_{i,l} \\ &+ \sum_{s\in PPC} c^0_s \mathbb{E}[\max(0, \sum_{i=1}^{N} \sum_{\substack{l=1\\|s=cm(i,l)}}^{L_i} x_{i,l} - Y_s)] \quad (14)\end{aligned}$$

$$\mathbb{E}[J] = \sum_{i=1}^{N-1}\sum_{l=1}^{L_i}\sum_{j=i+1}^{N}\sum_{m=1}^{L_j} b_{i,l,j,m}\mathbb{E}[z_{i,l}z_{j,m}] \quad (15)$$

The expected cost of Pay per Pass with Commitment cost models is then defined by the cost of a pass times the number of expected contacts over the committed contact threshold Y_s. We will see in next section that this is in fact easily linearizable.

For jamming, assuming Independence between $z_{i,l}$ and $z_{j,m}$ leads to :

$$\mathbb{E}[J] = \sum_{i=1}^{N-1}\sum_{l=1}^{L_i}\sum_{j=i+1}^{N}\sum_{m=1}^{L_j} b_{i,l,j,m}p_{i,l}p_{j,m}x_{i,l}x_{j,m} \quad (16)$$

4.2 Linear Programming Solution Methods

Linearization of constraints. Equation (13) is non linear due to the square root including variable $x_{i,l}$. It can be rewritten by introducing an additional variable $\Delta_{i,k}$:

$$\sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d_{i,k,l}p_{i,l}x_{i,l} - Q_{\text{target}}\Delta_{i,k} \geq D_{i,k} \quad (17)$$

with:

$$0 \leq \Delta_{i,k} \leq \overline{\Delta}_{i,k} \quad (18)$$

where:

$$\overline{\Delta}_{i,k} = (\sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d^2_{i,k,l}p_{i,l}(1-p_{i,l}))^{\frac{1}{2}} \quad (19)$$

the maximal value obtained when selecting all contacts. Considering $\beta_{i,k} = \Delta^2_{i,k}$, we have:

$$\beta_{i,k} = \sum_{l\in[L_i]/k\in\mathcal{Z}_{i,l}} d^2_{i,k,l}p_{i,l}x_{i,l}(1-p_{i,l}) \quad (20)$$

The McCormick envelope providing the tightest fit between $\beta_{i,k}$ and $\Delta^2_{i,k}$ is:

$$\beta_{i,k} \geq 0 \quad (21)$$

$$\beta_{i,k} \geq 2\Delta_{i,k}\overline{\Delta}_{i,k} - \overline{\Delta}_{i,k}\overline{\Delta}_{i,k} \quad (22)$$

$$\beta_{i,k} \leq \Delta_{i,k}\overline{\Delta}_{i,k} \quad (23)$$

In consequence, Equation (13) can be approximated by considering two additional variables, i.e. $\beta_{i,k}$ and $\Delta_{i,k}$, and Equations (17), (18), (20), (21), (22) and (23).

Linearization of criteria. Cost expression in Equation (14) only requires to linearize Pay per Pass with Commitment cost models, but we can see that replacing Equation (9) by:

$$\forall s \in PPC \; f_s + c_s = \sum_{i=1}^{N} \sum_{\substack{l=1\\|s=cm(i,l)}}^{L_i} p_{i,l}x_{i,l} \quad (24)$$

will change the semantics of c_s into the expected number of contacts requiring an additional cost, which is exactly what we needed in Equation (14).

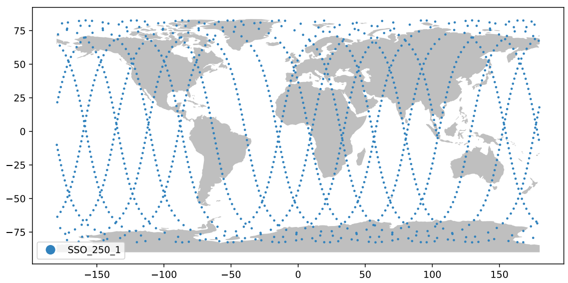
Adapting Equation (5) can be performed by introducing the probabilities product $p_{i,l}p_{j,m}$ into the sum term.

5 Experimental Evaluation

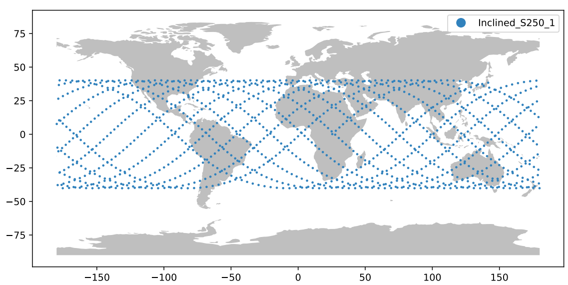
We present here the experimental setup we used to assess the feasibility and the performance of our solution methods, on a realistic scenario with multiple missions and stations.

5.1 Experimental Setup and Scenario

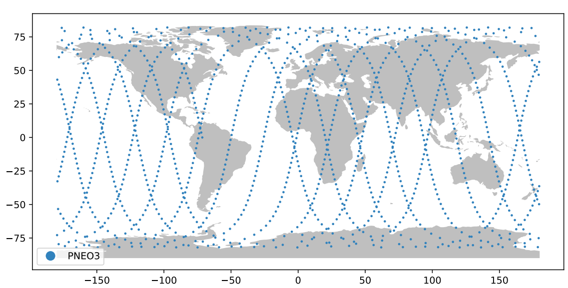
We consider scenarios over sixty consecutive days. Those days differ with respect to the communication needs of the satellites and constellations and with respect to positions of satellites on their orbits. Each day, a contact selection plan is computed for the next ten days. This computation is performed by applying ten times the considered algorithm



(a) SSO_250_1



(b) Inclined_S250_1



(c) PNEO3

Figure 3: Sample ephemerides for some satellites used in the scenarios

changing the initial position of satellites. The sums of criteria over these 10 days are provided as indicators for the performance of the considered scenario on this first day.

We developed all the proposed simulations and algorithms using Java (SDK 1.8) and the Java API of OR Tools (Perron and Furnon 2024). Experiments have been run on a 20-core Intel(R) Xeon(R) CPU E5-2660 v3 @ 2.60GHz, 62GB RAM, Ubuntu 18.04.5 LTS, within 5 seconds for each plan.

Missions. There are four constellations in the configuration. The first three constellations are handled by the system, while the last one contains the external satellites that can produce unforeseen jamming. The three internal constellations are configured as followed :

- **PNEO** : Two S950 satellites on the same SSO orbit, in phase opposition,
- **SSO** : Four S250 satellites on the same SSO orbit, in quadrant phases,

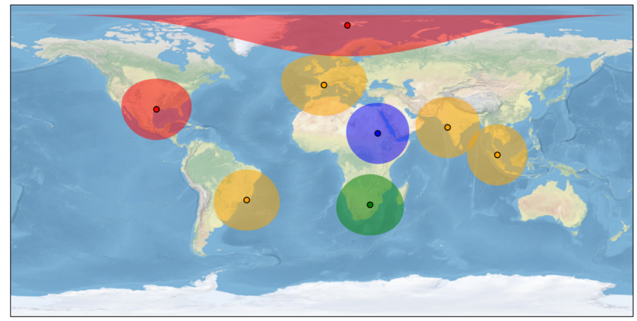


Figure 4: Stations and their respective visibility circles at 500km altitude: violet is Owned, green is Preferred, yellow is normal, red is Expensive.

- **Inclined** : Two pairs of S250 satellites in phase opposition, each pair on an 40° inclined orbit. The orbits have a 180° RAAN difference.

Figure 3 shows sample ephemerides of each constellation.

Station providers. There are four providers considered in the configuration:

- **Owned**: contains the stations that are owned by the system. Its cost is considered free. Its probability of accepting booking requests is 98% for each of its contacts.
- **Preferred**: this simulates a provider with optimized cost and location. Its cost model is a Pay per Pass with Commitment, associated with 6 committed contacts per day and a cost of 50. Its probability of accepting booking requests is 100% for each of its contacts.
- **Normal**: this simulates a bonus provider with basic contract. Its cost model is a Pay per Pass, associated with a cost of 200. Its probability of accepting booking requests is 99% for each of its contacts.
- **Expensive**: this simulates a premium provider that should be used only in emergency. Its cost model is a Pay per Pass, associated with a cost of 400. Its probability of accepting booking requests is 100% for each of its contacts.

The stations are created with a 5° mask, and are positioned as illustrated in Figure 4.

Needs. Needs consists of communication requirements to be fulfilled at each period of time (every 24h for Band X and every 6h for Band S). Needs are expressed in terms of minimum communication duration for each band, for each satellite and/or constellation. Initial needs are given in Table 1. Then, all along the 60-days period, the needs for observation, i.e. band X, evolve as illustrated in Figure 5, as to simulate growing or decreasing needs depending on the period of the two months. Needs for band S remain fixed to the values in Table 1. This variation of load is fixed in our scenario. The optimization algorithm only have access to the state of the demands for the first day of its 10 days optimization, then suppose it remains constant over this period. One possible perspective of this work could be to account for this

constellation/satellite	band	duration (min)
PNEO_S950	S	5
PNEO_S950	X	50
SSO_S250	S	5
SSO_S250	X	70
SSO_S250_1	X	60
Inclined_S250	S	5
Inclined_S250	X	50
Inclined_S250_1	X	50

Table 1: Initial routine needs per period

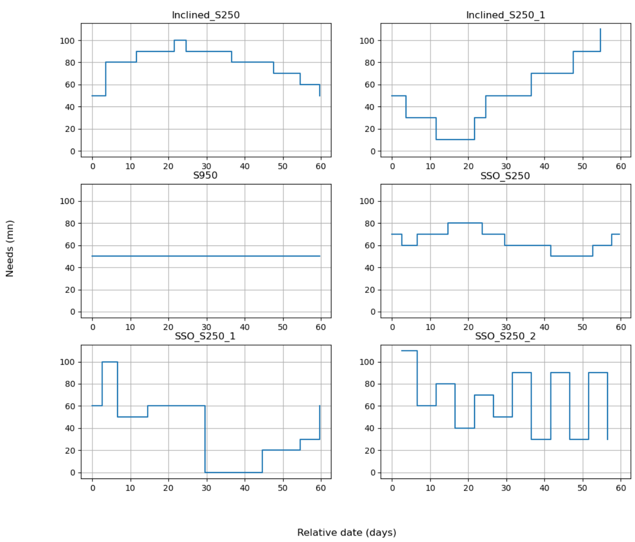


Figure 5: Band X needs evolution over time

variation in order to avoid overbooking over the next days when we could expect the load to reduce.

Measuring performance. To measure the impact of accounting for uncertainty through the model detailed in Section 4 compared to model in Section 3, we will measure the contact duration missing after applying rejections on the output of the model, relative to the load defined on that day. These values, obtained for each of the 60 days are averaged over several 100 draws using the *determinization* method. This method is used in problems with transition uncertainty, e.g. in Monte-Carlo Tree Search (Cowling, Powley, and Whitehouse 2012). It consists in fixing all uncertainty beforehand, in our case which contact will be refused and which will be accepted, before applying the methods. By sampling results several time by generating the acceptations using a different random seed we can have a finer comparison of the methods.

5.2 Results and Analysis

Fulfillment of communication needs. The results are plotted in Figure 6. ILP with expectations was computed with a $Q_{\text{target}} = 2$ and whenever the total expected time available was not large enough to fulfill Equation (17), we replaced the constraint with the selection of all the associated $x_{i,l}$. It follows that the ILP with expectations consistently reduces the gap to the objectives compared to the deterministic approach up to half the latter's value, in both settings (*Mini* and *Secure*). As a baseline we used the deterministic ILP after filtering out all the rejected contacts in the determinization, coined *Oracle*, which is plotted as a flat 0 line, meaning that in perfect information there was an optimal allocation fulfilling all needs.

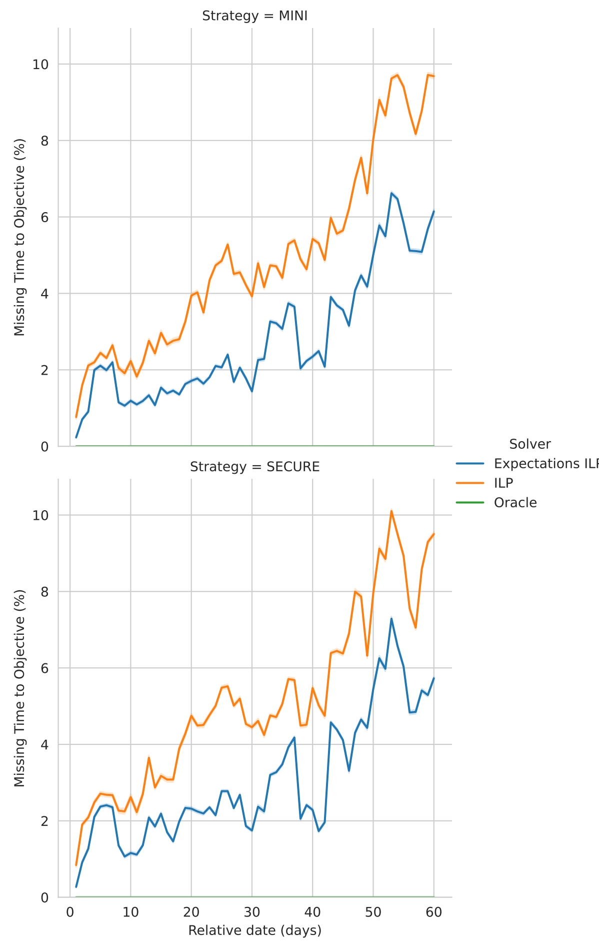


Figure 6: Percentage of missing communication time to fulfill all objectives evolution over time

Impact on cost. Considering the ILP with expectations has the consequence of generating overbooking of contacts, in order to maximize the chances of fulfilling needs. It results in an increase in cost, as depicted in Figure 7. The cost for the deterministic ILP is consistently slower than the oracle's as the outputted solution before filtering contacts is very similar to the one of the Oracle, but some contacts got refused.

Impact on jamming. Due to the reduced number of contacts for the two ILPs, their Jamming objective's value is almost always lower, but very similar, than the value obtained

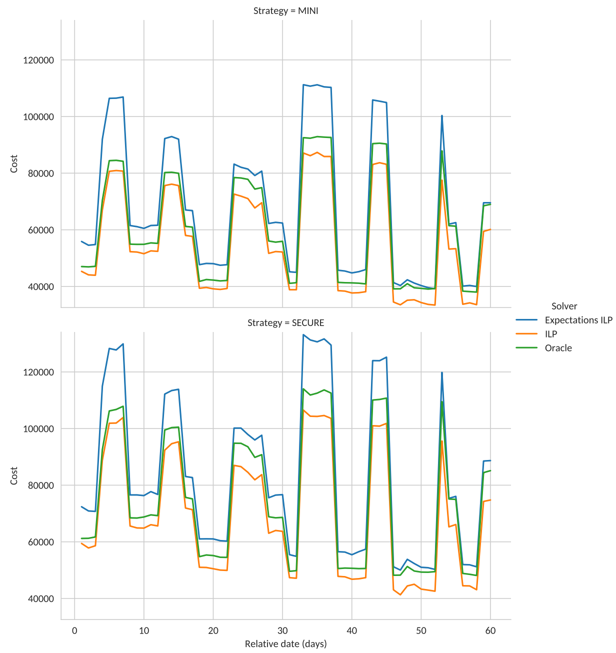


Figure 7: Cost evolution over time

Figure 8: Jamming evolution over time

by the Oracle, in both settings *Secure* and *Mini*, as depicted in Figure 8. In the *Secure* setting, we see that we can obtain almost jamming free allocation all the time, but doing so increase the overall cost as seen in Figure 7.

Experiment summary. In this Section we measured the impact of including expectations in our ILP formulation compared to the deterministic version while being faced with probabilistic acceptance of contacts from the GSaaS. All the results are averaged over 100 runs of the 60 scenario, and the mean value of the objective for each day is plotted within their 95% confidence interval. These intervals are very small as the probabilities of acceptance are high, leading to very stable outcomes. We can see that our probabilistic formulation is highly reducing the relative missing time to complete the communication needs while increasing cost but keeping jamming at the same level as an Oracle would have. As cost is often viewed as secondary compared to jamming for providing high quality service, the compromise provided by our ILP with expectation formulation is very admissible.

6 Conclusion

This paper presents two novel decision models for optimizing communication slot allocation in Ground Station as a Service (GSaaS)-based satellite communication resource management. The deterministic model provides a robust framework for resource management, ensuring satisfaction of satellite needs while minimizing costs and conflicts. The probabilistic model addresses the uncertainty of GSaaS network acceptance, approximating constraint respect using the central limit theorem. Our formulation effectively linearizes conflicts and jamming in both models, enabling efficient computation of optimal solutions. We also propose a Linear Programming approximation for the probabilistic model's non-linear constraints.

To further consolidate the impact of our research, several avenues for future work are envisioned. Firstly, we plan to refine our actual simulation setting. Indeed, these results are not obtained in a full closed loop, where bookings have openings several days before the day of the contact. By including this element, some contacts will be accepted in advance by previous optimizations, and if a contact was rejected, some other level of services might open (corresponding to a dynamic pricing policy). Also, we would be able to increase the communication needs of each day with the missing time of the day before because of the rejections. Additionally, we plan to conduct in-depth case studies with real-world satellite constellations and GSaaS providers (e.g., AWS Ground Station, KSAT) to empirically validate the effectiveness of our deterministic and probabilistic models in diverse operational settings. Finally, we aim to investigate finer models of uncertainties, like the load of GSaaS services due to the other missions and satellites. A first approach could consist in learning the correlation between the rate of acceptance and the number of overflying satellites. Methodwise, we are also investigating tree search-based techniques, such as MCTS, to solve the allocation problem, as in an adversarial setting (Browne et al. 2012).

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