Satellite Routing for mobile users under uncertainty in High Throughput constellations

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Abstract—In the past few years, the satellite communications landscape has undergone significant transformations, which increase the operational complexity of satellite systems. On one hand, the development of modern highly flexible payloads that provide the ability to adapt satellites’ resources to specific needs, together with reduced launch and manufacturing costs provide satellite operators with increased capacity. On the other hand, new market segments such as in-flight connectivity have made the overall demand for satellite communications increase. Not only that, demand has also changed its behavior, being more variable and unpredictable. Consequently, these new mobility segments entail new complexities due to their dynamic nature and uncertain behavior.

The objective of this paper is to build upon current methods to address the mapping of users to satellites (the Satellite Routing problem) in the presence of mobile users with uncertain behavior. While previous literature addresses these type of users from the perspective of the frequency assignment (i.e., the assignment of frequency spectrum to users), methods for other resources remain unaddressed. First, we formulate the problem, including the characteristics of new mobility segments. Then, we propose strategies in two stages: pre-operations, involving an initial plan based on users’ trajectories and schedule estimates using probabilistic constraints, and real-time adjustments during operations based on updated information.

Our approach, tested with Eurocontrol flight data, allows us to regulate the degree of conservativeness and control a trade-off between drop time and capacity, having a maximum reduction on the former of 11.68% but an increase on the latter by 11.85%. When combining satellite routing with frequency assignment strategies, we achieve to serve 99.7% of the users, compared to just 84.4% users served in the baseline, with a minor increase in power.

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1. INTRODUCTION

Motivation

Currently, we are witnessing the growth of the satellite communications market, which is expected to grow from 81.26B USD in 2022 to 211.34B USD in 2032 [1]. Constellations are growing in size, which Starlink exemplifies with its constellation of 4,519 satellites in orbit as of July 2023 [2], having approval to deploy 12,000 satellites, and a planned possible extension to 42,000 [3]. In general, it is estimated that 100,000 satellites are launched in the coming decade [4]. Furthermore, recent new communication technologies are boosting the capabilities of modern satellite systems. Technologies such as phased arrays, reconfigurable antennas, and other improvements in payload technologies such as digital processors or multiport amplifiers, have permitted to shift from static, wide area coverage beams to dynamic, steerable, spot beams, which allow for a better distribution of power and facilitate frequency reuse based on specific needs [5], [6], [7]. Thanks to the growth in satellite constellations, together with these new communication technologies, modern satellite communication systems are able to reach unprecedented levels of capacity, with global High Throughput Satellites capacity supply expected to excel the 60Tbps in the next five years [8], giving opportunities to new enterprises, such as Starlink, and to already-settled ones, such as SES.

Furthermore, new market segments, such as in-flight connectivity and ship broadband internet, are increasing the complexity of the environment that communication systems encounter. For instance, in-flight connectivity is expected
to grow after the pandemic, with most of flight passengers using connectivity services on board when available, around 79% according to a survey to 11,000 people by Immarsat [9]. Furthermore, 21,000 planes are expected to be equipped with in-flight connectivity by 2030 [10]. In a similar way, ships also commonly use satellite internet [11], and shipping companies are increasing their satellite internet access for members of the crew as a strategy to retain talent [12].

Nevertheless, mobile users add an additional layer of complexity when it comes to managing resources efficiently, due to their dynamic and uncertain behavior. Flights, for instance, can have important delays, which have the potential to entirely undermine the operators’ predictions for the operational phase. If we want to address these users effectively, it is necessary to consider their mobile characteristics when allocating resources, as their uncertainty can lead to a substantial loss [13].

While some aspects have already been addressed, other decisions under uncertainty remain to be studied, as current tools do not fully leverage the users’ information in those cases. In this paper, we address the challenges that mobile users pose to assigning users to satellites (i.e., the Satellite Routing problem) in the context of satellite communications by adapting an existing methodology for fixed users to the mobile users’ case and introducing probabilistic constraints to increase the robustness of the solution against uncertainty. In combination with this, we propose a real-time strategy to deal with emergency cases in which there are high delays and trajectory changes.

**Literature review**

The satellite routing problem involves deciding the mapping between users and satellites. When mobile users are introduced, the problem becomes more complex for two reasons:

1. Because users are moving, so mappings cannot be static.
2. Because of uncertainty.

The satellite routing problem has been addressed in different contexts throughout the literature. The most common one is task scheduling, where a task with a specific duration is assigned to a satellite for a particular time.

In [14], Barbulescu et al. examine communication scheduling between ground stations and satellites, employing a heuristic, local search, and genetic algorithm. Users specify an antenna at a particular ground station, a duration, and a time window. Solutions are represented as permutations of integers 1 to N (total requests). However, the study overlooks scenarios involving long-duration tasks requiring multiple satellite routing, as seen in satellite internet for flights. Additionally, they did not address flight-type users, as these were not their main use case.

In [15] Xhafa et al. propose four objectives for their task scheduling model: maximizing successful communications by scheduling links during ground station-satellite visibility, minimizing communication clashes between satellites and ground stations, maximizing spacecraft communication time, and maximizing ground station usage. However, some objectives are unsuitable for satellite communications such as satellite internet, e.g., scheduling tasks within user visibility should be a constraint, as infeasible schedules need to be avoided, and ground stations should have communications the whole time they need to. Furthermore, uncertainty is not considered in their problem definition.

Other satellite routing approaches use different information and objectives. In [16], Zhu et al. use past scheduling information to predict future scheduling and model the process with game theory. Their online algorithm shows that the congestion of the system is reduced. However, the scheduling prediction algorithm proposed bases its decisions on the similarity in measurement reports from past user groups with the current group that needs handover. It does not consider other information, such as the users’ positions and times.

In [17], Li et al. use an online scheduling algorithm to schedule tasks in real-time in the context of an Earth Observation satellite. The scheduling algorithm proposed includes two policies, one when-to-schedule policy and one how-to-schedule policy, used to classify tasks by normal or urgent tasks. However, the authors study scheduling strategies in real-time and onboard, where computational resources are scarce and there are tight time constraints. Solutions that leverage information that might be available before operations to build pre-operations schedules have to be studied. In this paper, we use this information to build schedules before operations that are robust against uncertainty.

In [18], Pachler et al. studied satellite routing for satellite communications as a task scheduling problem. The authors aim at minimizing the resource consumption by distributing the load of the constellation across satellites and reducing the interference between users. However, the paper solves the problem only for fixed users, which assumes that are always connected to the system and requiring service. The mobile characteristics and uncertainty of users such as planes are not addressed. This paper aims to follow the research direction of this previous paper, and expand upon their proposed approach and results to also address mobile users and spatiotemporal uncertainty.

Metaheuristics have proven to be successful in similar problems. Specifically, the particle swarm optimization (PSO) has shown good results in solving the fixed user satellite routing case [18] by Pachler et al. It has also been used in other problems related to satellites, such as power and bandwidth allocation [19] by Pachler et al. refuel scheduling in geosynchronous constellations [20] by Zhou et al. and for routing in pico satellite networks, [21] by Fdhila et. al. . It has also been successful in similar scheduling problems, such as satellite remote sensing [22] by Wu et. al., satellite task scheduling [23] by Fan et. al., task scheduling in cargo ports [24] by Tang et. al., task scheduling in cloud computing [25] by Awad et. al. , and general task scheduling in combination with other algorithms [26] by Lin et. al. .

Overall, the satellite routing problem has been generally studied as a task scheduling problem. To the best of the authors’ knowledge, there is no work that considers the spatiotemporal characteristics of mobile users within the context of the satellite routing problem, including the uncertainty that users such as flights pose. The purpose of this paper is to bridge this gap by addressing the satellite routing problem considering mobile users and their uncertainty in time and space.

**Paper objectives**

This paper pursues the following objectives:

1. Develop a formulation and methodology that captures mobile users’ behavior effectively.
2. Assess the performance of the proposed approach by performing experiments where we generate solutions and test
them against real world scenarios. The results from those experiments aim to show that our approach reaches robust solutions against users’ uncertainty and that captures their mobile characteristics effectively.

**Paper organization**

The remainder of the paper is organized as follows: in Section 2, the satellite routing problem is formally defined and formulated; in Section 3, the particle swarm optimization implementation used to solve the optimization problem is explained; in Section 4, the experiments performed are explained and the metrics used to evaluate performance, and their results are shown; and in Section 5, conclusions from the experiments are stated.

## 2. THE SATELLITE ROUTING PROBLEM

### Definition

The satellite routing problem consists in matching users to satellites for every point in time, or equivalently, deciding when to handover each user from satellite to satellite, thus generating a routing plan. Operators are interested in handover schedules that minimize resource consumption and minimize service drop time. In order to reduce resource usage, distributing users among satellites has proven to lead to increased capacity [18].

Our approach is to solve the problem in two instances, as proposed in [27] by Guerster et al.: the pre-operations and operations solvers, as shown in Figure 1. On one hand, the pre-operations solver serves the purpose of generating a pre-operations plan from the users’ estimates, and it focuses on determining the best allocation possible, as it has less tight time constraints, and can explore the solution space for longer. On the other hand, the operations solver serves the purpose of reallocating users who might deviate from the pre-operations plan in real-time, with the timely information of the users.

In the remainder of this Section, we first focus on the pre-operations phase, presenting our approach to developing the pre-operations plan. Then, we turn to the operations phase, presenting our strategy to reallocate users that deviate from the pre-operations plan.

### Problem description

We assume that we have a set of $N_{sats}$ satellites $S_k \in \{S_1, S_2, ..., S_{N_{sats}}\}$ and a set of $N_{users}$ mobile users. We assume that the constellation consists of $N_{sats}$ distributed in an equatorial orbit. During the pre-operations phase, we assume that we have the information for every user’s planned trajectory, which consists of temporal points with their respective geographical positions. From this information, and simulating the constellation, we can then extract the initial and final times in which each user is seen by each satellite (i.e. when the elevation angle between satellite $S_k$ and user $l$ is equal to the minimum elevation angle). This is the visibility window, and it is denoted by $t_{S_k}^{\text{start},l}$, $t_{S_k}^{\text{end},l}$. Users can only be served by a specific satellite within the visibility window. To define when each user performs a handover from satellite to satellite, we can also equivalently define the serving window, which is the time window for which each user is served in each satellite. In Figure 2, both the serving window and the visibility window for a mobile user are represented. Then, the problem consists of deciding when to place the serving window for each satellite and user within the visibility windows, and to ensure that the users are served continuously. We assume that users can only be served by a specific satellite once per satellite period.

![Figure 2. Visibility and serving windows](image)

**Figure 2. Visibility and serving windows.** In the Figure, a user is scheduled to each satellite during the time window represented in blue. The visibility windows for satellite $S_k$ are indicated by $t_{S_k}^{\text{start}}$ and $t_{S_k}^{\text{end}}$. Notably, in the pre-operations solver, the visibility windows are based on forecasted or planned trajectories. Due to external events, such as bad weather conditions producing
delays or traffic producing trajectory changes, real trajectories might deviate from the planned ones in time or space. This uncertainty affects visibility windows, as deviations from the plan will translate in different $t_{\text{start},l}^k, t_{\text{end},l}^k$. Then, these deviations are encoded as $\Delta t_{l,1}^k$ and $\Delta t_{l,2}^k$, for the start and end times, respectively. An example of how visibility windows can change due to delays and how that can affect to the planned serving windows is shown in Figure 3. As represented in the Figure, previously valid serving windows can be invalidated by delays, leading to the user not being visible to the planned satellite when the user requests service.

**Formulation**

The formulation presented in this paper is a modified version of the fixed users’ case formulation presented in [18] by Pachler et al. The formulation they presented in that work is the following:

$$
\min \sum_{l,p,l\neq p} y_{l,p} c_{l,p}
$$

$$
y_{l,p} = \begin{cases} 
1 & \text{if } t_l < t_p + T_S \\
0 & \text{otherwise} 
\end{cases} \quad \text{if } t_{\text{start},l} < t_l < t_{\text{end},l} (1)$$

In the original paper, the authors leveraged the characteristics of equatorial orbits together with fixed users. In those conditions, the visibility windows and overlapping conditions are periodic, and they are the same between satellites but delayed, which allows to solve the problem for a single satellite and propagate the solution to the other satellites.

The objective of this formulation is to assign an initial serving time $t_l$ to each user $l$ that meets visibility constraints while minimizing resource consumption. Since users are fixed, the serving window’s position relative to the visibility window remains constant and has a fixed duration $T_S$. Reducing resource consumption involved minimizing user overlap $y_{l,p}$. User pairs overlap when they are connected to the same satellite at some point, with the overlap cost $c_{l,p}$, determined by their demand and proximity.

For the mobile case, the visibility windows and overlapping conditions change for each satellite. In this paper, we adapted the previous formulation to this new case.

The purpose of the satellite routing problem studied in this paper is to assign a handover time that is valid, i.e. that fulfills visibility and continuous service constraints, and that is as optimal and robust as possible, i.e. minimizes resource consumption and is robust against deviations from the pre-operations information. The decision variable is now the final serving time $t_{f,l}^S$ for each pair satellite-user in the constellation, differently to the fixed user’s case, where the decision variable was the initial serving time $t_l$ for each user $l$ and a reference satellite. As the visibility windows change from satellite to satellite, a decision variable is needed for each satellite in the constellation. The solution cannot be propagated with a delay through the satellites, as happened in the original formulation.

Similarly to the fixed users’ case, the final serving time has to fulfill the visibility window constraints, which means that it has to be allocated within the times that the user is visible to the satellite (Equation 2). Visibility windows for mobile users are different from the ones for fixed users, as they are not periodic, and change from satellite to satellite. We also need to ensure that the user will be continuously served, that is, satellite $k+1$ is visible when satellite $k$ performs handover (Equation 3).

$$
t_{\text{start},l}^k + \Delta t_{l,1}^k < t_{f,l}^k < t_{\text{end},l}^k + \Delta t_{l,2}^k (2)
$$

$$
\max(t_{\text{start},l}^k + \Delta t_{l,1}^k, t_{f,l}^k - 1) \leq t_{f,l}^k (3)
$$

Furthermore, we slightly changed the definition of overlapping. The definition of overlapping is now per satellite since the serving window depends on the satellite, and thus there is different overlapping in different satellites:

$$
y_{l,p}^S = \begin{cases} 
1 & \text{if } t_{f,l}^k < t_{f,p}^k \\
0 & \text{otherwise} 
\end{cases} \quad \text{for all satellites} (4)
$$

Similarly, the objective function minimizes overlapping over all satellites:

$$
\sum_{l,p,l\neq p} \sum_{k} y_{l,p}^S c_{l,p} (5)
$$

where $c_{l,p}$ is a penalization based on the demand and proximity of the two users.

Then, the complete formulation of the satellite routing problem is:

$$
\min \sum_{k} \sum_{l,p,l\neq p} y_{l,p}^S c_{l,p}
$$

$$
y_{l,p}^S = \begin{cases} 
1 & \text{if } t_{f,l}^k < t_{f,p}^k \\
0 & \text{otherwise} 
\end{cases} \quad \text{for each pair satellite-user} \quad (6)
$$

$$
\min \sum_{k} \sum_{l,p,l\neq p} y_{l,p}^S c_{l,p}
$$

$$
\sum_{l,p,l\neq p} y_{l,p}^S c_{l,p} \geq 0 (7)
$$

**Probabilistic constraints**

In the pre-operations phase, operators do not possess the real information from the user. In this Section, we adapt the formulation considering uncertainty in the information we possess in this phase.

Previous to operations, $\Delta t_{l,1}^k$ and $\Delta t_{l,2}^k$ are modeled as random variables, and their distribution is estimated from data. In order to make a more robust plan and be able to account for possible user deviations, we transform visibility windows into probabilistic constraints, which are the expression of the conditions of the optimization problem so that the conditions hold with probability $p$.

To do that, we introduce the following equations:

$$
P(\Delta t_{l,1}^k < t_{f,l}^k) \geq p \Rightarrow 
\int_{t_{\text{start},l}^k}^{t_{f;l}^k - \Delta t_{l,1}^k} f_{\Delta t_{l,1}^k}(\Delta) d\Delta \geq p \quad (7)
$$
where \( P(\cdot) \) is a probability of an event occurring and \( f_{\Delta x_k}(\Delta) \) is the probability density function (pdf) of variable \( \Delta_{i,j} \). The probability density function is not an explicit function, it is extracted from the data available in the Eurocontrol dataset [28]. We can control the robustness with parameter \( p \).

By choosing a greater \( S_{k,j} \), probability \( p \) is higher in Equation 7, but is smaller in Equation 8. The objective is to have an equilibrium. For that, we fix a value for \( p \), and find the estimated visibility windows that fulfill that probability.

Apart from the constraints presented above, there are some practical considerations to be taken into account in order to make the resulting allocations feasible. For restrictive \( p \)’s, we can encounter scenarios where Equation 3 is not fulfilled. That happens in the visibility windows of consecutive satellites, that is, the estimated visibility windows do not overlap, so \( S_{k,j} \) can not be less than \( t_{end,l} \) and greater than \( t_{start,l} \) at the same time. In those cases, we reduce the probability \( p \) of those visibility windows to the maximum one that fulfills Equation 3, i.e., when the estimated \( S_{k+1} \) and \( t_{end,l} \) are, at least, equal. We look for the probability \( p \) that fulfills that condition iteratively, reducing \( p \) by steps until we find the value of \( p \) for which both times are, at least, equal:

1. First, reduce probability \( p \) by a certain step (in our case, 0.001) and recompute the estimated times.
2. Repeat the procedure until the estimated \( S_{k+1} \) and \( t_{end,l} \) are equal.

**Real-Time strategy**

Once a pre-operations plan has been computed, we can proceed to the operations phase. But, as mentioned before, the real schedule and trajectories that the users take might be different from the ones planned, and, even though a robust plan has been generated, there still will be users that deviate from the plan. A real-time strategy that reallocates those users is presented here. Note that, a user only needs to be reallocated if it deviates enough from the original plan such that the planned satellite is no longer visible. In the operations phase, we also possess the frequency assignment information, i.e., the specific frequency in which the users operate, their bandwidth and power. With that information, we can also check if there is resource overlapping between users (i.e., different users using the same resource at the same time), which would mean that one of the users should be dropped.

The proposed strategy consists of the following steps:

1. For each user that needs to be reallocated, we check which satellites are visible.
2. We start checking, for each satellite, in order of the elevation angle, highest to lowest, if there is a conflict in frequency between the user and any other user served by the satellite. A conflict arises when different users are using the same frequency at the same time. We keep checking every satellite until we find one in which the user does not have any frequency conflict.
3. If no feasible satellite is found, we assign the user to the highest elevation angle satellite in the satellite routing plan and we use other strategies [13], or the user is dropped.

### 3. Particle Swarm Optimization algorithm

This section presents the particle swarm optimization algorithm, used to solve the scheduling optimization problem. First, an introduction to the algorithm and examples of its application to different problems are presented. Secondly, the general characteristics of the algorithm are explained. Finally, the implementation used in this paper is described.

**Introduction**

In scenarios involving hundreds or thousands of users, satellite routing becomes a complex, high-dimensional problem that cannot be solved optimally in a computationally feasible time [29], [30]. In order to solve the problem, we use Particle Swarm Optimization (PSO). First introduced in 1995 by Kennedy et. al. in [31], Particle Swarm Optimization is an iterative algorithm inspired by the social behavior of bird flocks. It has shown to be successful in solving complex problems, and has properties that makes it suitable for this task, such as a capacity to get out of local optima [32].

**PSO concepts**

The PSO algorithm is based on particles, and each particle has a position and a velocity. For particle \( i \), its position represents a solution to the problem in the solution space at each iteration, which we denote by \( x_{i,t} \), and its velocity represents how the particle’s position evolves through the iterations of the algorithm, which we denote by \( v_{i,t} \). Each particle has associated the value from the objective function of our optimization problem. The solution space is explored by the particles, which move to a new position in each iteration according to their velocity \( v_{i,t} \). A group of particles is referred to as swarm, and it is composed by \( N_{part} \) particles.

In each iteration, the position of the particle \( x_{i,t} \) evolves as:

\[
x_{i,t} = x_{i,t-1} + v_{i,t}
\]

The velocity evolves as the algorithm runs following different parameters:

1. Global pull: it represents the attraction that each particle has towards the best solution found so far until iteration \( t \) by the swarm. It can be computed as:

\[
G = \alpha g(x_{i,t} - x^G)
\]

where \( \alpha \) is a random weight uniformly distributed over \([0,1)\), \( g \) is the weight factor of the global pull, and \( x^G \) is the best particle of the swarm.

2. Local pull: it represents the attraction that each particle has towards its best own solution found until iteration \( t \). It can be computed as:

\[
L = \beta l(x_{i,t} - x^L)
\]

where \( \beta \) is a random weight uniformly distributed over \([0,1)\), \( l \) is the weight factor of the local pull, and \( x^L \) is the best solution found by the particle until iteration \( t \).

3. Inertia: it represents the tendency that the particle has to follow its previous velocity in the previous iteration \( t-1 \). It can be computed as:

\[
I = w v_{i,t-1}
\]
where $w$ is the inertia weight, and $v_{i,t-1}$ is the velocity in the previous iteration.

Velocity is then computed as:

$$v_{i,t} = G + L + I$$  \hspace{1cm} (13)

The implementation of the Particle Swarm Optimization used in this paper has been extracted from [18] with some modifications. From the original paper, we have used the concept of mutation that the authors introduced in the PSO, where each particle has a certain probability $p_{mut}$ of suffering a mutation of a fraction $p_{mutx}$ of its coordinates. We have also used a velocity constraint, that limits the maximum velocity that particles can achieve.

**Adaptive weights**

In this paper, we have introduced the use of progressive/variable weights for the optimization algorithm, to have two different objectives in the optimization process, one at the beginning of the algorithm, and another one at the end. The objectives are:

1. **Exploration**: More weight is given to the local pull and inertia.
2. **Exploitation**: More weight is given to the global pull.

In this paper, a linear variation with the iterations has been considered. The weights vary according to the following evolution throughout the iterations:

$$I = (l_{min} - l_{max}) \frac{1}{N_{iter}} t + l_{max}$$  \hspace{1cm} (14)

$$G = (g_{max} - g_{min}) \frac{1}{N_{iter}} t + g_{min}$$  \hspace{1cm} (15)

$$w = (w_{min} - w_{max}) \frac{1}{N_{iter}} t + w_{max}$$  \hspace{1cm} (16)

By doing that, we are able to assess a wider variety of solutions in the exploration phase and then converge towards the best solution in the exploitation phase. The linear variation of the inertia weight was first introduced by Shi and Eberhart in [33] and it has already been widely used in the literature [34], [35]. Furthermore, in [36], Ratnaweera et. al. proposed the use of adaptive acceleration weights by linearly varying them throughout the iterations.

**4. RESULTS**

In this Section, the experiments performed are presented, as well as the metrics used to assess their results. Three experiments have been performed: first, the pre-operations satellite routing approach is tested to assess if it can effectively create robust pre-operations plans. Next, an analysis of the users who are dropped is conducted to investigate the reasons behind their service unavailability. Finally, a full simulation with the operations phase is conducted, and we assess the performance of the proposed satellite routing approach together with other strategies from the literature. Throughout the remainder of the paper, we use two baselines that serve as lower and upper bounds, respectively: 1) We use the solution to the satellite routing with additional strategies to address uncertainty (i.e., without using probabilistic constraints and any operations phase strategies), solved with the PSO, and 2) We use the solution to the satellite routing in the case where there is no uncertainty (i.e., the users’ planned information in the pre-operations phase is the real information in the operations phase).

**Simulation parameters**

The satellite constellation used is based on the O3b constellation operated by SES [37]. It consists of $N_{sats} = 10$ satellites equally distributed in an equatorial orbit at 8063km of altitude. The users have been extracted from the Eurocontrol dataset [28], which consists of aerial users with planned trajectory and time and the real trajectory and times. This dataset is used to characterize the distribution of the random variables presented in Section 2 and to simulate users. For the simulation, we randomly select a total of $N_{users} = 2500$, and we have excluded flights that fly above 47º and below −47º. The users are extracted from a single day of the dataset (in our case, day 12/21/2019). The pool of users from which we select the $N_{users}$ users is plotted in Figure 4.

The constellation parameters used are summarised in Table 1.

**Satellite routing**

This experiment aims to show how the proposed pre-operations approach increases the time that users are served from a scheduling perspective. Results with global metrics, such as power or users served, are provided in the next Sections, once the frequency assignment experiment has been solved.

The metrics used in this experiment are the following:

1. **Drop time**: it is the time that users are out of plan when using the pre-operations plan (computed based on estimations) with the real information of the users. It is normalized against the total time that the users require service.
2. Maximum load: it is the number of users connected to the satellite with the most number of connected users, normalized against the total number of users at each point in time, and time-averaged.

By using the maximum load metric, we show that system capacity is reduced (i.e. there is more overlapping). With this fact, we can assess the impact on the system of building a robust plan.

In Figure 5, the results of 10 Monte Carlo simulation runs for 4 different values of \( p \) are presented. Each of those runs are performed with a different set of randomized users. The confidence ellipses are computed with the method explained in [38]. In Table 2, the numerical results of the graph are shown. In the Figure, we observe different values for the probability \( p \) defined in Section 2 and the drop time and constellation load for each resulting schedule. We observe that, for the most conservative point with \( p = 0.99 \), we achieve to reduce the drop time by 11.68%, but the constellation load increases by 11.85%. By introducing uncertainty considerations in the form of probabilistic constraints, we reduce the time that users are out of plan, as we schedule the users in smaller visibility windows, which allows us to produce robust schedules against changes in the visibility windows. The cost of reducing the drop time is that the system’s load increases, as more users are connected to the same satellites, also as a consequence of scheduling users in smaller time windows. Furthermore, we have the ability to control the trade-off by tuning \( p \), which allows us to be more or less conservative in our decisions. From the operator’s view, if reducing the time that users will not be able to connect to the pre-operations planned satellite is a priority, we could argue that the best solution is \( p = 0.99 \), as it reduces the amount of time users experience drop time to almost 2%. However, that comes at the expense of constellation capacity, which is also of importance to operators. Then, other values of \( p \) can be of interest. By tuning \( p \), operators can find the value that best fits their system and situation, providing more robustness against uncertainty, or being less robust but with a higher capacity to better distribute users through the constellation.

Frequency assignment strategies
In this paper, we assess the performance of the satellite routing strategies combined with frequency assignment strategies that address uncertainty. To do that, not only the satellite routing problem has to be solved, but also the frequency assignment problem. For that, we use the solution proposed in [39] by Garau et. al., and we use the strategies presented in [13] by Casadesus et. al., by solving both problems, we can analyze the effect of combining strategies in both problems together.

From the strategies presented by Casadesus et. al., two have been chosen because of their complementary characteristics to the satellite routing ones:

1. Reserved Spectrum: it is a real-time frequency assignment strategy that reserves a portion of the available spectrum in the pre-operations phase in order to use it to reassign users that deviate from the pre-operations frequency plan.
2. Trajectory deviations: it is a pre-operations frequency assignment strategy that considers possible trajectory deviations in the pre-operations phase to compute more restrictive constraints.

The different combinations assessed in this paper can be found in Table 3. All combinations use the PSO implementation presented in Section 3 to solve the satellite routing optimization problem, and the optimization framework presented in [39] to solve the frequency assignment. We have selected the best values of \( p \) for each strategy combination to run the experiments.

Dropped users characterization
The purpose of such characterization is to give a better insight into the causes of drop time and how our approach addresses them. In this experiment, we analyze the baseline case, i.e. not using neither probabilistic constraints nor the trajectory deviations strategy in the pre-operations phase, and not using any real-time strategy in the operations phase. That analysis consists of, while the system is simulated, counting the number of users that are dropped (i.e. users that cannot be served) because of a deviation from the pre-operations plan in satellite routing and because of a deviation from the pre-operations plan in frequency assignment.

From the values found in Table 4, we can see that most of the users are dropped due to satellite routing, that is, users that deviate from the routing schedule defined before operations. From that, we can conclude that most of the users’ deviations in trajectory and time are sufficiently low to increase the time that users are out of schedule, but not enough to produce new frequency conflicts between users, which translates into a higher fraction of the users being dropped because the planned satellite in the pre-operations phase is not visible to them in the operations phase as planned. From these results, we can conclude that addressing uncertainty in the satellite
Table 3. Combination of strategies.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Description</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>No uncertainty</td>
<td>-</td>
</tr>
<tr>
<td>B</td>
<td>No strategies (Baseline)</td>
<td>-</td>
</tr>
<tr>
<td>C</td>
<td>Real-time SR</td>
<td>$p = 0.7$</td>
</tr>
<tr>
<td>D4</td>
<td>PC</td>
<td>$p = 0.99$</td>
</tr>
<tr>
<td>E</td>
<td>PC + RT SR</td>
<td>$\gamma = p_{50}, p = 0.9$</td>
</tr>
<tr>
<td>F</td>
<td>Trajectory deviations + PC</td>
<td>$p = 0.7, x_{spec} = 0.05$</td>
</tr>
<tr>
<td>G</td>
<td>PC + Reserved spectrum</td>
<td>$\gamma = p_{50}, x_{spec} = 0.05$</td>
</tr>
<tr>
<td>H</td>
<td>RT SR + Trajectory deviations</td>
<td>$p = 0.7, \gamma = p_{50}$</td>
</tr>
<tr>
<td>I</td>
<td>RT SR + Reserved spectrum</td>
<td>$p = 0.9, x_{spec} = 0.05$</td>
</tr>
<tr>
<td>J</td>
<td>PC + RT SR + Trajectory deviations</td>
<td>$p = 0.7, \gamma = p_{50}$</td>
</tr>
<tr>
<td>K</td>
<td>PC + RT SR + Reserved spectrum</td>
<td>$p = 0.99, x_{spec} = 0.05$</td>
</tr>
<tr>
<td>L</td>
<td>PC + RT SR + Trajectory deviations + Reserved spectrum</td>
<td>$p = 0.7, \gamma = p_{50}, x_{spec} = 0.05$</td>
</tr>
</tbody>
</table>

PC = Probabilistic Constraints, RT SR = Real-time satellite routing

Table 4. Users dropped characterisation. The percentage of dropped users in the baseline case for each possible cause is presented.

<table>
<thead>
<tr>
<th>Cause</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total users dropped</td>
<td>15.41</td>
</tr>
<tr>
<td>Users dropped due to frequency assignment</td>
<td>1.74</td>
</tr>
<tr>
<td>Users dropped due to satellite routing</td>
<td>14.01</td>
</tr>
</tbody>
</table>

Satellite routing + frequency assignment

This experiment aims to show the results of the different combinations of strategies. Once the frequency assignment has been solved, global metrics, such as power and users served, can be used, as we possess all the information to compute them. They are used in this experiment to characterize the improvement in performance, from the baseline case, when satellite routing and frequency assignment strategies are combined. In order to do that, the following metrics are used:

1. Users served: it is the number of users successfully served normalized against the users that require service, and time-averaged.
2. Power consumption: it is the amount of total power consumed. Normalized against the power consumed by the case without uncertainty, i.e. when the users do not deviate from the planned trajectories and times known before operations.

In Figure 6, the results for 10 Monte Carlo simulation runs of each of the experiments are shown. The 10 runs are performed for different users, that is, generated with different random seeds. In Table 5, the numerical results are presented. The confidence ellipses are computed with the method explained in [38]. From these results, an interesting outcome is that the satellite routing strategy that serves most users is the real-time satellite routing strategy. That means if the system has the real-time capabilities to perform that strategy in a relatively short time, it is best to use the real-time strategy than its pre-operations counterpart. It is also important to note that, even though the real-time satellite routing strategy (strategy C) performs better than the combination of real-time with probabilistic constraints satellite routing (strategy E), strategy E consumes less power. That is because probabilistic constraints schedule the users closer toward the center of the visibility windows, which means they are closer to the satellite, thus consuming less power. We can also see that the best combinations of strategies use the real-time satellite routing strategy and the real-time frequency assignment strategy. Furthermore, strategies that use the trajectory deviation strategy use more power.

The strategies that serve most of the users are strategies I, K, and L, serving 99.7%, 99.69%, and 99.89% users, respectively. However, strategy L consumes more power, 13.45% more than the case without uncertainty. There is a trade-off between strategies D4, E, C, I, K, and L. However, from the operator’s view, we could argue that possibly strategy combinations I and K are the best, as serve almost all the users, which is the operators’ main concern, at a low power consumption cost, 3.25% and 2.44% respectively. However, the operator can always decide to use another combination of strategies that uses less power if reducing power is a priority, or choose to use strategy combination L if serving the most users possible is a priority and power is not a constraint.
Table 5. Results satellite routing + frequency assignment. The results of the satellite routing experiment together with frequency assignment are presented. The combination of strategies can be found in Table 3.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Users served</th>
<th>Power consumed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Std. Dev</td>
<td>Mean Std. Dev</td>
</tr>
<tr>
<td>A</td>
<td>1 (0)</td>
<td>1 (0)</td>
</tr>
<tr>
<td>B</td>
<td>0.8441 (0.0044)</td>
<td>0.9845 (0.0138)</td>
</tr>
<tr>
<td>C</td>
<td>0.9591 (0.0027)</td>
<td>0.9718 (0.0125)</td>
</tr>
<tr>
<td>D4</td>
<td>0.9457 (0.0034)</td>
<td>0.9576 (0.0171)</td>
</tr>
<tr>
<td>E</td>
<td>0.9560 (0.0038)</td>
<td>0.9516 (0.0106)</td>
</tr>
<tr>
<td>F</td>
<td>0.9623 (0.0032)</td>
<td>1.0686 (0.0148)</td>
</tr>
<tr>
<td>G</td>
<td>0.9823 (0.0016)</td>
<td>1.0210 (0.0157)</td>
</tr>
<tr>
<td>H</td>
<td>0.9713 (0.0028)</td>
<td>1.0690 (0.0170)</td>
</tr>
<tr>
<td>I</td>
<td>0.9970 (0.0013)</td>
<td>1.0325 (0.0140)</td>
</tr>
<tr>
<td>J</td>
<td>0.9739 (0.0019)</td>
<td>1.0714 (0.0124)</td>
</tr>
<tr>
<td>K</td>
<td>0.9969 (0.0008)</td>
<td>1.0244 (0.0110)</td>
</tr>
<tr>
<td>L</td>
<td>0.9989 (0.0008)</td>
<td>1.1345 (0.0187)</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

In this paper, we have adapted a fixed-user satellite routing formulation to the dynamic behavior of mobile users, accounting for the uncertainty that characterizes them. The satellite routing problem is solved in two instances, in the pre-operations phase, and in the operations phase. In the pre-operations phase, to address spatiotemporal uncertainty, we have proposed a probabilistic constraints formulation, based on statistical data, and we are able to generate an optimized robust baseline schedule by using a particle swarm optimization algorithm, adapted from previous works, to solve the formulation proposed. In real-time, we have proposed a satellite routing strategy to re-route users that deviate from the baseline schedule. Then, we have conducted three experiments, to assess the performance of the pre-operations satellite routing strategy, to analyze the reasons that produce dropped users, and to assess the performance of different combinations of satellite routing and frequency assignment strategies. Our main findings are the following:

1. The results show that the pre-operations satellite routing strategy effectively reduces drop time, at the expense of system load. With the formulation proposed, the trade-off between both metrics can be controlled by tuning $p$.

2. From our analysis, we can conclude that the satellite routing problem under user uncertainty is the main cause of drop time when the plan is not robust, with around 14% of dropped users. That emphasizes the importance of building robust satellite routing plans.

3. By combining satellite routing and frequency assignment strategies, the results show we can serve around a 99.7% of the users for minimal power cost. At an extra power cost, we can serve 99.9% of the users by using all the strategies.

Directions for future research include studying the satellite routing problem when there are inter-satellite links, studying the grouping of users in beams when there are fixed and mobile users under uncertainty, and including uncertainty in the users’ demand.

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