IAC–19–B4,IP,20,x52943

AN OPTIMIZATION APPROACH FOR DESIGNING OPTIMAL TRACKING CAMPAIGNS FOR LOW-RESOURCES DEEP-SPACE MISSIONS

Lorenzo Gentile[a*], Cristian Greco[b], Edmondo Minisci[b], Thomas Bartz-Beielstein[a], Massimiliano Vasile[b]

[a] *TH Köln, Germany*, {lorenzo.gentile, thomas.bartz-beielstein}@th-koeln.de
[b] *University of Strathclyde, United Kingdom*, {c.greco, edmondo.minisci, massimiliano.vasile}@strath.ac.uk
[*] Corresponding author

Abstract

This work contributes to the autonomous scheduling of orbit determination campaigns for tracking spacecraft in deep-space by developing a dedicated optimisation algorithm. Given a network of available ground stations, the developed method autonomously generates optimized tracking observation campaigns, in terms of stations to use and time of measurements, which minimize the uncertainty associated to the state of the satellite. The outcome is a set of optimal solutions characterized by different allocated budgets, among which the operators can choose the most appropriate or promising one. The developed approach relies on a Structured-Chromosome Genetic Algorithm that copes with mixed-discrete global optimization problems with variable-size design space. This operates on a hierarchical reformulation of the problem by means of revised genetic operators. The estimation of the spacecraft state and its uncertainty, given a set of measurements is performed using a sparse Gauss-Hermite Kalman Filter. The proposed approach has been tested to the design of observation campaigns for tracking a satellite in its interplanetary cruise to an asteroid. Uncertainty is considered in the initial conditions, execution errors and observation noises.

1. Introduction

In the last years, the technology readiness level reached by low-budget small platforms has allowed small organizations, such as universities and research centres, to launch low-budget satellites in the near-Earth orbits. In spite of a constant platform technological development, space missions beyond the near-Earth environment are still out of the reach of these stakeholders. One of the key limiting factors is the maturity of the associated ground segment and, on the specific focus of this paper, its tracking capabilities. While traditional deep-space missions rely on dedicated and extensive networks, near-Earth missions by small organizations often depend on amateur stations or third-party services with reservation slots. As for the scenario of a low-resource deep-space mission, tracking would be even more critical as the number of suitable stations is smaller, the associated efforts more onerous, and the construction of competent amateur stations may be unrealistic.

In the aim of moving deep-space missions for small organizations one step closer to feasibility, this paper presents an approach for the optimal scheduling of observation campaigns for tracking deep-space small spacecraft under limited resources. Indeed, in such scenarios, optimisation becomes an essential tool to handle the increased uncertainty and complexity arising from lower availability of information.

A proper definition of the observation schedules of spacecrafts cruising in the deep-space is of utmost importance for the success of the missions. However, the methodologies used nowadays often need a priori parameter specification that limits the search for optimal observation schedules. One of these is the number of observation campaigns to be performed. Common practice is, on the basis of the previous experiences, fixing this parameter at the early stage of the schedule design and keeping free the parameters defining each observation campaign. Indeed, in cases in which the operator already gained a deep knowledge about the mission, this approach may be successful and will lead to optimal low-budget observation schedules. In others, this can represent a severe limitation and compromise the quality of the state estimation of the spacecraft and the success of the mission. In light of these considerations, the approach used in this research work aims at increasing the degrees of freedom keeping the number of observation campaigns as a free variable of the observation schedules design process. Hence, the number of design variables is not constant among different solutions. Furthermore, as described in Section 3, the variables are not all continuous but belong to different categories. Then, the observation scheduling optimisation can be classified as a variable-size mixed-discrete global optimisation problem.

Several additional challenges harden dramatically the complexity of the search algorithm if varying search spaces come into play[15] . To cope with these difficulties, researchers proposed many approaches. A variety of strategies for handling variable-sized global optimisation can be found in the literature, employed mainly for space trajectory design[1,13,14] . The Genetic Algorithms (GAs) have proven to be among the most robust[15] . In fact, their flexibility in encoding information, allow facing most of the associated issues.

Noteworthy, the *hidden gene* adaptation of GA for the optimisation of interplanetary trajectories is presented in[1] . However, this algorithm requires a priori setting of the maximum number of genes that can encode a candidate. Then, each candidate is represented using all the possible genes and a set of *activation genes* indicating whether the genes have to be considered when computing the objective and constraint functions.

The authors of[13,14] firsts introduced a more complex but efficient adaptation of GA. Its distinguishing feature is the use hierarchical multi-level chromosome structure that replaces the standard *string* one.

The algorithm can take into account the logical hierarchy of the information encoded in chromosomes through the genes. Compared to the *hidden genes* approach, this strategy has the advantage of not wasting computational resources performing crossover and mutation operations on inactive genes. This concept has been then further investigated in[4,5] where the Structured-Chromosome Genetic Algorithm (SCGA)[3] has been used for generating optimal schedules for tracking objects in near-Earth environment. The results of these studies show the capability to enhance resources allocation strategies in space object tracking and to rapidly identify optimal or sub-optimal tracking schedules.

In the presented paper, the SCGA is used as a tool for the design of optimal tracking campaigns for deep-space missions under limited resources.

This paper is structured as follows. Section 2 introduces the scheduling problem and the model formulation for the optimisation loop. Moreover, it presents the orbit determination routine run during the call of the objective function to compute the spacecraft state given tracking measurements. Details about the SCGA and the problem formulation are given in Section 3. Section 4 details the experimental setup and the specifics of the test case along with the analysis of the results obtained. Finally, Section 5 recall the take-home aspects of the study and concludes the paper.

2. Navigation Model

This section first presents the employed general formulation for the scheduling of tracking campaigns for deep-space trajectories in Section 2.1. Then, the approach to perform the navigation analysis for a given tracking schedule is shown in Section 2.2. The selection process for relevant metrics for the optimisation objective and constraints is discussed, and the selected choice presented in Section 2.3.

2.1 General Formulation

The optimal scheduling of observation campaigns falls within the field of sensor control[6] , and the formulation presented hereafter stems from previous work on sensor scheduling for space objects[5] .

A probabilistic state space model is used to describe the state uncertainty evolution, as

$$p(\mathbf{x}_0) \tag{1a}$$

$$p(\mathbf{x}_k|\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) \tag{1b}$$

$$p(\mathbf{y}_k|\mathbf{x}_k, \mathbf{u}_k) \tag{1c}$$

where $\mathbf{u}_k$ is the sensor action at time t_k to be optimised. Equation (1a) is the probability distribution of the stochastic initial condition $\mathbf{X}_0$. Equation (1b) is the transition likelihood of arriving to the state $\mathbf{x}_k$ at time t_k given the system state $\mathbf{x}_{k-1}$ and the sensor action $\mathbf{u}_{k-1}$ at time t_{k-1}, and it models a stochastic dynamical evolution. Equation (1c) is the observation likelihood of observing $\mathbf{y}_k$ given the system state $\mathbf{x}_k$ and the sensor action $\mathbf{u}_k$ at time t_k, and it models measurement noises.

Starting from $k = 1$ with the initial uncertainty $p(\mathbf{x}_{k-1}|\mathbf{y}_{1:k-1}, \mathbf{u}_{1:k-1}) = p(\mathbf{x}_0)$, the state density function evolves in time according to the Chapman-

Kolgomorov equation

$$p(\mathbf{x}_k|\mathbf{y}_{1:k-1},\mathbf{u}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1},\mathbf{u}_{k-1})\, p(\mathbf{x}_{k-1}|\mathbf{y}_{1:k-1},\mathbf{u}_{1:k-1}) d\mathbf{x}_{k-1} \;, \tag{2}$$

a step often called *prediction*. At the observation time, when the observation $\mathbf{y}_k$ is received as resulting from the sensor action $\mathbf{u}_k$, the state distribution incorporates the measurement information by Bayes' rule as

$$p(\mathbf{x}_k|\mathbf{y}_{1:k},\mathbf{u}_{1:k}) = \frac{p(\mathbf{y}_k|\mathbf{x}_k,\mathbf{u}_k)\, p(\mathbf{x}_k|\mathbf{y}_{1:k-1},\mathbf{u}_{1:k-1})}{p(\mathbf{y}_k|\mathbf{y}_{1:k-1},\mathbf{u}_{1:k})} \;, \tag{3}$$

in a step usually called *update*. The two steps are sequentially repeated to map between observation times and to update with the new received measurements, until the final time of interest.

Given the model in (1), and the rules to propagate, Equation (2), and update, Equation (3), the state distributions in a partially observed system, the optimal tracking problem is defined as

$$\begin{aligned} \min_{\mathbf{u}_{1:l}\in\mathcal{U}_{1:l}} \; & \mathcal{J}\Big(\mathbf{u}_{1:l}, p(\mathbf{x}_f|\mathbf{y}_{1:l},\mathbf{u}_{1:l})\Big) \\ \text{s.t.} \;\; & \mathcal{G}\Big(\mathbf{u}_k, p(\mathbf{x}_k|\mathbf{y}_{1:k},\mathbf{u}_{1:k})\Big) \in \mathbf{\Phi}_{\mathcal{G}} \;, \end{aligned} \tag{4}$$

where $\mathcal{U}_{1:l}$ is the definition set for the sensor controls, l indicates the last observation at time t_l before the final time, i.e. $t_l \leq t_k$, and $\mathcal{J}$ and $\mathcal{G}$ indicate functions which return (deterministic) statistics of interest from the sensor actions and the random state variable conditional on the received observations, respectively for the objective and the constraints.

2.2 Navigation Analysis

The probabilistic model in (1) results from stochasticity in the initial conditions $\mathbf{x}_0$, in parameters $\mathbf{d}$ of the dynamical model

$$\dot{\mathbf{x}} = f(t,\mathbf{x},\mathbf{d}) \;, \tag{5}$$

and in the observation model

$$\mathbf{y} = h(t,\mathbf{x},\boldsymbol{\varepsilon}) \;, \tag{6}$$

where ε models observation errors. The specific uncertainty sources considered for the test case solved in this paper are further specified in Section 4.1.

In the general nonlinear case, where the dynamical and observation models are nonlinear functions, the prediction and update steps in Equations (2)-(3) have no closed form solution.

In this work, the prediction and inference steps are solved with a sparse Gauss-Hermite quadrature filter (SGHQF),[9] which employs sparse grid quadrature rules to compute the mean and covariance prediction and update. The square-root of the covariance matrix is employed in place of the covariance itself to improve the numerical stability of the method.

As this work focuses on the offline optimisation of tracking schedules, the measurements are employed just to model the reduction of second moment of the state uncertainty. The actual realisation of the observation is not known during this stage, and therefore it has to be simulated. As a design choice, the simulated observation value $\mathbf{y}_k$ is taken along the current mean of the state uncertainty $\boldsymbol{\mu}_{\mathbf{x}_k}$ with zero observation error

$$\mathbf{y}_k = h(t_k,\boldsymbol{\mu}_{\mathbf{x}_k},\mathbf{0}) \;, \tag{7}$$

i.e. the observation is taken along the best estimate of the trajectory. This choice is further justified by the Kalman-like measurement update, as in the SGHQF, in which the posterior covariance depends only on the prior and the observation covariance matrices, but not on the actual observation realisation. Hence, this approach is equivalent to just update the covariance information, and therefore is often called *covariance analysis*, and it has been applied to the navigation analysis of several deep space missions.[7,8] A Monte Carlo sampling over the observation realisations should be performed if the effects of changing the state uncertainty mean are to be taken into account, e.g. for trajectory correction maneuvers quantification.

2.3 Performance Metric and Constraints

As discussed in previous works[5] , the state covariance matrix is one of the most suitable measure for comparing the orbit accuracy resulting from different tracking schedules. Indeed, the state covariance matrix is directly computed when solving the filtering steps, and although it is generally an optimistic indicate, just a relative measure is needed in schedule optimisation.

Specifically, the sum of the square root of the diagonal covariance elements is selected as performance metric to quantify the confidence on each element of the state vector given an observation campaign. Hence, the function $\mathcal{J}$ is expressed as

$$J = \sum_i \sqrt{\mathrm{cov}(\mathbf{x}_f|\mathbf{y}_{1:l},\mathbf{u}_{1:l})_{(i,i)}} \;, \tag{8}$$

where the subscript $(\cdot)_{(i,i)}$ indicates the i-th diagonal element.
To simulate a real-life scenario, a *cost* is introduced for each observation campaign to model the significant operational resources of tracking a satellite in a deep-space mission. Within the scheduling optimisation, this total cost is then imposed as a constraint, to ensure that the optimal schedule satisfies an allocated budget. In the addressed application, the cost solely depends on the sensor actions $\mathbf{u}_{1:l}$ defining a tracking schedule, e.g. the more observation arcs the higher the cost will be. Hence, the constraint can be formulated as

$$\mathcal{G}(\mathbf{u}_{1:l}) \in \mathbf{\Phi}_{\mathcal{G}} \tag{9}$$

where $\mathcal{G}$ returns the observation campaign cost given the sensor controls $\mathbf{u}_{1:l}$, and $\mathbf{\Phi}_{\mathcal{G}}$ is the set of admissible tracking budgets.

3. Optimisation

This section introduces the methodology adopted for minimising the uncertainty associated with the final state of a satellite in its cruise to an asteroid.
Depending on the ground stations network definition and the time span of the tracking window, multiple observation campaigns may be used to track the object. Given these premises, referring to the notation used in Section 2.1, the design variables are the number of observation campaigns, l, and the sensor action $\mathbf{u}_k$ associated to each one of the k campaigns. In this work, four quantities define an observation campaign: the final time of the observation campaign, the specific ground station to be employed, the number of observations to perform and the the type of measurements. This means that schedules with different number of observation campaigns are encoded by a different number of design variables. Therefore, classical optimisation strategies cannot be straightforwardly used avoiding redundant variables. The objective definition introduced in Section 2.3 is further discussed in Section 3.1. The problem formulation is presented in detail in Section 3.2 and a thorough explanation of the adopted algorithm is given in Section 3.3.

3.1 Cost Function

The objective function is the performance indicator J specified in (8). It is the sum of the positive diagonal elements of the covariance of the final state of the tracking window conditional to the previous observations and actions. Being the sum of only positive terms, the theoretical minimum is zero, i.e., the case of perfect knowledge of the satellite state.

3.2 Formulation as a Structured Chromosome

The adopted formulation aims at reducing the number of free variables generally considered applying the concept of hierarchy.
This research leverages an adapted genetic algorithm for handling structured chromosomes of different lengths, the SCGA freely available at[3] as R Package. The search space is formulated hierarchically by imposing dependencies between genes. Consequently, the operators do not act on single selected genes but on all the chromosomes substructures.
In standard GAs, a chromosome is represented by a single string of genes all at the same unique level and every gene is treated independently. Contrarily, in the SCGA[4] a chromosome contains the information of the values of the genes, their position in the hierarchy of the chromosome[5] . Every gene belongs to a *gene class* which contains crucial information for collocating it in the rest of the chromosome: data type, children, and bounds (lower *LB* and upper *UB*). In the presented problem, the hierarchy is indeed very simple because constituted by only two levels. The gene class *Number of observation campaigns* (*NOC*) forms the top of the hierarchical structure. The value of this gene indicates the number of observation campaigns characterising the specific scheduling. The second level of the hierarchy consists in all the other genes that define the observation campaign. Particularly, these are the gene class *Ending time* (*ET*) *Number of observations* (*NO*), *Measures acquired* (*MA*) and *Ground Station* (*GS*). The specific problem formulation discussed is schematised in Table 1.

3.3 The Algorithm

The adopted algorithm is a population-based genetic optimiser that employs two operators to pursue the search of the global optimum: the crossover and the mutation. These operators, nowadays established in stochastic fixed-length mixed-discrete optimisation, are redefined in order to manipulate candidates characterised by different length and structure. Then, these strategies are integrated in the classical GAs structure.[12] The next sections provide a short description of the key processes distinguishing the SCGA.

Table 1: Decision variables of the Observation Scheduling Optimisation. The table details the variable type and possible values the variables can assume. These are expressed specifying the bounds for integer and real variables and detailing all the possibilities for the discrete ones. For the gene *Measure acquired*, R stands for *Range*,RR for *Range rate* and AE for *Azimuth and Elevation*.

Gene	Variable type	Lower Bound	Upper Bound
Number of observation campaigns	Integer	1	10
Starting time	Real	0	1
Number of observations	Integer	1	20
Gene	Variable	Possibilities	
Measures acquired	Discrete	$[R, RR, AE, [R, RR], [R, AE], [RR, AE], [R, RR, AE]]$	
Ground Station	Discrete	[GS-1,GS-2,GS-3]	

3.3.1 Initial population

The starting point of the optimisation process is the creation of a set of random chromosomes that will be used as the initial population. If for the classical population-based optimiser, the common practice is to rely on sampling techniques with the aim of uniformly cover the search space, this is much more complex in case of structured chromosomes[15] . In the SCGA an iterative algorithm that creates syntactically feasible candidates has been developed. The creation starts from the firsts genes in the hierarchy, assigning values using random uniform sampling in the range of feasible values. Once the value is defined, it recomputes the feasible values the dependent genes can assume. This procedure is then repeated for every dependent gene until the values of all the genes in the chromosome are assigned.

3.3.2 Respect of constraints

During the optimisation process, the satisfaction of two different constraints has to be guaranteed. The first is a syntactic constraint: for the guarantee of the correctness in the computation of the tracking scheduling cost, a solution cannot indicate two identical observation campaign. For facing this scenario, a repair function that removes identical observation campaigns and corrects the total number of campaigns in the schedule has been implemented. The second constraint restricts the cost $\mathcal{G}$ of the overall tracking scheduling to an imposed limit. As a rule of thumb, the more precise is the tracking, the more it costs. Consequently, the optimiser has to deal with two conflicting indicators. Furthermore, if a very tight cost limit is imposed, much of the computation resources are spent for the search of feasible solutions rather than for good performing ones. A popular solution for constraint handling, especially in genetic algorithms, is to using penalty functions. In this work, an adaptive penalty function has been adopted. The penalisation aims at lower the likely of unfeasible solutions to be selected by the genetic operators despite their eventually good performance. Moreover, the concept of evolutionary constraint relaxation has been adopted to promote near feasible solutions especially at the beginning of optimisation. Many studies show the presence of near-feasible solutions usually positively contributes to escape from large basin local-minima often created by the combination of the objective and constraint function. The details of the implementation of the employed penalisation function are shown in the Alg. 1.

3.3.3 Selection

The backbone of genetic algorithms is that it is more likely that new proposed solutions inherit their characteristics from good performing candidates rather from bad ones. In stochastic optimisation the way candidates are selected for undergoing to the genetic operators is of utmost importance, especially in presence of constraints. On the one hand, selecting for reproduction only promising feasible solutions leads to a collapse of the population toward a region that may not contain the global optimal solution. On the other hand, promoting the selection of not good performing and unfeasible candidates degrades the effect of the genetic operations and slows the convergence of the overall search to optimal solutions.

In the tracking campaign designing problem, the objective function can assume a wide range of values that can differ of more than 5 order of magnitude or even be impossible to compute because of model divergence. For this study, the *tournament* selection with tournament size equal to 1/10 of the population size has been

Algorithm 1 Penalisation function

$y \leftarrow F(x)$
$costs \leftarrow C(x)$
$wY \leftarrow max(y)$
$wC \leftarrow max(costs)$
$feasible \leftarrow costs <= budget$
$unfeasible \leftarrow costs > budget$
if $feasible != \varnothing$ **then**
  $wY \leftarrow max(y[feasible])$
end if
$relaxedBudget \leftarrow MaxBudgetRelaxed - (((MaxBudgetRelaxed - budget)/(evaluationsPureFeasible)) * evaluations))$
$relaxedCRef \leftarrow max(budget, relaxedBudget)$
if $feasible != \varnothing$ **then**
  $feasibleRelax \leftarrow (costs <= relaxedBudget \wedge costs > budget \wedge y < min(y[feasible])$
else
  $feasibleRelax \leftarrow (costs <= relaxedBudget \wedge costs > budget)$
end if
$unfeasibleRelax \leftarrow (costs > relaxedBudget)$
$scaledCons \leftarrow pmax(con[unfeasibleRelax]/wC * wY, wY)$
$y[unfeasibleRelax] \leftarrow scaledCons + y[unfeasibleRelax]$

adopted. In addition, the best 5% members of the population are preserved immutably. This can sometimes have a dramatic impact on performance by ensuring that the algorithm does not waste time re-discovering previously found solutions.

3.3.4 Crossover

The crossover is an operator that aims at emulating the evolutionary reproduction mechanism exchanging genes between two different chromosomes (parents) to produce two new candidates (children). The information contained in the parents is combined and transmitted to the children. In such a way, hopefully, the children will be distinguished by the relevant characteristics that originated the performance of their parents.

In classical fixed-size algorithms, all the genes lie on the same level and have a well-defined position and meaning. Genes in the same positions in the strings of two different chromosomes represent the same variable. This is not the case for structured chromosomes. Here, swapping genes among parent chromosomes on the basis of their position may result in selecting genes that represent different variables and creating unfeasible and meaningless solutions. The number of exchanging genes belonging to each class is computed in regards to the structure of the two parents chromosomes. This helps to homogenise the crossover operation all over the hierarchy of the chromosome. Moreover, the already swapped genes are removed from the list of eligible genes for crossover. This helps to prevent the repetition of the crossover operation on the same genes that would reduce the exchange of information. A thorough description of this operator can be found in[5] . The procedure adopted is then able to create meaningful children that respect the hierarchical structure of the parents.

3.3.5 Mutation

Together with crossover, the mutation operation represents the peculiar feature of genetic algorithms. It introduces a perturbation in the current value of the genes in order to increase randomness in the chromosomes' evolution. Many different variants of this operator can be found in the literature for standard fixed dimension optimisation[10] . The majority of them is not appropriated to cope with mixed-discrete problems, much less structured chromosomes. The SCGA adopts a three-step mutation operation. First, the genes to be mutated are randomly selected. Then, the mutation process operates recursively on them and their dependent genes. Indeed, the mutation first changes the value of the selected gene then as a second step treats and modifies also its hierarchically dependent genes. The SCGA operates differently depending on the type of gene selected. It recognizes three types of genes: reals, integers and discretes. The operator ads a normally distributed noise to real-valued variables. For integer variables, the distribution is based on the difference of two geometrical distributions. Categorical variables are simply re-sampled (uniform randomly) with some probability[11] . The probability and the magnitude of mutation depend on hyperparameters that evolve during the optimisation in a self-adaptive fashion. The philosophy behind self-adaptation is that the evolutionary process is able to autonomously changes and evolve the hyperparameters properly during the optimisation. To each candidate, a set of hyperparameter is associated. This evolves undergoing the same crossover operations of the associated chromosome as extensively described in[4] . Hence, the mutation strength itself is also governed by an evolutionary process. The last step consists in operating the mutation on the dependent genes.

4. Experiment

4.1 Problem scenario and experimental setup

The test-case used in this research work considers the interplanetary cruise of a spacecraft to an asteroid. Specifically, the spacecraft leaves the Earth the 22nd of October 2026, and arrives on the 10th of April 2028 to the asteroid 99942 Apophis, with a time of flight of 537 days. The dynamic model considers the Sun's central gravitational pull only. A more complex and complete dynamical model can be used, but the primary interest of this application is intended to test the developed approach to optimize orbit determination schedules, therefore a simple dynamical model is preferred. The interplanetary trajectory is plotted in Figure 1.

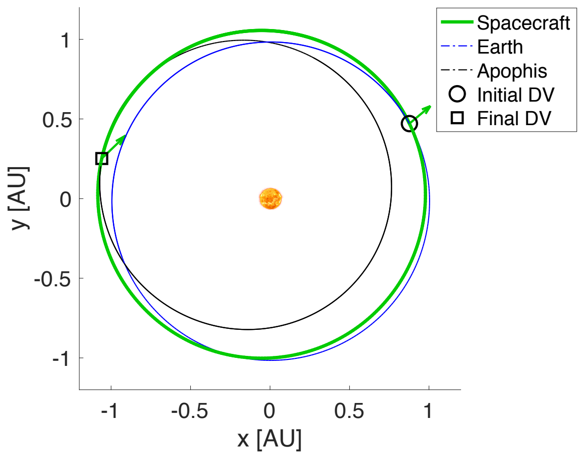


Fig. 1: Nominal interplanetary trajectory of spacecraft departing from Earth and arriving at asteroid Apophis.

The uncertainty on this trajectory stems from:

- initial assumed knowledge error, due to the initial insertion inaccuracies, modelled as a multivariate Gaussian distribution;
- execution errors at the time of trajectory correction maneuvers, which are assumed executed to be two days after the end of each observation campaign, and are modelled with the Gates' model;[2]
- noisy observations, where to each received observation $\mathbf{y}_k$ is associated a likelihood distribution which accounts for sensor and external noises, modelled as Gaussian.

The standard deviations for the initial dispersion and the parameters of the Gates' model are reported in Table 2, whereas the standard deviations for the observation likelihoods are detailed in Table 3.

Table 2: Initial dispersion 1-σ standard deviations for position and velocity in RTN components, and execution error parameters for Gates' model.

Uncertainty	Component	Value	
Initial Dispersion	Position (RTN)	[166, 166, 166]	[m]
	Velocity (RTN)	[70, 10, 15]	[mm/s]
Execution Error	Fixed Pointing	3.0	[mm/s]
	Prop. Pointing	7.0	[mrad]
	Fixed Magnitude	5.0	[mm/s]
	Prop. Magnitude	3.3e-3	[-]

Three ground stations compose the network used for tracking from ground a satellite for the entire duration of its voyage. All of them can measure the *Range*, *Range Rate* and *Azimuth and Elevation*. However, the quality and the costs of each observation varies for each ground station. As shown in Table 3, GS-1, GS-2 and GS-3 provide respectively low-fidelity, medium-fidelity and high-fidelity measurements. Going along with the real-life needs where the adopted schedule is often a trade-off between final accuracy and cost, search optimal solutions varying the available resources. The algorithm starts imposing a budget (in this case equal to 0.2) and increases it until a stopping criterion, based on the performance convergence, is met. In the presented study, the budget has been increased until the expected covariance trace at the end of the tracking window has not increased at least by 0.1% with respect to the current best solution.

The population size has been set to 50. All the other parameters of SCGA are set to their default values. For each configuration,58 instances with different random number generator seed have been run to have statistical significant results.

4.2 Results

In this section are reported and commented the observation schedules for a low-budget deep-space mission coming from an optimisation-based design by means the SCGA algorithm.

Table 3: Details about the different levels of fidelity of the measurements provided by the different ground stations and the corresponding artificial costs.

Ground Station	Measure	1-σ std.	Cost
GS-1	Range	1	0.05
	Range rate	10	0.025
	Azimuth and Elevation	50	0.025
GS-2	Range	0.1	0.1
	Range rate	4	0.05
	Azimuth and Elevation	20	0.05
GS-3	Range	0.02	0.2
	Range rate	1	0.1
	Azimuth and Elevation	2	0.1

In the left picture in Figure 2 the history of the mean of the performance of the best found solution during the optimization is depicted for each configuration investigated. Intuitively, higher the budget, better the state estimation at the end of the tracking window. The right picture in Figure 2 shows that the success of the SCGA in finding optimal observation schedules grows together with the budget. In fact the spread box-plots, especially with very low budget, indicate the difficulty of designing optimal schedules under severe budget limitation. Indeed, as can be seen from Figure 3, large part of the optimal solutions found with these configurations are characterised by only two observation campaigns and only one observation per campaign obtained using the lower-fidelity ground station. Increasing the budget, the optimal number of observation campaigns remains stable to 3. Contrarily, the number of observation per campaign always increases with the budget.

Intuitively, the ground station with higher fidelity are preferred if the available budget allows to perform at least two observation campaigns. This indicates that the importance of using the right number of observation campaigns impacts more on the performance than the accuracy of the measurements. An interest characteristic that joins all the schedules obtained is the timing of the measurements. It is evident that measuring at the beginning and toward the end of the mission is determining for the quality of the final state estimation. Indeed, from a navigation analysis angle, early measurements are beneficial because: they reduce the initial dispersion uncertainty, therefore decreasing the uncertainty growth with dynamical propagation; they enable early, thus more efficient, trajectory correction maneuvers. Late measurements are critical to improve the spacecraft knowledge at arrival, and to adjust the final braking manoeuvre to rendezvous the asteroid. Increasing the budget and the number of observation campaigns, the algorithm found that is beneficial firstly acquiring measurements toward the 75% of the duration of the mission and secondly toward the 25%. These intermediate observation windows help reducing the uncertainty growth due to pure uncertainty propagation, and allow the operator to perform trajectory correction maneuvers with large time margins before the rendezvous.

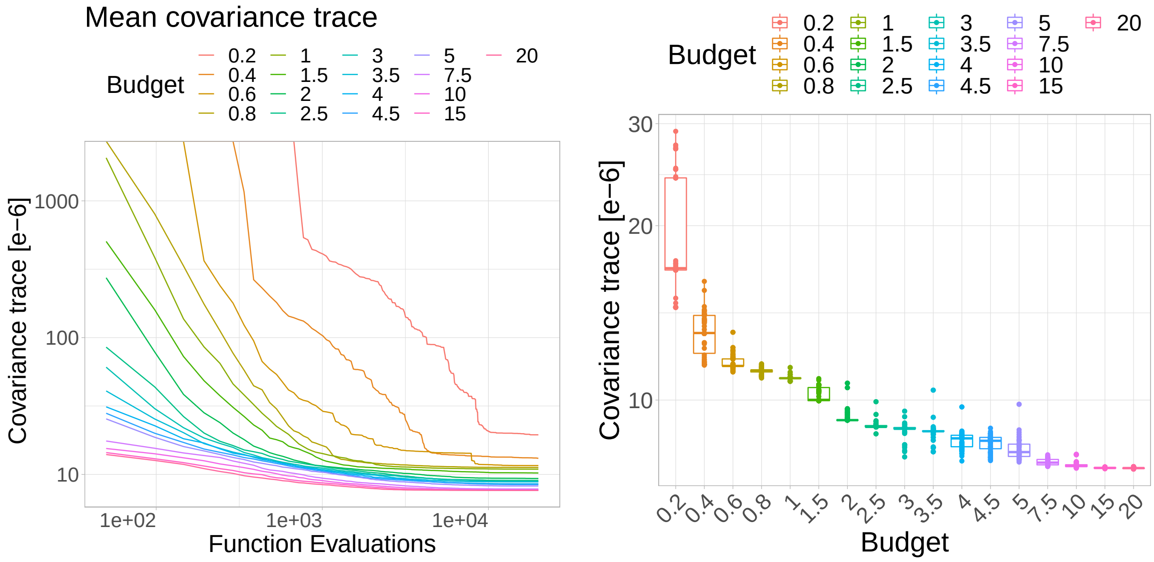
5. Conclusions

This paper presents the application of a novel optimization routine to the problem of observation schedules for deep-space missions under limited resources. This aim at offering a spectrum of solutions with different performance and costs to leave the analyst be free to choose the appropriated trade-off. In the test case solved, the ground station network is composed of three ground stations that can acquire different type of measures with different fidelity.

The optimization of the navigation plan involved has been framed under the optimal sensor control framework. The navigation analysis is performed by means of a sparse Gauss-Hermite Kalman Filter, that is a sample-based filtering approach with enhanced numerical stability. Such method employs sparse grids to overcome the curse of dimensionality, which is particularly critical because the navigation model is called numerous times within the optimisation loop.

The searching strategy has been formulated as a variable-size mixed-discrete global optimisation. To face its complexity the Structured-Chromosome Genetic Algorithm has been used. This makes use of revised genetic operators and a relaxed penalisation function for handling different size chromosomes and constraints. Furthermore, an automatic procedure for creating a Pareto front with respect to budget allocation and performance has been used. This autonomously increases the budget parameter from a given minimum to the one leading to the most precise state estimation. The flexibility, reliability and efficiency of the SCGA have been shown by testing it on a quasi-realistic scenario. The results indicate that the used methodology can successfully and efficiently enhance resources allocation strategies in deep-space objects tracking problems. The algorithm has been implemented to work with any dynamical and measurement model, and any station network, such that different test cases can be tested in future. The authors will focus on producing a

Fig. 2: Left: history of the best found schedules during the optimization process. The values depicted are mean over the 58 independent runs. Right: box-plot representation of the optimal solutions found at the end of the optimisation for each budget.



comprehensive study for comparing the existing state-of-the-art techniques and the the SCGA in facing observation schedules design under severe budget restrictions.

In addition to the tracking campaigns, future work will focus on the quantification and optimisation of the times of the statistical manoeuvres to correct trajectory deviations.

Acknowledgements

This work was funded by the European Commission's H2020 programme, through the H2020-MSCA-ITN-2016 UTOPIAE Marie Curie Innovative Training Network, grant agreement no. 722734.

References

[1] Shadi A Darani and Ossama Abdelkhalik. Space trajectory optimization using hidden genes genetic algorithms. *Journal of Spacecraft and Rockets*, 55(3):764–774, 2017.

[2] C. R. Gates. A simplified model of midcourse maneuver execution errors. Technical report, Jet Propulsion Laboratory, California Institute of Technology, 1963.

[3] Lorenzo Gentile. Lorenzogentile/scga: Scga first release. `https://doi.org/10.5281/zenodo.3464039`, September 2019.

[4] Lorenzo Gentile, Cristian Greco, Edmondo Minisci, Thomas Bartz-Beielstein, and Massimiliano Vasile. Structured-chromosome ga optimisation for satellite tracking. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, GECCO '19, pages 1955–1963, New York, NY, USA, 2019. ACM. doi: 10.1145/3319619.3326841.

[5] Cristian Greco, Lorenzo Gentile, Gianluca Filippi, Edmondo Minisci, Massimiliano Vasile, and Thomas Bartz-Beielstein. Autonomous generation of observation schedules for tracking satellites with structured-chromosome ga optimisation. In *2019 IEEE Congress on Evolutionary Computation (CEC)*, pages 497–505. IEEE, 2019. doi: 10.1109/CEC.2019.8790101.

[6] A. O. Hero, D. Castañón, D. Cochran, and K. (Eds.) Kastella. *Foundations and applications of sensor management*. Springer Science & Business Media, 2007.

[7] Rodica Ionasescu. Orbit determination covariance analysis for the Cassini solstice mission. In *AIAA/AAS Astrodynamics Specialist Conference*, 2010.

[8] Rodica Ionasescu, Tomas Martin-Mury, Powtawche Valerinoy, Kevin Criddley, Brent Buffington, and Timothy McElrath. Orbit determination covariance analysis for the Europa Clipper mission. In *AIAA Space 2014*, 2014.

[9] Bin Jia, Ming Xin, and Yang Cheng. Sparse gausshermite quadrature filter with application to spacecraft attitude estimation. *Journal of Guidance, Control, and Dynamics*, 34:367–379, 03 2011.

[10] Imtiaz Korejo and Shengxiang Yang. Comparative study of adaptive mutation operators for genetic algorithms. In *in MIC 2009: The VIII Metaheuristics International Conference, 2009. 196 Journal of Emerging Technology and Advanced Engineering Website: www. ijetae. com (ISSN 2250-2459, Volume 2, Issue 2*. Citeseer, 2012.

[11] Rui Li, Michael TM Emmerich, Jeroen Eggermont, Thomas Bäck, Martin Schütz, Jouke Dijkstra, and Johan HC Reiber. Mixed integer evolution strategies for parameter optimization. *Evolutionary computation*, 21(1):29–64, 2013.

[12] Melanie Mitchell. *An introduction to genetic algorithms*. MIT press, 1998.

[13] Hui Meen Nyew, Ossama Abdelkhalik, and Nilufer Onder. Autonomous interplanetary trajectory planning using structured-chromosome evolutionary algorithms. In *AIAA/AAS Astrodynamics Specialist Conference*, page 4522, 2012.

[14] Hui Meen Nyew, Ossama Abdelkhalik, and Nilufer Onder. Structured-chromosome evolutionary algorithms for variable-size autonomous interplanetary trajectory planning optimization. *Journal of Aerospace Information Systems*, 12(3):314–328, 2015.

[15] Julien Pelamatti, Loïc Brevault, Mathieu Balesdent, El-Ghazali Talbi, and Yannick Guerin. How to deal with mixed-variable optimization problems: An overview of algorithms and formulations. In *World Congress of Structural and Multidisciplinary Optimisation*, pages 64–82. Springer, 2017.

Fig. 3: Analysis of the free variables considered in consideration of the budget imposed. The histograms show the occurrences of the values assumed over the 58 solutions obtained for each configuration.