DOI: 10.13009/EUCASS2023-927
Aerospace Europe Conference 2023 – 10TH EUCASS – 9TH CEAS

Sensitivity Analysis of Propulsion System Parameters on GNC Strategies for Multi-Orbit Deliveries

Iñigo Alforja Ruiz†, Lily Blondel-Canepari**, Alberto Sarritzu**, Angelo Pasini** and Michèle Lavagna**

** Politecnico di Milano, Aerospace Science and Technology Department, Via La Masa 34, Milano, Italy*
*** University of Pisa, Department of Civil and Mechanical Engineering, Pisa, Italy*
† Corresponding Author, inigo.alforja@polimi.it

Abstract
This research investigates the delivery of 6U CubeSats to eight LEOs with a kick stage system. The study aims to highlight the synergy between mission analysis and propulsion system design in achieving optimal delivery. The objective is to analyse the sensitivity of the optimal trajectory definition to various propulsion system parameters by comparing different propellant options, assessing the optimisation algorithm's response to anticipated or unexpected engine failures, determining the minimum specific impulse required, and analysing the impact of varying propulsive system mass. These analyses ensure the robustness and reliability of the GNC tool, enhancing mission success and optimizing multi-orbit deliveries.

1. Introduction

The development of a society increasingly globalised has entailed the parallel, and necessary, development of technologies related to communications and access to information. Today's lifestyle cannot be understood without the dependence to spaceborne systems which provide these services, and this has subsequently been traduced into a dramatic increase in the number of systems which are required to be in orbit. Some studies predict the growth rate of launch of small satellites this decade to be four times the rate of the previous one [1]. In addition, this increase has been pushed by the irruption of new players into the space sector (due to its democratization) as well as the rise in the interest of large constellation missions by well-established big corporates. The space access infrastructure is then facing a challenging position in terms of logistic arrangements to accommodate all launches, but also in ecological terms, due to the corresponding increase in fuel consumption and materials usage. The need of innovative, as well as efficient, space transport strategies is therefore obvious.

The space access bottleneck situation does not have simple solutions. The immediate resolution is launching several satellites at once, reducing the number of necessary launches. While some of the historically used systems allow for multiple-payload injection, based on piggyback strategies, they usually entail some degree of rigidity in the achievable orbits for the launched satellites, either due to a primary load driving the main launch, or by the system being able to deliver in certain specific orbits. The satellites need manoeuvring capabilities to reach their desired orbital position, increasing the fuel budget. These practices can discourage new projects, especially those coming from the private sector or smaller and low-budget institutions, such as universities.

The new way of accessing space should, therefore, focus on injecting the different satellites into their respective operating orbits. This concept is not new and has already been tested by means of *kick-stages*, or *orbital stages*, which act as intermediary stages between a primary orbit and the secondary ones. The ASTRIS kick stage for example, specifically developed and optimized for the upcoming Ariane 6 (A6) launcher, aims to enable direct satellite placement in geostationary orbits, to facilitate Moon and deep space exploration and to reduce the transport time to orbit [2]. Other devices developed overseas, SL-OMV by MOOG or SHERPA by Andrews Space for example, have already flown with different payloads onboard. The multi-payload, multi-orbit missions are a class of missions that present themselves as strategic for the planning and performance of future launches.

However, designing such a vehicle is a complex and multi-faceted task as it is highly dependent on the mission planning, presenting challenges related to the trajectory definition, driving factor of most of the requirements for the system, especially in terms of propulsion. In fact, planning a multi-orbit injection trajectory is not straight-forward, as not only the definition of the transfers must be optimized, but also the order in which these will be done [3]. Such a problem, which can be defined as a multi-rendezvous scenario, is found also in other types of missions, especially

DOI: 10.13009/EUCASS2023-927

those related to Active Debris Removal (ADR) and On-Orbit Servicing (OOS). In fact, most of the literature on the topic is related to these mission types, as can be observed in the following analysis of current strategies. The general approach found in literature towards the full obtention of a feasible (and ideally optimal) trajectory is to separate both the visitation and the transfer problems to solve them individually by means of numerical optimizers specific or adapted to their nature. The connection between those, however, must be kept and is conventionally performed by attributing the cost of a set of transfers to a certain sequence, based on the manoeuvres estimated to be done given an orbit order. This way, this information is fed-back to research for the optimal order and its related set of orbital transfers, maintaining their coupling. Thus, the overall problem is divided into two queries: the visitation sequence and the transfers definition.

The visitation sequence is, by nature, a combinatorial problem in which the optimal order of the orbits must be found such that the total cost of the tour is minimized, similarly to the very well-known Travelling Salesman Problem (TSP) in integer optimization [4]. Typical extensive search algorithms have been applied to solve this part of the multi-rendezvous problem, such as the ones used in Chen et al. [5] and Daneshjou et el. [6], in which all possible combinations are calculated and compared to each-other to find the global optimum. This strategy, however, becomes unfeasible for larger number of orbits to be visited, as the number of possible combinations rises in a factorial fashion. Alternatively, other studies have proposed adaptations of the extensive search, those called tree-search algorithms, in which tours are built node by node by "branching" and these branches are cut or let continue depending on specific problem-defined criteria. Among these, the most prevalent is the use of Branch-and-Bound algorithms [7-10], although alternatives such as the Series Method [11] is also worth mentioning. These strategies can also become unfeasible in computational efforts if the number of orbits is too high, and the allowed number of branches is not limited. In addition, the gradual building and evaluation of the tour limits an examination on global costs of full trajectories. To overcome both issues, it has been proposed to use heuristics that allow to evaluate full paths and reduce the computational effort, trading it by sub-optimal results. Some examples of these strategies are the use of Genetic Algorithms [7, 12], Simulated Annealing [13, 14], or Ant Colony Optimization [15-17]. The latter provides an additional characteristic which is the natural resemblance of the ant tour-building to the tree-structure of combinatorial problems.

The multi-rendezvous trajectory definition also entails the sub-problem of the definition of the individual transfers among the orbits. The most common strategy is to generate a data storage of costs (generally in terms of ΔV) associated to certain pre-computed transfers and to which the algorithm can quickly access to attribute to the current evaluation. This cost can be assumed to be time-independent [9, 18], although, to make it more realistic, most studies include the dependence on time by establishing a time grid and calculating all possible costs between two orbits [8, 10, 14]. These are then stored in arrays, allowing for fast attribution of a cost to a specific transfer at the cost of large data storage. To compensate this issue, Bang et al. [19] proposes a preliminary local optimization of each one of the possible transfers in the search of local minima to store instead. Nevertheless, several studies have shown that by introducing the optimisation of the manoeuvres within the overall algorithm can improve the quality of the final solution. Due to the enormous size of the search-space of this problem, authors tend to use heuristic algorithms, such as Genetic Algorithms [12] or other Evolutionary Algorithms [7, 13]. Like the generation of pre-computed arrays of data, using these strategies requires of discretizing the time variable, limiting the possibilities of optimal finding. This can be overcome using methods working on the continuous spectrum, such as the Particle Swarm Optimisation (PSO) [5, 6, 20]. All the shown strategies, however, rely on building the sequence node by node by individually optimizing the transfers in a way that resembles the semi-exact methods (branch-and-bound) instead of optimizing at once all transfers. Therefore, later transfers are influenced by the decisions of previous ones, which limits the search-space and could be detrimental as it might stagnate in sub-optimal tours.

All literature related to the generation of a reference trajectory for the multi-rendezvous problem, however, has been focused on the orbit optimization and feasibility of the mission, assuming a pre-defined vehicle design. The effect of the design, especially in terms of the propulsion system, has a remarkable impact on the mission definition, and on the feasibility of different case scenarios or options. The current paper aims at studying the sensitivity that a multi-rendezvous trajectory optimization tool has to the parameters related to the propulsion system to evaluate its usefulness as a Mission Analysis tool both for planning the mission and aiding on the sizing and design of the spacecraft. To do so, in the remaining of Section 1 the problem to be solved as well as the vehicle considered will be presented. This is followed by a description of the used optimisation tool in Section 2, where the case scenario is also introduced. The different test relating the trajectory definition and the vehicle systems are shown in Section 3. Finally, the conclusions are presented in Section 4.

DOI: 10.13009/EUCASS2023-927

1.1. Multi-Orbit Multi-Payload Problem Definition: CubeSats Deliveries to LEO

To investigate the effect of vehicle design in a multi-orbit multi-injection mission, a reference mission is defined. The outlined scenario is based on a spaceborne vehicle tasked with the delivery of *N* payloads into *N* distinct orbits in space. Both the orbital elements and the masses of the different payloads are known and specified towards the design of the optimized trajectory. The latter is considered to start at the orbit of the first deployed satellite, after its release. Therefore, the cost of launching from ground into this first orbit is not included in the full trajectory definition, although the selection of this first orbit is still an output of the optimization. The trajectory is assumed to be finished once the vehicle deploys the last satellite and performs a final manoeuvre towards a disposal orbit to comply with the space debris mitigation guidelines. The design of such an orbit is outside the scope of this work, and as such is pre-determined based on the payloads to be delivered, in an arbitrary manner.

The full mission can then be summarized as:

1) The vehicle, after deploying the first payload, moves into the following orbit to release the next satellite. Then, after sufficient time has passed to ensure correct deployment, it moves to the next one.
2) The sequence is repeated *N-1* times, after which the vehicle disposes itself by moving into the designed final disposal orbit, after whose reach the mission is finished. It must be noted that, as the activity entails injecting orbits, there is no specific point within the final orbit which is necessary to reach, and thus all possible points are considered in the search space when performing the optimization.
3) Considering a hypothetical point of view of customers, the release of satellites should be done as cheap and quick as possible. Therefore, both objectives (namely, total fuel mass consumed and overall mission time) are to be minimised in the optimization.
4) Considering the typical propulsion system of a kick stage, the manoeuvres are assumed to be impulsive.

The previously defined mission profile can be now formulated mathematically. The multi-rendezvous problem can be categorised as a graph problem of the TSP-type, such that a pre-defined set of nodes (or cities) must be visited only once while minimising the travel cost among them. Nevertheless, in this particular case of TSP, there are substantial differences with respect to the usual formulation of the problem. On the one hand, as stated before, the multi-orbit multi-injection problem is highly dependent on time, due to the nonlinearity of the orbital dynamics involved in the motion of the vehicle and the effect this has on initial and final positions of possible transfers. Properly implementing time is crucial to account for the infinite account of possible transfer arcs between two consecutive orbits. On the other hand, the problem under consideration is open route, such that the vehicle does not start and finish at the same node. This will affect the order of the sequence in a sense that the final disposal manoeuvre is also included in the set, and as such the optimizer might tend to different visitation strategies. In fact, the sequential nature implies that any transfer will affect any subsequent manoeuvre on the possible decisions to be performed as well as on the remaining time and fuel. The proposed method to minimise this effect is the simultaneous optimisation of the complete set of transfers, with the increment of complexity that it entails. Based on these described characteristics, the mathematical formulation of the optimization problem at hand can be stated as:

Minimise:

$$\left\{\sum_{i=1}^{N+1} m_{f,i}\, , t_{tot}\right\} \tag{1}$$

Subject to:

$$\dot{\boldsymbol{r}} = -\frac{\mu}{r^3}\boldsymbol{r} + \frac{T}{m}\boldsymbol{e_T}\delta + \boldsymbol{f_{dist}} \tag{2}$$

$$\dot{m} = -\frac{T\delta}{I_{sp}g_0} \tag{3}$$

$$\sum_{i=0}^{N+1} s_{i,j} = 1\,;\ \sum_{j=0}^{N+1} s_{i,j} = 1 \tag{4}$$

$$\sum_{k=1}^{N+1} m_{f,k} \le m_{f,max}\,;\ \sum_{k=1}^{N+1} t_k \le t_{max} \tag{5}$$

Equations (2) and (3) express the equations of motion of the system. On the one hand, Equation (2) represents the orbital dynamics under the effect of a thrust force T with direction $\boldsymbol{e_T}$, which is turned on or off (expressed by the main engine relay on-off function δ) and under the effect of environmental disturbances $\boldsymbol{f_{dist}}$. In the case under consideration, for simplification, the thrust manoeuvres are assumed to be impulsive ΔVs, which allow for the generation of Lambert transfers among the different target orbits. In addition, disturbances are neglected, such that

DOI: 10.13009/EUCASS2023-927

ideal Kepler orbits can be assumed. On the other hand, Equation (3) expresses the evolution of fuel mass according to Tsiolkovsky's, considering a system of constant thrust and constant specific impulse I_{sp}. Equations (4), on their turn, express the condition of the combinatorial problem that each orbit must be visited only once, and all orbits must be passed through. Finally, Equations (5) mathematically express the constraints on maximum fuel consumption and maximum total mission time. This mathematical formulation easily shows the distinction between the transfer problem (Nonlinear Continuous Programming) and the combinatorial one (Integer Programming). The tightly coupling of both, however, categorises the full problem as a Mixed-Integer Nonlinear Programming problem (MINLP).

1.2. The Multi-Orbit Delivery System: The Kick Stage

The reference in-space delivery system, hereby referred to as kick stage, but also called tug stage or orbital stage, stands as a crucial component in the development of current space activities. Its main purpose is to optimize launch costs for specific payloads by increasing the versatility of the launcher. Mounted as an additional stage, on top of the upper stage, the kick stage serves as a modular element that offers additional propulsion capabilities to classical systems, enabling a wider range of missions. Many kick stages are under-development worldwide, and some have already flown and demonstrated their ability to deliver multiple payloads to precise diversified orbits [21].

The introduction of kick stage systems has significant implications for space missions. Its presence forces to rethink the mission analysis of many common strategies, enabling the direct placement of satellites into their intended orbits. These systems have the potential to reduce the transport time to orbit from several months to just a few days, particularly benefiting satellites equipped with electrical drives. This system's ride-sharing capability provides a cost-effective solution by allowing multiple payloads to share a common propulsion system, simplifying satellite designs, and increasing the chances of successful delivery [21, 22]. In addition to its enhanced payload delivery capabilities, the kick stage stands out due to its versatility in undertaking diverse missions. Apart from facilitating multi-orbit deliveries, it can support emerging space needs such as active space debris removal, on-orbit servicing, and general in-orbit operations. Overall, the kick stage system represents a game-changing technology in the space industry, offering increased access to space, cost-efficiency, and the potential for novel missions. It provides opportunities for the integration of environmentally friendly technologies, such as green propulsion, further aligning with the industry's growing focus on sustainability. As more kick stage systems are being developed worldwide, they are expected to play a pivotal role in shaping the future of space exploration and commercial activities.

In the context of multi-orbit payload delivery by a kick stage, the present study focuses on the trajectory reference for the GNC system, established by optimizing the visitation sequence and the transfers, and how the plan is affected by varying propulsive parameters. This involves careful evaluation of factors such as propellant selection, allocation of the propulsion system's dry mass, capability for re-ignition and the analysis of worst-case scenarios such as engines' malfunctioning or complete loss of functions.

2. The Mission Analysis Tool

The following section aims at giving an overview of the working structure of the algorithm; however, the purpose is not giving a detailed description of its functioning, but only introducing its capabilities. Once the fundamental functionalities of the tool are introduced, the focus shifts towards outlining the modifications made to the inputs, as well as the specific mission at hand, which ultimately led to the results described below.

2.1. Overview of the Trajectory Optimization Algorithm

The previously described MINLP problem is classified to be of the NP-hard class, in a way that deterministic resolutions grow factorially with the size of the problem. For the solution of these problems, heuristic algorithms provide a computationally efficient alternative, although resulting in sub-optimal results. Following the literature approach described in Section 1, the proposed architecture utilized to solve the two different sub-problems is to separate them into the integer and the continuous parts while keeping their coupling.

A bi-level structured algorithm was implemented, with each level dealing with a separate sub-problem. While the internal layer solves the optimal set of transfers among a certain defined sequence of visitation, the external deals uniquely with solving the optimal order of orbits. Nevertheless, the inner level requires the sequences given by the outer one to calculate the optimal transfers, and the external algorithm uses the costs associated to the optimal transfers as a cost function to compare and generate new sequences towards the optimum. Such interconnection is performed

DOI: 10.13009/EUCASS2023-927

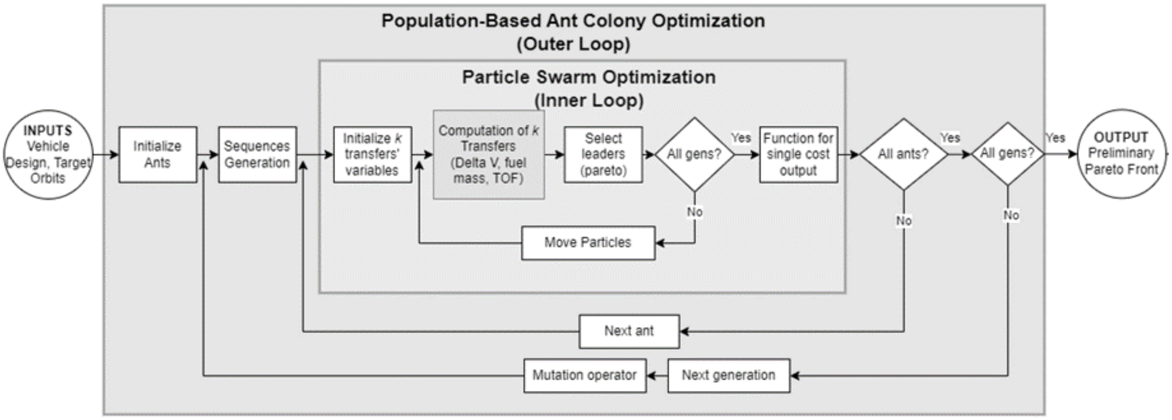

Figure 1 – Schematic of the Trajectory Optimization Algorithm

by structuring both levels in a nested manner, as shown schematically in Figure 1. The picture clearly shows the tight coupling between the sub-problems.

Keeping this connection can be complicated as, especially in the case under analysis, the optimization is bi-objective, hence attributing a Pareto front of possible solutions to a single tour is complicated. Therefore, a single solution within the optimized set of solutions for the transfers given a certain combination of orbits is picked to be then forwarded to the outer loop. The solution can be analysed by different points, as will be explained later. An extended explanation on how the tool works can be found in [23] and [24].

Outer Layer

The outer layer is the one in charge of solving the combinatorial problem using the output of the inner layer as the cost associated to each sequence. In the proposed methodology, a heuristic-based algorithm is used which can exploit the tree-shape of combinatorial problems: the Population-based Ant Colony Optimization (P-ACO). This algorithm was introduced in [25] and improved to account for multi-objective functions in [26]. It has been already proven to be useful in previous studies of multi-rendezvous, for instance in the work of L. Simöes et al. [27]. As in typical ACO methods, a certain ant traverses a single tour of the search-space of possible sequences leaving on it a trail of pheromones (τ). The probability for an ant to follow the same path is dependent on the quantity of pheromones laid on it by the previous generations of ants. Nevertheless, the node connection is also influenced by a “desirability” factor, given by a problem-related heuristic (η). In the problem under consideration, the desirability is related to the theoretical ΔV necessary to change individually all Kepler elements among two orbits [26]. Both factors (pheromones and desirability) are weighted to account to their relative importance in accordance with some design exponential factors. Thus, the probability for an ant to move from node *i* to node *j*, corresponding to any subset of S nodes still unvisited, is given by:

$$p(i,j) = [\tau(i,j)^{\alpha}\eta(i,j)^{\beta}] / \sum_{z\in S}\tau(i,z)^{\alpha}\eta(i,z)^{\beta} \quad \textbf{(8)}$$

The main difference of this algorithm with respect to the classic ACO is that, contrary to the latter, the former does not allow all ants to leave pheromones in the trail, but only a subset of those (the Population) composed by the best ants of each generation (the elite), which enter it in a FIFO-queue fashion. In the problem at hand, being bi-objective, the elite is composed of ants pertaining to the Pareto Front of the previous generation [27]. At each new generation it is emptied and updated with the new Population of best ants to recalculate the pheromone matrix. The implementation for this study is a modification of the open-source code developed by L. Simões et al. [27], to which in addition some mutation strategies have been added to promote exploration rather than exploitation.

Inner Layer

The fitness evaluation of each one of the ants is done by an internal optimization of the transfers given the sequence of the individual tour. Like the outer loop, a heuristic algorithm is used, except in this case one that can exploit the continuous nature of the sub-problem is selected: a Multi-Objective PSO (MOPSO) [28]. The particularity of this type of PSO is that instead of having a single leading particle, a set of non-dominated particles are kept in a repository and lead the motion of new generations. Its usefulness for the problem at hand has been already proven in other studies, as

DOI: 10.13009/EUCASS2023-927

in Daneshjou et al. [6]. The implemented algorithm is a modified version of the open-source code of V. Martínez-Cagigal [29].

The transfers are modelled to be Lambert manoeuvres, in which impulsive ΔVs are assumed, for which both the transfer time and fuel mass necessary are calculated. To solve each one of the Lamberts, a hybrid implementation of already developed algorithms is used. On a first calculation, D. Izzo's algorithm [30] computes the Lambert manoeuvre which trades a faster solution for less robustness. In case of non-convergence, Gooding's algorithm [31] is called, much more robust but slower. This way, there will always be a solution for every Lambert problem computed, and the slower but more robust strategy is only called in case of necessity, speeding up the calculation process. This implementation was based on the work of R. Oldenhuis [32]. For each one of the transfers, both the ΔV and Time-of-Flight (TOF) are calculated, after checking that: 1) the transfer orbit is elliptical (ensuring TOF to be greater than Barker's time [33]); and 2) the vehicle does not enter the atmospheric altitude limit. Then, for each set of manoeuvres, the fuel consumed is calculated using Tsiolkovsky's equation:

$$m_{prop} = m_0 \left(1 - exp\left(\frac{-\Delta V}{I_{sp} g_0}\right)\right) \quad \textbf{(9)}$$

It must be noted that after each transfer, the specific payload related to the final orbit is released, producing a discrete change in total mass which affects the subsequent transfers. This discrete change of mass, therefore, does not allow to correlate directly the ΔV cost to the expended fuel mass, and it must be this second quantity the one optimized for a realistic analysis of the vehicle's performance. In addition, to account for constraints in terms of maximum fuel available and maximum mission time, a penalty function approach is followed. These functions have the form:

$$\lambda(f, L) = (max\{0, f - L\})^2 \quad \textbf{(10)}$$

$$f = f + F \cdot \lambda(f, L) \quad \textbf{(11)}$$

In these equations, f is the objective, L is the constraint, and F is a design factor. The output of this inner layer is a Pareto front of all particles with the objectives of TOF and fuel mass for the mission optimized. Nevertheless, as specified before, only a single solution can be attributed to a certain tour of the outer loop; for instance, the minimum fuel one or the minimum time one. In the current study, a weighted function of both is used, in a way that the compliance with both requirements is maximised. In this approach, the weights are calculated in a way that the variable which has consumed the most fraction of its maximum allowed value is more important than the other one, such that solutions with safer margins for both variables are selected. A more in-depth explanation of the selection process can be found in [24].

2.2. The Mission Scenario: Tool Parameters

The presented algorithm relies on diverse inputs to establish the mission strategy, including the space environment, the spacecraft characteristics, the payloads specifications, and the mission parameters. The algorithm researches the optimal specific set of trajectories, these being strongly dependent on the latter categories, which are key elements of the overall mission scenario definition. The input parameters particularly interesting for the study are those linked with the in-space delivery system propulsion system, hence its specific impulse, thrust and dry mass. By introducing variations to these inputs, it is possible to study the impact and effect of scenarios different from the ideal one and how any change propagates in the overall GNC design by affecting the reference trajectory.

The baseline mission scenario considers that the vehicle must deliver 8 different 6U-sized cube-sats in differentiated orbits, after which it manoeuvres itself into a disposal orbit. The Kepler elements of the target orbits as well as the payloads' masses are summarized in Table 1. These orbits were randomly picked from a database generated for university-owned launched and planned satellites, described in [24]. For the purposes of the study, it was decided to pick a subset of Sun-synchronous polar orbits to not introduce unfeasible inclination changes into the problem.

Regarding the vehicle and the mission inputs, the driving parameters of the problem are summarised in Table 2. Those which are examined in the study are referred to as variables (Var.). However, it should be noted that these variables are assigned fixed values for each analysis, as better described in the following section.

DOI: 10.13009/EUCASS2023-927

Table 1 - Kepler elements and masses of target payloads.

Index	$a-R_E$ [km]	e [-]	i [deg]	m [kg]
1	624.5	0.0014	97.90	12
2	571.6	0.0176	98.20	12
3	784.0	0.0013	98.62	12
4	646.9	0.0084	97.66	12
5	628.4	0.0018	97.97	12
6	823.0	0.0008	98.73	12
7	484.5	0.0023	97.20	12
8	713.4	0.0095	98.10	12
Disposal	300.0	0.0000	97.98	-

Table 2 – Vehicle Parameters and Mission Requirements.

Mission Parameters	Parameter	Description	Value
Vehicle			
	M_0	Vehicle dry mass without propulsion system	500 [kg]
	$M_{prop,sys}$	Propulsion system mass	Var. [kg]
	I_{sp}	Specific Impulse of engine	Var. [kg]
	T_{max}	Thrust of the engine	Var. [kg]
	g_0	Gravitational acceleration at Earth's surface	9.81 [m/s^2]
Requirements			
	t_{serv}	Minimum time in-orbit to deliver the satellite	5 [min]
	h_{min}	Minimum altitude allowed	120 [km]
	t_{max}	Maximum mission time	24 [hr]
	$M_{prop,max}$	Maximum allowed fuel	2000 kg

3. Sensitivity Analysis Study

Following the description of the mission analysis tool and the definition of the mission scenario, a comprehensive sensitivity analysis is performed to assess the influence of the main propulsion system parameters used as inputs of the tool. The primary objective is to enhance the realism and robustness of the trajectory design algorithm by evaluating its performance across multiple variations. By systematically examining the impact of these parameters, a more thorough understanding of the algorithm's behaviour and its ability to adapt to different scenarios can be attained.

The mission scenario remains constant during the different sensitivity studies, providing a consistent basis for evaluating the impacts of propulsive-specific parameters on the GNC logistics. The study revolves around four main investigations:

- Comparison of two propellant options: one conventional, toxic, with one greener alternative. The performance parameters used for this study are the respective ideal ones.
- Analysis of the eventuality of an engine failure in a dual-engine configuration system. The thrust is reduced by 50% during the mission.
- Research of the minimum specific impulse requirement to accomplish the mission scenario.
- Variation of the propulsion system mass by ±20%, simulating potential variations that could occur in real-case scenarios.

By exploring the margins and feasibility thresholds associated with these variations, the study aims at identifying the sensitivity of the trajectory definition, and subsequent GNC system design, to successfully accomplish the mission objectives. Ultimately, the analysis aims to inform the development of the Mission Analysis process by providing

DOI: 10.13009/EUCASS2023-927

valuable insights into performance and flexibility under different propulsive parameter scenarios, as well as serving as reference point towards the recursive design process of the vehicle and the mission.

3.1. Legacy vs Greener Bipropellant Systems

As mentioned in the description of the reference system, the introduction of novel space vehicles like kick stages offers a prime opportunity for the implementation of greener propulsion systems. However, like any new alternative, "green" propellants pose certain challenges compared to the highly reliable and well-established legacy propellants. Common upper stage propulsion systems built in the last decades are based on hydrazine, its derivatives monomethyl hydrazine (MMH) and unsymmetrical dimethylhydrazine (UDMH), and Nitrous Tetroxide (NTO) or Mixed Oxides of Nitrogen (MON). These compounds, commonly referred to as conventional propellants, are based on decades of research and heritage use. Despite being highly toxic and targeted for prohibition in Europe they still stand as the preferred option. In recent years, greener alternatives have emerged as viable options. These propellants promise to largely reduce ground operations' complexity and connected costs. As such, they are being studied and analysed as valid alternatives in many entities in the world [21, 22]. One of the most common green alternatives is doubtlessly the combination between rocket-grade kerosene (RP-1) and high-grade hydrogen peroxide (HTP) [34]. The properties of these two compounds are very similar to the toxic ones, allowing a partial switch of existent technologies to the alternative.

In this context, the first study focuses on the comparison of two bipropellant options: a legacy system utilizing MON/MMH and a greener alternative using HTP/RP-1. The performance of these systems is compared towards the achievement of the reference mission, which aims to deliver 6U CubeSats to eight LEO orbits. Table 3 summarizes the main characteristics of the reference kick-stage system. In this analysis, we consider a main engine providing a thrust of 1kN and a maximum allowable propellant mass of 2 tons. Furthermore, an additional fixed system dry mass of 500 kg is assumed, encompassing the structure, avionics, and other subsystems that are not detailed in this study.

Transitioning from the legacy propulsion system to the greener alternative unfortunately means a decrease in specific impulse, as reported in Table 5, due to different overall propulsive performances. The differences between the alternatives are many and influence various aspects of the overall design. For instance, the oxidizer-to-fuel ratio between the greener and legacy options is very different. The greener option requires a much higher proportion of oxidizer (HTP) compared to the fuel (RP-1) as reported in Table 4. Respective oxidizer densities (MON & HTP) and fuel densities (MMH & RP-1) are similar, hence although the respective volumes occupied are similar, the green option requires a larger amount of oxidizer. To obtain a balanced volume distribution, the green option requires a higher number of tanks that influences and increases the propulsion system dry mass compared to the legacy option, as reported in Table 5.

One of the main objectives of this study is therefore to assess the impact of the various performance penalties on the generation of a reference trajectory, with the aim of developing an effective GNC strategy that could work with both options.

Table 3: Common parameters of the two options considered for the bipropellant systems.

	MON/MMH	**HTP/RP-1**
m_{prop} [kg]	2000	2000
Thrust [kN]	1	1
$m_{fixed\ dry\ spacecraft}$ [kg]	500	500

Table 4: Densities, masses, volumes, and propellant tank specificities for the two selected options.

	MON	**MMH**	**98%-HTP**	**RP-1**
Densities [kg/m^3]	1440	880	1440	800
Mass [kg]	1298	702	1765	235
Volume [m^3] (incl. ullage)	~ 1.0	~ 0.9	~ 1.35	~ 0.33
No. Tank	1	1	3	1
$P_{propellant\ tank}$ [bar]	15	15	15	15

DOI: 10.13009/EUCASS2023-927

Table 5: Propulsion system parameters of the two bipropellant options

	MON/MMH	**HTP/RP-1**
I_{sp} [s]	330	310
O/F	1.85	7.5
$m_{\text{dry propulsion system}}$ [kg]	165	205
Feeding system	Pressure-fed	Pressure-fed

3.1.1 Discussion of results

To reduce the inherent effect of randomness connected to the use of heuristics of the optimization tool [24], the optimiser was executed multiple times. The results of the overall runs are shown in Figure *2* for the two options, where each datapoint corresponds to a mission execution, or solution given by the tool. The Pareto fronts of the analyses are then extracted and compared in Figure 3. As expected, the MON/MMH combination, possessing a higher I_{sp} and a lighter propulsive system, required a smaller amount of propellant mass and shorter time to fulfil the mission. The MON/MMH option can complete the mission using less fuel at similar total mission times, but the difference is assessed in the order of dozens of kilograms. The legacy option offers, in addition, more freedom of manoeuvres, since the higher I_{sp} allows the exploration of diverse mission strategies, granting the analysis of more combinations in the generation of orbit sequences.

Considering the sole mission analysis cost, the trade-off between toxic and greener option is clearly in favour of the toxic one. However, it must be recognized that the green option still shows many promising characteristics and allows the complete fulfilment of the missions with the required excess fuel for attitude control, emergency manoeuvres and de-orbiting. It is the authors' belief that, since the overall mission analysis strategy is compatible with both options, the many other advantages of the green options, especially during ground operations, will push many more players to make the best use of them in the near future.

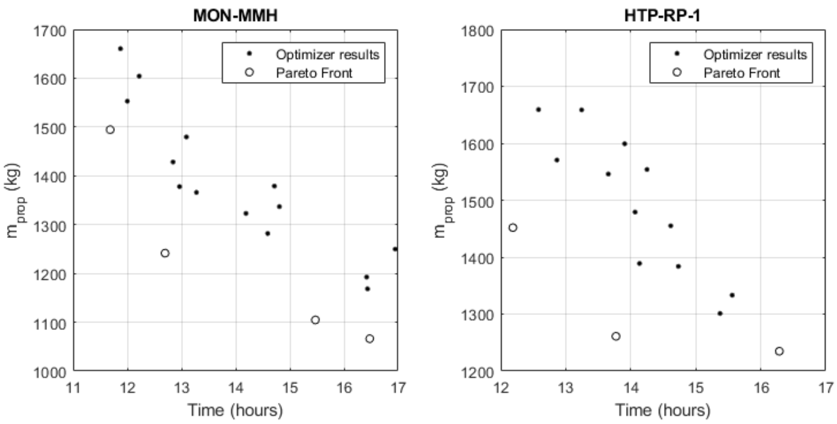

Figure 2: Optimizer results for the mission when with MON/MMH (left graph) and with HTP/RP-1 (right graph)

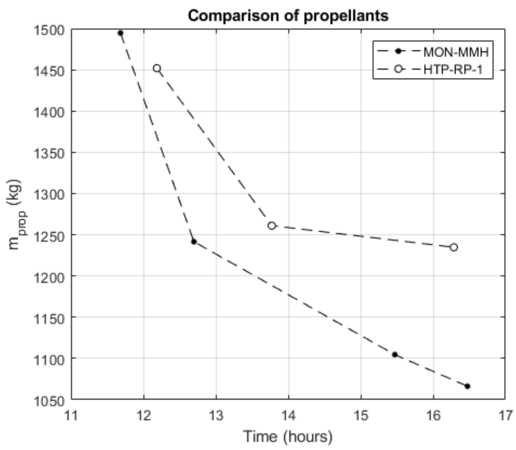

Figure 3: Pareto fronts found for MON/MMH and for HTP/RP-1

DOI: 10.13009/EUCASS2023-927

Table 6: Burning time necessary to complete the mission with respect to the re-ignition number at which the failure happens. Top row represents the re-ignition event at which the engine failure occurs. Time in minutes.

Tour ID	No failure	14	12	10	8	6	5	4	3	2	1	0
3	62.6	70.0	75.7	77.9	79.6	92.3	99.0	105.7	113.2	122.1	123.8	125.2

3.2. Real Case: Dealing with an Engine Failure

The second study analyses how the mission strategy may cope with the specific case of unexpected engine shutdown and/or failure occurring during the operation of the kick stage propulsion system. The origin of the failure is not detailed, since it can occur from various causes, including technical malfunctions, component failures, or generic anomalies within the propulsion system. While significant efforts are dedicated to minimizing such incidents within the space sector, it is important to acknowledge the possibility of hardware or subsystem malfunctions. This consideration becomes especially relevant when the system operates under highly demanding conditions, such as those encountered by the propulsion system. Issues connected to combustion chamber cooling, improper propellant injection, valve failure, but even propellant impurities can easily disrupt the engine's cores functioning, resulting in a reduced thrust or even in a complete engine shutdown.

The present study, analyses the event of an engine failure, and its effects on the kick stage's guidance, navigation, and control system, specifically when generating the reference trajectory. For the case under analysis, it is supposed that the system is equipped with a dual main engine configuration instead of a more classical one with a single main engine. Leaving the thrust level unvaried to 1kN, the system is therefore equipped with 2 engines of 500 N. The system studies and trade-offs between the additional weights and the reliability factor are left to further considerations, although the present study can give a clear incentive of following the dual strategy instead of a singular one in case of an engine shutdown.

The study analyses the case of one engine malfunctioning and shut-off after 6 re-ignitions of the engine (after 3 manoeuvres, considering each Lambert transfer needs 2 procedures), studying how the optimizer strategy can respond by initiating appropriate actions and recalculating the best delivery scenario. Two cases are considered:

1) The tool knows in advance that the engine is going to fail at a certain re-ignition. Therefore, it can include the reduction of thrust already in the optimization process and calculate the best strategy to follow.
2) The engine fails after a certain re-ignition manoeuvring through an already calculated trajectory and needs to re-optimize the remaining sequence. In this case, the optimizer must quickly re-calculate based on the remaining fuel and burning time available to maximize the visitation of remaining orbits.

In both cases, the system tries to minimize both the fuel and time of the mission, while maximizing the number of orbits visited. In the two case-scenarios under study, it is assumed that the full tank can still be accessed, but that there is an 80-minute limit in the total burning time of the engine, after which the engine is supposed to fail regardless. If the engines had theoretically unlimited burning time, the system would still fulfil the mission, igniting for longer periods. While ideally the case is feasible, in real cases engines that remain ignited for long periods could easily incur in more failure, and the thermal management of the entire system should be designed accordingly. Only the use of the "green" propellant is considered for this test, being the more conservative option and what is more probable to be used in future systems. The ability to dispose itself into a disposal orbit must always be considered in the given tour, so that the cost of this manoeuvre is also included into every calculated solution.

Table 6 provides a calculation on the burning time of the complete mission according to the re-ignition number at which the failure happens (top row), using a selected case (Tour ID), which is the lowest fuel-consumption solution of the "green" propellant from Section 3.1. The first column analyses the ideal no-failure case, and the following columns the re-ignition event at which one engine fails to operate. It can be seen that if the re-ignition failure happens at a value below 8, the mission cannot be completed. The flexibility and adaptability of the tour-generating optimizer are, hence, tested in an effort to analyse its robustness to failure both in pre-conceived cases or in-flight errors.

3.2.1 Discussion of results

Case 1) The tool knows when the failure will happen:

The computation of the orbit sequences, in this case, analyses the fulfilment of the mission with a reduction of the thrust after a defined number of re-ignitions. Table 7 shows the overall results, in which the reference is Tour 3 of Table 6. Even without considering an engine failure, with the limit of 80-minute total burning time the system could only reach up to 5 orbits (plus the disposal).

DOI: 10.13009/EUCASS2023-927

Table 7: Orbit sequences, taking into account the reduction in thrust after a certain number of re-ignition

Tour ID	Mission Time [hours]	Fuel mass [kg]	Burning Time [mins]	Number of visited orbits	Sequence
Reference	12.98	1167.4	76.81	5	[6,3,8,5,2]
1	12.79	1135.1	79.22	7	[1,3,2,7,4,8,5]
2	10.55	883.6	54.75	6	[2,4,6,1,5,8]
3	9.75	1026.2	73.49	6	[5,4,6,8,3,2]
4	8.75	1054.5	79.55	6	[7,4,8,1,3,5]
5	12.44	1010.1	79.53	6	[3,1,4,8,5,2]

However, by introducing the engine failure in the algorithm, the tool can quickly adapt the set of possible solutions to maximize the number of visited orbits and comply, as much as possible, with the delivery requirements of the kick stage. Up to 7 of the 8 payloads can be delivered in one of the solutions, while a bigger pool of tours is seen for the 6-orbits rendezvous trajectory. Nevertheless, both solutions are better than the baseline (without considering the error). It is interesting to notice, however, the tendency of the optimizer to leave outside of the tour orbits 6 or 7 (sometimes both). This is because both show the maximum and minimum altitude, respectively, as well as inclinations in the extreme values of the set. It is logical, therefore, that the algorithm leaves outside one of the orbits which is more difficult (or more distant) from the set of all orbits, remaining close to the bulk to maximize the number of visits.

Case 2) The kick stage started a tour and, after an engine failure, the tool re-optimizes the remaining sequence

In this case, the kick stage already started a tour and thus did not consider the possible failure into the design, depleting a certain amount of time, fuel and burn time. The amount of each is shown in Table *8*, including the number of orbits visited up until that point and the sequence of these. The algorithm was run after reducing the maximum allowable value for these parameters, looking to maximise remaining orbits as possible and then disposing themselves. The results are given in Table 9, in which in all provided feasible tours, the kick stage would be able to manoeuvre into a maximum of 7 total orbits. It is observed, however, the preference of the tool for the [5,1,4,2] sequence, providing up to 11 different sets of manoeuvre plans, ranging from total mission times of 11.18 to 14.47 hours, fuel consumptions from 920.44 to 1038.3 kg, and burning times from 61.64 to 79.72 minutes, depending on what strategy is followed. In all of the cases, the requirements in terms of these 3 parameters are completely fulfilled, although the final 8th orbit can never be reached. Interestingly, orbit 7 is normally left outside of the tour being on the extreme values of the altitude and inclination (since orbit 6 is de-facto included due to the original tour set). Nevertheless, the adaptability of the tool to maximize the number of orbits after failure is proved, as it can reach 2 additional orbits with respect to the 5 that it would have reached without re-optimizing.

3.3. Feasibility Study: Minimum I_{sp} necessary for Mission Success

This study delves deeper into the green HTP/RP-1 bipropellant option and examines its impact on the reference trajectory strategy by considering variations in the primary performance parameter for propulsion systems: the specific impulse. Specifically, the investigation focuses on determining the minimum specific impulse required for the onboard engine to successfully accomplish the reference mission. The study analyses a gradual decrease in specific impulse in intervals of 10s from its originally designated ideal nominal value of 310s. During early design phases, the specific impulse is commonly defined and serves as a critical requirement for propulsion systems. The value of 310s used in this study is obtained through the utilization of theoretical performance software like NASA CEA or the Rocket Propulsion Analysis software (RPA). However, it is important to note that the actual nominal value may differ significantly from the calculated result.

The analysis of minimum specific impulse holds significant importance in understanding the sensitivity of the kick stage mission strategy to factors that could potentially lead to performance degradation during operations. To begin with, it is important to recognize that the utilized specific impulse value is derived from theoretical calculations under ideal conditions, and that the actual value may be lower. Moreover, inefficiencies within the propulsion system can arise unexpectedly during operations, resulting in an overall reduction in the operational specific impulse. Such inefficiencies may stem from various factors, including incomplete combustion, lower mass-flow rate, and losses due to heat or other causes. Consequently, a more realistic scenario is examined here to account for the possibility of a lower operational specific impulse.

DOI: 10.13009/EUCASS2023-927

Table 8: Mission parameters at engine failure.

Tour completed	Time [hours]	Fuel mass [kg]	Burning Time [mins]	Number of visited orbits	Sequence
Reference	6.55	637.06	37.14	4	[6,3,8,5]

Table 9: Parameters of re-optimized orbit sequences after an unexpected reduction in thrust during operation.

Tour ID	Total time [hours]	Total fuel mass [kg]	Burning Time [mins]	Number of visited orbits	Remaining sequence	Times Appearing
1	11.18-14.47	920.44-1038.3	61.64-72.97	7	[5,1,4,2]	11
2	14.60	987.71	67.84	7	[5,4,1,2]	1
3	12.92	1003.4	69.43	7	[5,1,4,7]	1

In addition to overall propulsion system degradation, the delivered specific impulse can also be influenced by propellant degradation over time, particularly in long missions. Propellants can undergo chemical changes or degradation during storage or operation, leading to decreased performance and subsequently lowering the specific impulse of the propulsion system. For instance, Hydrogen Peroxide may decompose over time, leading to a reduction in its grade. Although steps are typically taken to avoid this process, the possibility must be considered. This study focuses solely on the effect of degradation without exploring further risks associated with it.

In summary, the actual delivered specific impulse of a kick stage system may be lower than the design value due to various factors, including inefficiencies and propellant degradation. These considerations are essential in optimizing mission logistics. The analysis aims to capture how the guidance, navigation, and control algorithm adapts to such performance changes that may occur during operations.

3.3.1 Discussion of results

Figure 4 reports the different mission scenarios accomplishable with a given specific impulse value. As expected, for high I_{sp} values all the solutions easily converge, have a low fuel consumption and are generally faster. With the I_{sp} decreasing, the optimized solutions require more fuel consumption and time to be accomplished, moving towards the top right-hand side of the graph in Figure 4. For values much lower than the design one, fewer optimized solutions are possible. In particular, for values lower than 220s, the software converged on a single possible solution, while no solution was found under 200s. The conclusion is therefore that 210s is the minimum I_{sp} required to fulfil the mission scenario set in this study. Interestingly, the solutions found for 210s and 220s are both more performing than the 2 solutions identified with an I_{sp} of 240s. The outcome is intricately linked to the algorithm strategy used to reach the optimal trajectory. The use of ant colonies is more efficient when a singular solution is found, and the solution is more comprehensively optimized, analogous to the scenario where the entire workforce of ants focuses on optimizing that particular solution rather than dispersing their efforts across all possible solutions. This is due to the natural tendency of the ACO algorithm to pursue exploitation rather than exploration.

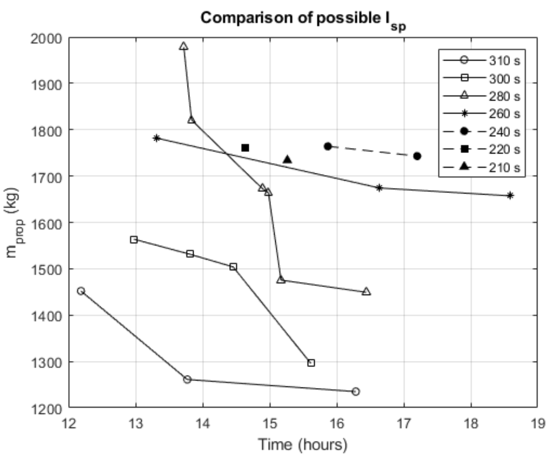

Figure 4: Comparison of the different tours that can be accomplished with a given I_{sp}.

DOI: 10.13009/EUCASS2023-927

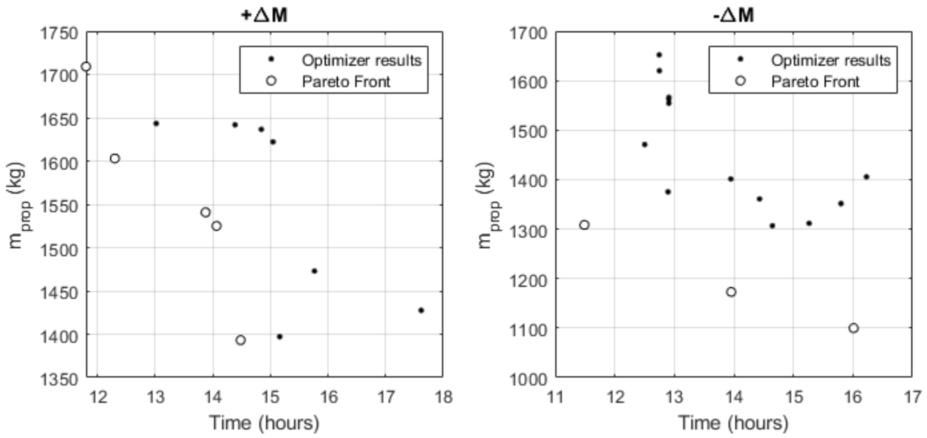

Figure 5: Comparison of the different optimizer results and pareto front identified for the mission when accomplished with higher (left graph) or lower (right graph) propulsion system mass.

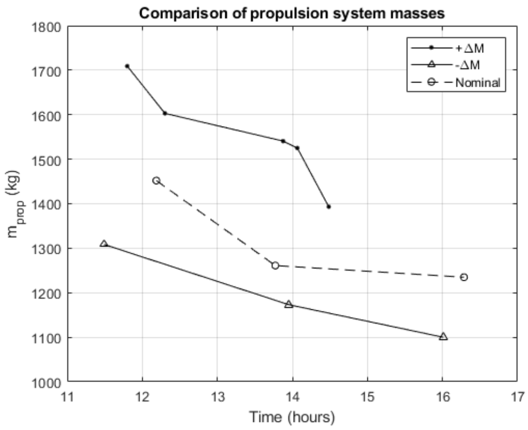

Figure 6: Comparison of the different tours that can be accomplished with a varying propulsion system mass.

3.4. Sensitivity Analysis: Impact of Propulsion System Sizing

Starting from the propulsive system mass of the greener selection, 205 kg, this fourth study explores the sensitivity of the algorithm to this parameter by making it vary by ±20%. The purpose is to study the sensitivity of the trajectory to a parameter not directly related to the propulsion performance but rather to the overall design.

3.4.1 Discussion of results

Like in the previous analysis, the study starts from the nominal propulsive system mass computed for the green HTP/RP-1 option and analyses the impact of its variation by ±20%. The results for both cases individually are shown in Figure 5, providing a picture of the various results obtained and their resulting Pareto Front. Figure 6, on the other hand, shows the comparison of these Pareto Fronts, and with respect to the nominal results for the “green” propellant solution obtained in Section 3.1. As expected, a heavier system drives the mission towards higher fuel consumption, for a given time of mission. The difference between the two extreme gives a difference of total mass of propellant in the order of between 200 and 400 kg for equal times. Such a big effect comes from the exponential component of Tsiolkovsky’s formula, underlining the importance of compact and light system designs. It is observed, however, the disparity of shape of Pareto Front, which is mainly attributed to the randomness effect of heuristic algorithms, although the overall distancing between the three sets of results shows itself apparent. Finally, it is important to highlight how the tool was able to find solutions that fulfilled mission in both cases and showed to be particularly robust towards changes in the baseline design of the vehicle.

4. Conclusions

This study has investigated the sensitivity of a trajectory optimisation algorithm designed for multi-orbit injections to several parameters related to the propulsion system. The tool has the capability to optimise both the sequence and

DOI: 10.13009/EUCASS2023-927

transfer manoeuvres minimising both total mission time and fuel consumption. The proposed methodology consisted in solving separately the integer combinatorial problem (using a P-ACO algorithm) and the transfer problem (using a MOPSO algorithm) in a linked bi-level fashion. The output of this tool is the set of optimized tours for both mission requirements. The algorithm has been applied to four cases in which different characteristics of the propulsion system were varied to check the robustness of the procedure as well as study the outputs.

In a first study, two propellant strategies were compared: a conventional solution with higher I_{sp} and lower weight based on toxic propellants, and a “green” solution with lower I_{sp} and higher weight. The former provided solutions with lower total fuel consumption to complete the visitation of all orbits. However, the notable result is that the green option, while being slightly more expensive, gives sufficient margins with respect to maximum fuel and time. The outcome is crucial for future utilization of the green option that outweighs the toxic solution during ground operations, while still fulfilling the mission requirements. A second study examined the eventuality of an engine failure after 6 re-ignitions. The test proved the robustness of the algorithm to external changes, and demonstrated the optimization feasibility, solving for the maximum number of reachable orbits. Two separate subcases were studied. First, the tool was considered to have information on the engine failure occurrence and could calculate the full optimal trajectory with this knowledge. Secondly, it was considered that the engine shutdown happened during the in-orbit operations and the algorithm had to re-optimize the remaining trajectory. In both cases, the algorithm proved to be extremely successful into optimizing the sequence, reaching even more orbits than the nominal tour would have done in some cases. A third study was done by varying the main propulsion performance parameter, the specific impulse, to analyse the minimum value that would ensure the mission completion. A minimum I_{sp} of 210 s is necessary to reach all orbits of the reference scenario and, as expected, reducing this value from the nominal 310 s towards lower values had an effect both on the needed fuel and time, but also in the number of possible tours that the tool was able to compute. The fourth and final study examined the effect of different propulsion system dry masses, considering a change of ±20%. It was observed how lighter systems provide solutions that require less fuel mass, as expected, while the opposite effect was seen in heavier systems, with an average difference among them of around 300 kg. It was concluded however, that the tool was successfully able to find solutions in both cases and was flexible to accommodate changes in the design.

The results demonstrate the tool's ability to successfully generate solutions across different propulsion system parameters, enabling an insightful trajectory analysis for GNC system design. It can also be concluded that it shows its robustness in cases of failure, such as a turned-off engine, as well as in cases of varying vehicle parameters. Finally, the study has also proven the feasibility of green propellants towards this multi-rendezvous kind of missions. In conclusion, the development of such a flexible and robust tool, as well as the feasibility of the mission with green propellants, brings closer this innovative, efficient, and more ecological way of satellite injection in the current quickly growing space access sector.

5. Acknowledgments

The work presented here has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement N◦860956.

6. References

[1] Euroconsult, Satellites to be built and launched by 2028. 2019. A complete analysis and forecast of satellite manufacturing and launch services, Tech. Report.

[2] R. R. S.-T. GmbH. RST. https://www.rst-rostock.com/news/news-detail/arianegroup-wins-esa-astris-competition.html.

[3] Blondel Canepari, L., Riuz, I., Ayala Fernandez, L., Glaser, C., Gelain, R., Ordonez Valles, L., Sarritzu, A. 2021. Conceptual study of technologies enabling novel green expendable upper stages with multi-payload multi-orbit injection capability. In: *72nd International Astronautical Congress (IAC)*, Dubai.

[4] Izzo D. et al. 2015. Evolving Solutions to TSP Variants for Active Space Debris Removal. In: *2015 Annual Conference on Genetic and Evolutionary Computation, New York, USA*.

[5] Chen Y. et al. 2020. Optimal mission planning of active space debris removal based on genetic algorithm. IOP Conference Series: Materials Science and Engineering 715.

[6] Daneshjou K., Mohammadi-Dehabadi A.A., Bakhtiari M., 2017. Mission planning for on-orbit servicing through multiple servicing satellites: A new approach. *Adv. Space Res*. 60.6: 1148–1162.

[7] Conway B. A., Chilan C. M., and Wall, B. J. 2007. Evolutionary principles applied to mission planning problems. *Celest. Mech. Dyn. Astron*. 97: 73–86.

DOI: 10.13009/EUCASS2023-927

[8] Cerf, M. 2013. Multiple Space Debris Collecting Mission—Debris Selection and Trajectory Optimization. *J Optim. Theory Appl.* 156.3: 761–796.
[9] Bérend N. and Olive, X. 2016. Bi-objective optimization of a multiple-target active debris removal mission. *Acta Astronaut.* 122: 324–33.
[10] Madakat D., Morio, J., Vanderpooten, D. 2018. A bi-objective branch and bound procedure for planning spatial missions. *Aerospace Science and Technology* 73: 269–277.
[11] Barbee B.W., et al. 2011. Design of spacecraft missions to remove multiple orbital debris objects. In: *2011 Aerospace Conference.*
[12] Federici L., Zavoli A., Colasurdo, G. 2021. Evolutionary Optimization of Multi-rendezvous Impulsive Trajectories, *Int. J. Aerosp. Eng.* 2021: 1–19.
[13] Federici L., Zavoli A., Colasurdo, G. 2019. A Time-Dependent TSP Formulation for the Design of an Active Debris Removal Mission using Simulated Annealing. *ArXiv* abs/1909.10427.
[14] Cerf, M. 2013. Multiple Space Debris Collecting Mission—Debris Selection and Trajectory Optimization. *J Optim. Theory Appl.* 156.03: 761–796.
[15] Stuart J., Howell K., Wilson R. 2016. Application of multi-agent coordination methods to the design of space debris mitigation tours. *Adv. Space Res.* 57.8: 1680–1697.
[16] Zhang T. et al. 2018. Ant Colony Optimization based design of multiple-target active debris removal mission. In: *2018 SpaceOps Conference.*
[17] Li H., Haoyin H. 2020. Optimization of Multiple Debris Removal Missions Using an Evolving Elitist Club Algorithm. *IEEE Transactions on Aerospace and Electronic Systems* 56.1: 773–784.
[18] Bourjolly J. M., Gurtuna O., Lyngvi, A. 2006. On-orbit servicing: A time-dependent, moving-target traveling salesman problem. *International Transactions in Operational Research* 13: 461–481.
[19] Bang, J., Ahn, J. 2018. Two-phase framework for near-optimal multi-target Lambert rendezvous. *Adv. Space Res.* 61.5: 1273–1285.
[20] Yu, J., Chen, X., Chen, L. 2015. Optimal planning of LEO active debris removal based on hybrid optimal control theory. *Adv. Space Res.* 55: 2628–2640.
[21] Sarritzu, A., Blondel-Canepari, L., Gelain, R., Hendrick, P., Pasini, A. 2023. Analytical Hierarchy Process-based trade-off analysis of green and hybrid propulsion technologies for upper stage applications. *International Journal of Energetic Materials and Chemical Propulsion*. DOI:10.1615/IntJEnergeticMaterialsChemProp.2023047590
[22] Sarritzu, A., Lauck, F., Werling, L., Pasini, A. 2022. Assessment of Propulsion System Architectures for Green Propellants-based Orbital Stages. In: *73rd International Astronautical Congress (IAC), Paris, France*.
[23] Alforja Ruiz I., Lavagna M. 2022. Design of the Optimal Trajectory for Multi-Payload Multi-Orbit Injection of an Upper Stage. In: *European Conference for Aeronautics and Space Science (EUCASS), Lille, France.*
[24] Alforja Ruiz I., Lavagna M., Bastante J.C. 2022. Analysis of Multi-Orbit Multi-Payload Injection Scenarios for an Upper Stage. In: *73rd International Astronautical Congress (IAC), Paris, France, 2022*.
[25] Guntsch M., Middendorf, M. 2002. A Population Based Approach for ACO. In: *Applications of Evolutionary Computing*, 72–81.
[26] Guntsch M., Middendorf, M. 2003. Solving Multi-criteria Optimization Problems with Population-Based ACO. In: *Evolutionary Multi-Criterion Optimization, Second International Conference (EMO'03).*
[27] Simões L. F., et al. 2017. Multi-rendezvous Spacecraft Trajectory Optimization with Beam P-ACO, Evolutionary Computation in Combinatorial Optimization, Lecture Notes in Computer Science, 141–156.
[28] Coello, C.A.C. Pulido, G.T. Lechuga, M.S. 2004. Handling multiple objectives with particle swarm optimization. *IEEE Transactions on Evolutionary Computation* 8.3: 256–279.
[29] Martínez-Cagigal V. Multi-Objective Particle Swarm Optimization (MOPSO). https://www.mathworks.com/matlabcentral/fileexchange/62074-multi-objective-particle-swarm-optimization-mopso MATLAB Central (accessed 25.01.2022).
[30] Izzo, D. 2014. Revisiting Lambert's Problem. *Celest. Mech. Dyn. Astron*.
[31] Gooding R. H. 1990. A procedure for the solution of Lambert's orbital boundary-value problem. *Celest. Mech. Dyn. Astron.*48: 145–165.
[32] Oldenhuis R. Robust solver for Lambert's orbital-BVP. https://github.com/rodyo/FEX-Lambert/releases/tag/v1.4, GitHub (accessed 20.01. 2022).
[33] Wakker K.F. 2015. Fundamentals of Astrodynamics, TU Delft Library.
[34] Blondel-Canepari, L., Ordonez-Valles, L., Jasjukevics, A., Wolf, M., Dussy, S., Apel, U., Tajmar, M., Pasini, A. 2022. Roadmap Towards a Greener Kick-Stage Propulsion System. In: *73rd International Astronautical Congress (IAC), Paris, France.*