



Original software publication

GTOPX space mission benchmarks

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ABSTRACT

This contribution introduces the GTOPX space mission benchmark collection, which is an extension of the GTOP database published by the European Space Agency (ESA). The term GTOPX stands for Global Trajectory Optimization Problems with eXtension. GTOPX consists of ten individual benchmark instances representing real-world interplanetary space trajectory design problems. In regard to the original GTOP collection, GTOPX includes three new problem instances featuring mixed-integer and multi-objective properties. GTOPX enables a simplified user-handling, unified benchmark function call and some minor bug corrections to the original GTOP implementation. Furthermore, GTOPX is linked from original C++ source code to Python and Matlab based on dynamic link libraries, assuring computationally fast and accurate reproduction of the benchmark results in all programming languages. We performed a comprehensive landscape analysis to characterize the properties of the fitness landscape of GTOPX benchmarks. Space mission trajectory design problems as those represented in GTOPX are known to be highly non-linear and difficult to solve. The GTOPX collection therefore aims in particular at researchers wishing to put advanced (meta)heuristic and hybrid optimization algorithms to the test.

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Matlab, C/C++ and Python
C++ source code, Matlab mex source code, pre-compiled dll/so libraries for Python on Windows, Linux and MacOS
<http://www.midaco-solver.com/index.php/about/benchmarks/gtopx>
info@midaco-solver.com

1. Motivation and significance

The optimal design of interplanetary space mission trajectories is an active and challenging research area in aerospace and related communities, such as the evolutionary and metaheuristic

optimization community. Since 2005, the European Space Agency (ESA) maintained a set of real-world space mission trajectory design problems in form of numerical black-box optimization problems, known as the GTOP database [1]. Note that the term “black-box” refers here to an optimization problem, where the actual problem formulation is unknown, inaccessible or unrelated to the optimizer. These kind of black-box problems frequently occur in many areas, where complex computer simulations are applied. Given the usefulness and success of the GTOP endeavor in the past, here we present an extended and refurbished version,

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Table 1
GTOPX Benchmark Instances (see [1] for solution references).

No.	Name	Objectives	Variables	Constraints	Best known $f(x, y)$
1	Cassini1	1	6	4	4.9307
2	Cassini2	1	22	0	8.3830
3	Messenger (reduced)	1	18	0	8.6299
4	Messenger (full)	1	26	0	1.9579
5	GTOC1	1	8	6	−1581950.0
6	Rosetta	1	22	0	1.3434
7	Sagas	1	12	2	18.1877
8	Cassini1-MINLP	1	10	4	3.5007
9	Cassini1-MO	2	6	5	na
10	Cassini1-MO-MINLP	2	10	5	na

named GTOPX, as continuation to the no longer maintained GTOP database.

While all problems of the original GTOP database were single-objective and continuous in the nature of the search space domain, the GTOPX collection includes three new problem instances featuring mixed-integer and multi-objective problem properties. The general mathematical form of the considered optimization problem in GTOPX is given as multi-objective Mixed-integer Non-linear Programming (MINLP):

$$\text{Minimize } f_i(x, y) \quad (x \in \mathbb{R}^{n_{con}}, y \in \mathbb{N}^{n_{int}}, n_{con}, n_{int} \in \mathbb{N})$$

$$\text{subject to: } g_i(x, y) \geq 0, \quad i = 1, \dots, m \in \mathbb{N}$$

$$x_l \leq x \leq x_u \quad (x_l, x_u \in \mathbb{R}^{n_{con}})$$

$$y_l \leq y \leq y_u \quad (y_l, y_u \in \mathbb{N}^{n_{int}})$$

(1)

where $f_i(x, y)$ and $g_i(x, y)$ denote the objective and constraint functions depending on continuous (x) and discrete (y) decision variables, which are box-constrained to some lower (x_l, y_l) and upper (x_u, y_u) bounds. The ten individual benchmark instances of GTOPX are listed in Table 1 with their name, the number of objectives, variables and constraints together with the best known objective function value $f(x, y)$. Note that due to the many years these benchmarks have been available and been tested, it is believed that all listed solutions are essentially converged.

The GTOP database has attracted a significant amount of attention and results have been published, see for example [2–15]. Note that the majority of publications discussing results on GTOP focus on only one or a few problem instances. This is due to the difficulty of these problems, which often require many millions of function evaluations to allow an optimization algorithm to converge to the best known solution. This difficulty is what makes this collection of benchmark problems interesting and a real challenge, even requiring the use of massively distributed computing power by supercomputers in the most difficult cases (see Shuka [16] or Schlueter [17]).

While the focus of the original GTOP database was rather on the nature of the application itself, the GTOPX collection aims to address the broad community of numerical optimization researchers. It does so by a simplified and more user-friendly source code base, that allows easy execution of the benchmarks in three programming languages: C/C++, Python and Matlab. The entire source code base of GTOPX has been compressed into a single file (namely “gtopx.cpp”) that is linked via dynamic link libraries (DLL) into the Python and Matlab language. The linking of a pre-compiled DLL has the significant advantage of computation speed and accurate reproduction of results among all considered programming languages, in contrast to a native re-implementation in other languages, which is computationally slower and error prone.

The function call to the individual GTOPX benchmark instances has been generalized, so that any problem instance can easily be

accessed with only switching one integer parameter (namely the benchmark number). The generalized call to the GTOPX problem functions in each language is given as follows:

C/C++	:	<code>gtopx(benchmark, f, g, x);</code>
Python	:	<code>[f, g] = gtopx(benchmark, x, o,n,m)</code>
Matlab	:	<code>[f, g] = gtopxmex(benchmark, x)</code>

In above table, f denotes the objective function value(s), g denotes the constraint function values, x denotes the vector of decision variables and o, m and n denote their corresponding dimensions. All GTOPX benchmark instances are thread-safe for execution. This means that the GTOPX problems can be executed in parallel, which is a highly desired feature in modern optimization algorithm design. The GTOPX source code files are free software and published under the GPL license [18].

The remainder of this paper is structured as follows. Section 2 describes each of the ten individual instances from Table 1 in detail. Section 3 contains a comprehensive fitness landscape analysis of the GTOPX single objective benchmarks to provide a better perception of a proper optimization algorithm selection. A brief summary is given with some conclusive statements. This paper is to provide researchers with a manual and reference to the GTOPX benchmark software.

2. Software description

This section gives detailed information to the ten GTOPX benchmark instances. Note that the definitions of the first seven instances¹ are taken from Schlueter [19], while the last three instances are new.

2.1. Cassini1

The Cassini1 benchmark models an interplanetary space mission to Saturn. The objective of the mission is to get captured by Saturn's gravity into an orbit having a pericenter radius of 108,950 km and an eccentricity of 0.98. The sequence of fly-by planets for this mission is given by Earth–Venus–Venus–Earth–Jupiter–Saturn, whereas the first item is the start planet and the last item is the final target. The objective function of this benchmark is to minimize the total velocity change ΔV accumulated during the mission, including the launch and capture maneuver. The benchmark involves six decision variables (see Table 2):

This benchmark further considers four constraints, which impose an upper limit on the pericenters for the four fly-by maneuvers. The best known solution to this benchmark has an objective function value of $f(x) = 4.9307$, and the respective vector of solution decision variables x is available online [20].

¹ Note that an individual benchmark problem is also called an *instance* in the optimization community.

Table 2

Description of optimization variables for Cassini1.

Variable	Description
1	Initial day measured from 1-Jan 2000
2~6	Time interval between events (e.g. departure, fly-by, capture)

Table 3

Description of optimization variables for Cassini2.

Variable	Description
1	Initial day measured from 1-Jan 2000
2	Initial excess hyperbolic speed (km/s)
3	Angles of the hyperbolic excess velocity (polar coordinate frame)
4	Angles of the hyperbolic excess velocity (polar coordinate frame)
5~9	Time interval between events (e.g. departure, fly-by, capture)
10~14	Fraction of the time interval after which DSM occurs
15~18	Radius of fly-by (in planet radii)
19~22	Angle measured in B plane of the planet approach vector

Table 4

Description of optimization variables for Messenger (reduced).

Variable	Description
1	Initial day measured from 1-Jan 2000
2	Initial excess hyperbolic speed (km/s)
3	Angles of the hyperbolic excess velocity (polar coordinate frame)
4	Angles of the hyperbolic excess velocity (polar coordinate frame)
5~8	Time interval between events (e.g. departure, fly-by, capture)
9~12	Fraction of the time interval after which DSM occurs
13~15	Radius of fly-by (in planet radii)
16~18	Angle measured in B plane of the planet approach vector

2.2. Cassini2

The Cassini2 benchmark models an interplanetary space mission to Saturn, including deep space maneuvers (DSM) and is therefore considerably more difficult than its counterpart benchmark Cassini1. The sequence of fly-by planets for this mission is given by Earth–Venus–Venus–Earth–Jupiter–Saturn, where the first item is the start planet and the last item is the final target. The objective of this benchmark is again to minimize the total ΔV accumulated during the full mission; however, the aim here is a rendezvous, while in Cassini1 the aim is an orbit insertion. The benchmark involves 22 decision variables (see Table 3):

The best known solution to this benchmark has an objective function value of $f(x) = 8.3830$, and the respective vector of solution decision variables x is available online [20].

2.3. Messenger (reduced)

This benchmark models an interplanetary space mission to Mercury and does not include resonant fly-bys at Mercury. The sequence of fly-by planets for this mission is given by Earth–Earth–Venus–Venus–Mercury, where the first item is the start planet and the last item is the final target. The objective of this benchmark to be minimized is again the total ΔV accumulated during the mission. The benchmark involves 18 decision variables (see Table 4):

The best known solution to this benchmark has an objective function value of $f(x) = 8.6299$, and the respective vector of solution decision variables x is available online [20].

2.4. Messenger (full)

This benchmark models an interplanetary space mission to Mercury, including resonant fly-bys at Mercury. The sequence of fly-by planets for this mission is given by Earth–Venus–Venus–Mercury–Mercury–Mercury–Mercury. The objective of this benchmark to be minimized is – as before – the total ΔV accumulated

Table 5

Description of optimization variables for Messenger (full).

Variable	Description
1	Initial day measured from 1-Jan 2000
2	Initial excess hyperbolic speed (km/s)
3	Angles of the hyperbolic excess velocity (polar coordinate frame)
4	Angles of the hyperbolic excess velocity (polar coordinate frame)
5~10	Time interval between events (e.g. departure, fly-by, capture)
11~16	Fraction of the time interval after which DSM occurs
17~21	Radius of fly-by (in planet radii)
22~26	Angle measured in B plane of the planet approach vector

Table 6

Description of optimization variables for GTOC1.

Variable	Description
1	Initial day measured from 1-Jan 2000
2~8	Time interval between events (e.g. departure, fly-by, capture)

Table 7

Description of optimization variables for Rosetta.

Variable	Description
1	Initial day measured from 1-Jan 2000
2	Initial excess hyperbolic speed (km/s)
3	Angles of the hyperbolic excess velocity (polar coordinate frame)
4	Angles of the hyperbolic excess velocity (polar coordinate frame)
5~9	Time interval between events (e.g. departure, fly-by, capture)
10~14	Fraction of the time interval after which DSM occurs
15~18	Radius of fly-by (in planet radii)
19~22	Angle measured in B plane of the planet approach vector

during the full mission. The benchmark involves 26 decision variables (see Table 5):

The best known solution to this benchmark has an objective function value of $f(x) = 1.9579$, and the vector of solution decision variables x is available online [20].

2.5. GTOC1

This benchmark models a multi gravity assist space mission to asteroid TW229. The mission model drew inspiration from the first edition of the Global Trajectory Optimization Competition (GTOC) held by ESA in 2007 [21]. The objective of the mission is to maximize the change in the semi-major axis of the asteroid orbit. The sequence of fly-by planets for this mission is given by Earth–Venus–Earth–Venus–Earth–Jupiter–Saturn–TW229. This benchmark involves eight decision variables (see Table 6):

This benchmark further considers four constraints, which impose an upper limit on the pericenters for the four fly-by maneuvers. The best known solution to this benchmark has an objective function value of $f(x) = -1581950.0$, and the vector of solution decision variables x is available online [20].

2.6. Rosetta

The Rosetta benchmark models multi gravity assist space mission to comet 67P/Churyumov-Gerasimenko, including deep space maneuvers (DSM). The sequence of fly-by planets for this mission is given by Earth–Earth–Mars–Earth–Earth–67P. The objective of this benchmark is to minimize the total ΔV accumulated during the mission. The benchmark involves 22 decision variables (see Table 7):

The best known solution to this benchmark has an objective function value of $f(x) = 1.3434$, and the vector of solution decision variables x is available online [20].

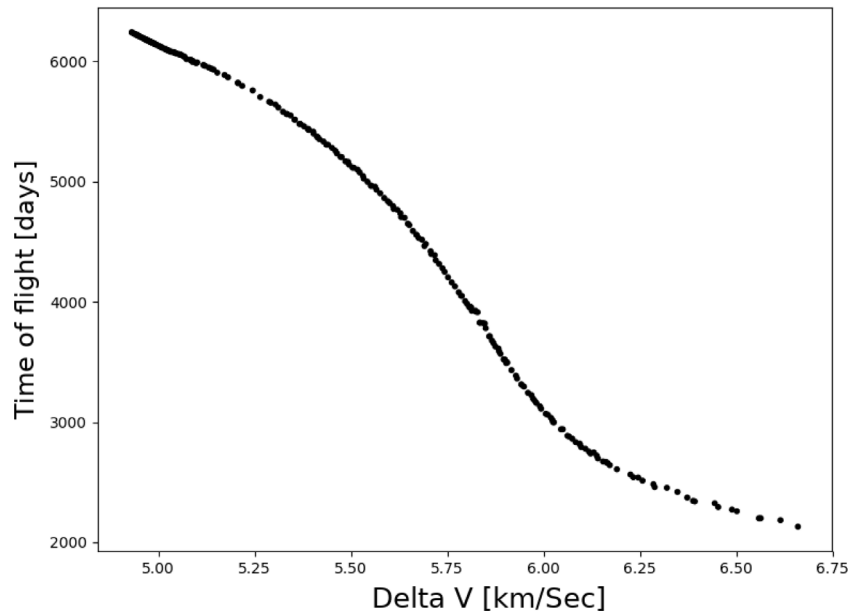


Fig. 1. Pareto front of Cassini1-MO.

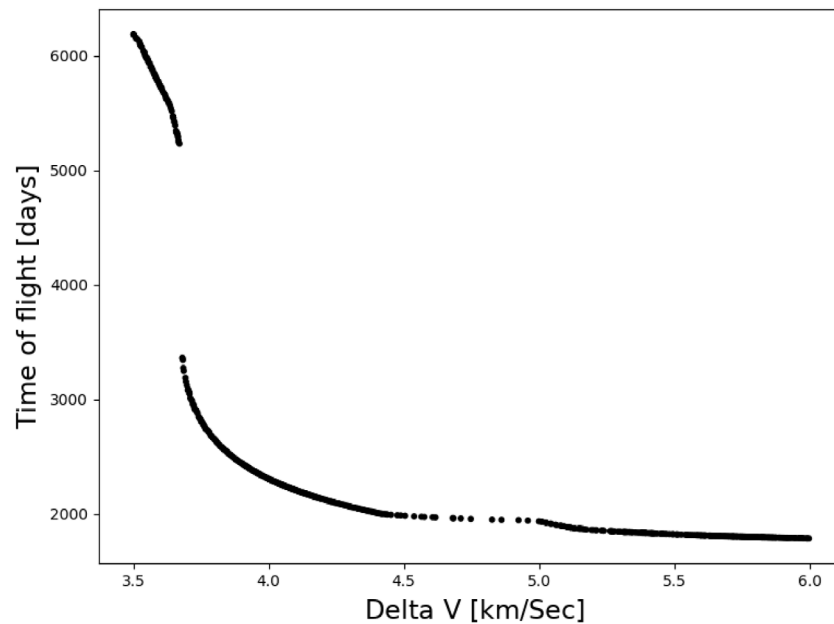


Fig. 2. Pareto front of Cassini1-MO-MINLP.

2.7. Sagas

This benchmark is described as a ΔV -EGA maneuver to fly-by Jupiter and reach 50AU. The sequence of fly-by planets for this mission is given by Earth–Earth–Jupiter, where the first item is the start planet and the last item is the final planet. The objective of this benchmark is to minimize the total ΔV accumulated during the mission. The benchmark involves 12 decision variables described in Table 8.

This benchmark further considers two constraints, which impose an upper limit on the on-board fuel and launcher performance. The best known solution to this benchmark has an

objective function value of $f(x) = 18.1877$, and the respective vector of solution decision variables x is available online [20].

2.8. Cassini1-MINLP

This new benchmark is a mixed-integer extension of the Cassini1 instance. While in the original Cassini1 instance the sequence of fly-by planets is fixed as Venus–Venus–Earth–Jupiter, the Cassini1-MINLP considers all four fly-by planets as discrete decision variable. Each planet of the solar system (plus the dwarf planet Pluto) is a feasible choice for any of the four fly-by planets. Table 9 lists all possible choices for fly-by planets together with

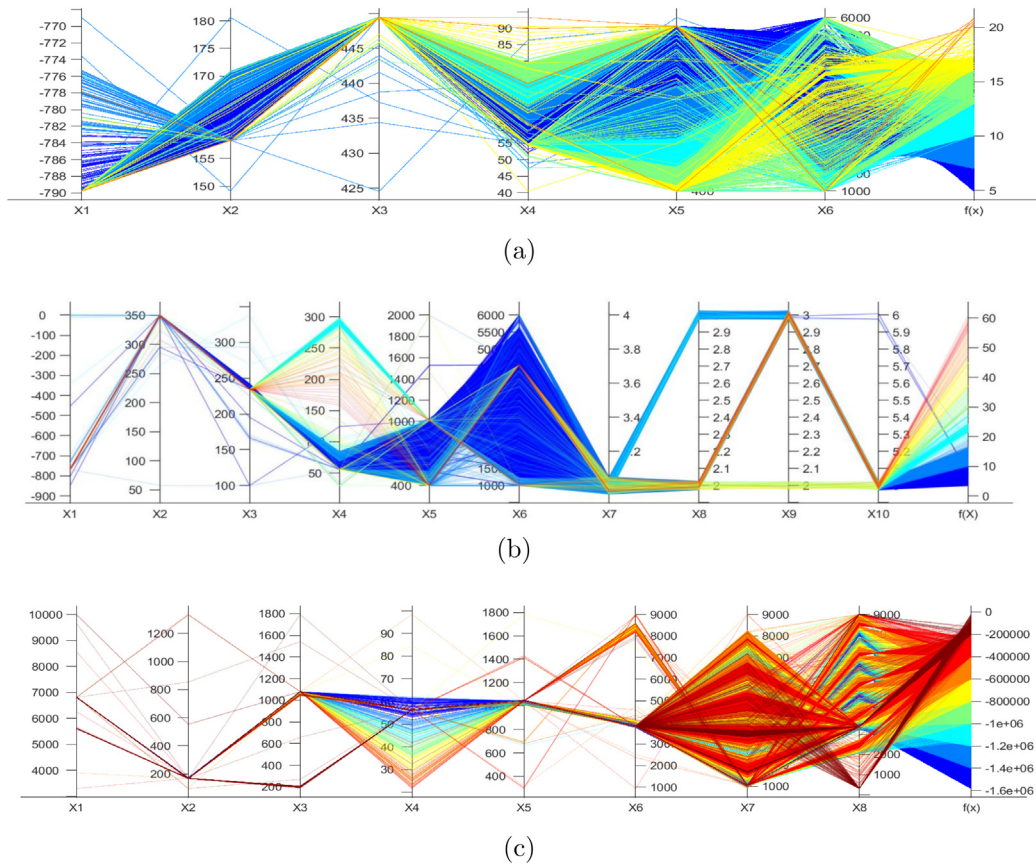


Fig. 3. Parallel coordinate plots of (a) Cassini1, (b) Cassini1-MINLP and (c) GTOC1. The color of each line corresponds to the objective function value $f(x)$ given at the right side of each plot. Because all GTOPX benchmarks are to be minimized, a cold color (e.g. blue) indicates a better good solution, while a warm color (e.g. red) indicates a bad solution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
Description of optimization variables for Sagas.

Variable	Description
1	Initial day measured from 1-Jan 2000
2	Initial excess hyperbolic speed (km/s)
3	Angles of the hyperbolic excess velocity (polar coordinate frame)
4	Angles of the hyperbolic excess velocity (polar coordinate frame)
5~6	Time interval between events (e.g. departure, fly-by, capture)
7~8	Fraction of the time interval after which DSM occurs
9~10	Radius of fly-by (in planet radii)
11~12	Angle measured in B plane of the planet approach vector

Table 9
Possible choices of fly-by planets.

Value	Planet
1	Mercury
2	Venus
3	Earth
4	Mars
5	Jupiter
6	Saturn
7	Uranus
8	Neptune
9	Pluto

their numerical value, to be used as variable for the GTOPX solution vector x . Table 10 lists the ten decision variables.

The Cassini1-MINLP problem has been previously investigated with numerical results in Schlueter [22]. In that paper it was

revealed, that this benchmark has a strong local minimum corresponding to the fly-by planet sequence {Earth, Earth, Earth, Jupiter}. This local minimum appeared to be the second best solution (in regard to the combinatorial part) and holds an objective function value of $f(x) = 3.6307$. The best known solution to Cassini1-MINLP has the fly-by planet sequence {Earth, Venus, Earth, Jupiter} and corresponds to an objective function value of $f(x) = 3.5007$.

The decisive nature of the above described local minima makes the Cassini1-MINLP exceptionally hard to solve. It is therefore noteworthy that the Cassini1 instance and the Cassini1-MINLP instance are significantly different in their complexity and difficulty.

Note that the technical modification in the source code of the GTOX database, necessary to enable the integer choice of fly-by planets, is given in the C++ function `cassini1minlp`. In such function, the following original source code line:

```
sequence_[CASSINI_DIM] = {3,2,2,3,5,6}
```

is replaced with the following:

```
sequence_[CASSINI_DIM] = {3,x7,x8,x9,x10,6}
```

where the sequence elements x_7, x_8, x_9, x_{10} represent the integer variables. Note that the first and last entry in the above source code sequence represent the start and target planet, which is in this case Earth (\rightarrow start) and Saturn (\rightarrow target). Therefore the first and last entry in the original sequence remain unaffected by the above modification.

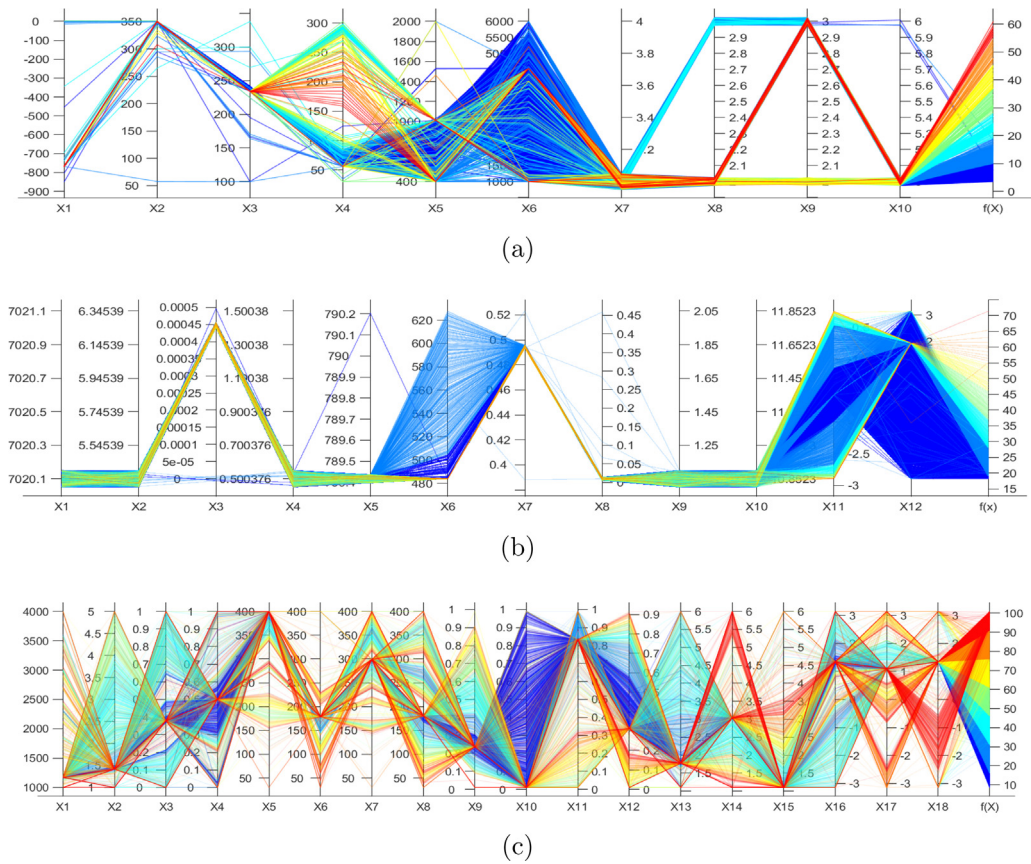


Fig. 4. Parallel coordinate plots of (a) Cassini1-MINLP, (b) Sagas and (c) Messenger (reduced).

Table 10

Description of optimization variables for Cassini1-MINLP.

Variable	Description
1	Initial day measured from 1-Jan 2000
2~6	Time interval between events (e.g. departure, fly-by, capture)
7~10	fly-by planet (discrete value, see Table 9)

Table 11

Description of optimization variables for Cassini1-MO.

Variable	Description
1	Initial day measured from 1-Jan 2000
2~6	Time interval between events (e.g. departure, fly-by, capture)

2.9. Cassini1-MO

This benchmark is a multi-objective extension of the Cassini1 instance. While in the original Cassini1 instance only one objective (the total ΔV) was considered, the Cassini1-MO benchmark considers as the second objective the total time of flight (measured in days). The decision variables for Cassini1-MO are identical to the Cassini1 instance (see Table 11):

The Cassini1-MO has one more constraint than Cassini1. This additional constraint bounds the objective space to solutions with a first objective-function (Delta V [m/s]) value of $f_1(x) \leq 7.0$. This additional constraint is introduced to focus the area of the Pareto front to the truly challenging region of low fuel-consuming space mission trajectories.

There is yet no comprehensive analysis conducted on this benchmark, but an approximation of the Pareto front was obtained by the MIDACO solver [23] and is displayed in Fig. 1. There,

the Pareto front of Cassini1-MO reveals a very distinctive non-separated shape, exhibiting convex (right half of Fig. 1) as well as non-convex (left half of Fig. 1) areas. The set of non-dominated solutions is available online at [20] as a text file.

Note that while the benchmark definition allows feasible points with $f_1(x) \leq 7.0$, there appears to exist only feasible non-dominated solutions with a value of around $f_1(x) \leq 6.7$.

Note that in contrast to single-optimization, there does not exist a commonly agreed on performance measure in multi-objective optimization. Among the most widely used methods to measure the performance in multi-objective optimization are the hyper-volume (HV) indicator and the general and inverse general distance (GD & IGD) indicators [24]. Thus the authors provide only the raw data of the Pareto front approximation and interested users must choose their own choice of multi-objective performance measure in order to compare specific algorithms.

2.10. Cassini1-MO-MINLP

The Cassini1-MO-MINLP benchmark combines the previous two extensions of Cassini1-MINLP and Cassini1-MO. This benchmark is therefore a multi-objective mixed-integer problem and very challenging to solve. The decision variables are the same as for Cassini1-MINLP, and the fly-by planet choices are listed in Table 12:

As in Cassini1-MO, the first objective of Cassini1-MO-MINLP is the total ΔV and the second objective is the total time of flight of the space mission. Like the Cassini1-MO benchmark the Cassini1-MO-MINLP has an additional constraint on the objective space. However, in contrast to Cassini1-MO this benchmark bounds the objective space to solutions with a first objective-function (Delta V [m/s]) value of $f_1(x) \leq 6.0$ instead of a value of 7.0, as the

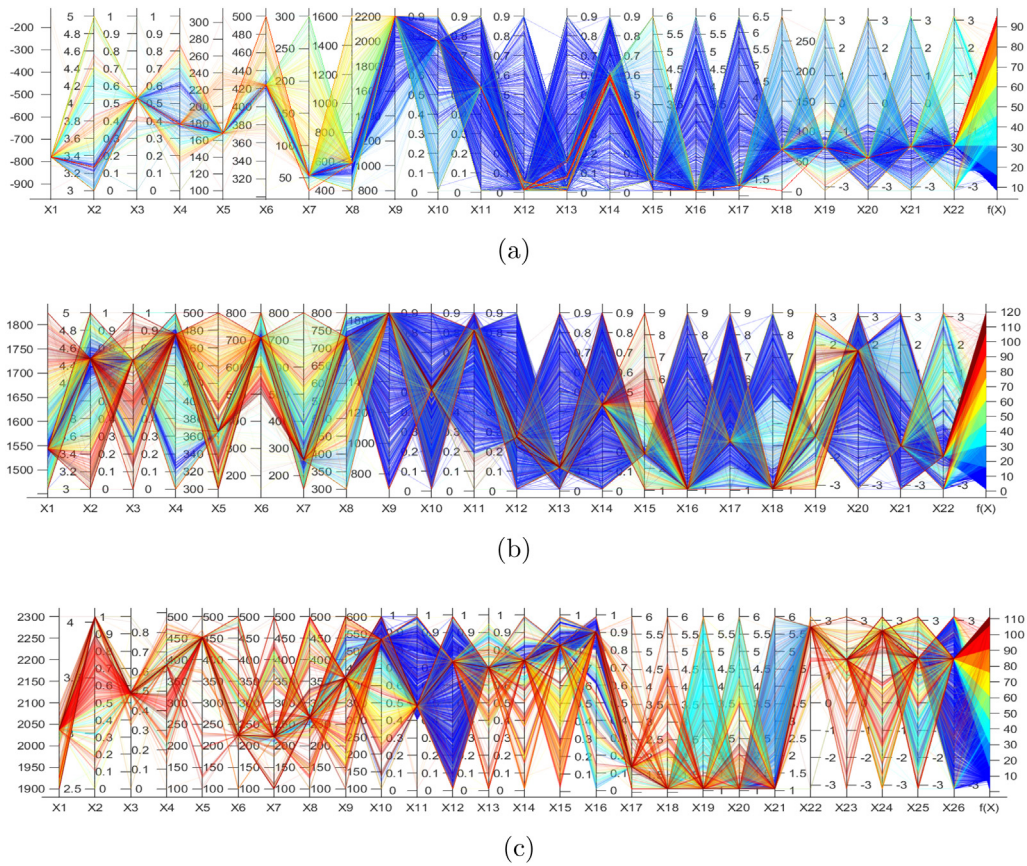


Fig. 5. Parallel coordinate plots of (a) Cassini2, (b) Rosetta and (c) Messenger (full).

Table 12

Description of optimization variables for Cassini1-MO-MINLP.

Variable	Description
1	Initial day measured from 1-Jan 2000
2~6	Time interval between events (e.g. departure, fly-by, capture)
7~10	Fly-By planet (discrete value, see Table 9)

changed search space landscape allows for better solutions than the Cassini1-MO benchmark.

The Pareto front (as approximated by the MIDACO solver in [23], see Fig. 2) of Cassini1-MO reveals a distinctive separated shape, where it is to note that the upper left part is mostly corresponding to solutions with the best² known integer sequence while the lower part is corresponding to the second best known integer sequence. The full set of non-dominated solutions is also available online at [20] as a text file.

3. Landscape analysis

Landscape analysis methods can be employed to characterize the features of fitness landscapes by representing the levels of ruggedness, smoothness, multi-modality and neutrality [25]. Characteristics like these can be exploited by algorithm designers in the construction of an algorithm, but also in an online fashion by algorithms themselves. For example, when fitness values vary very little in a particular region (and the algorithm might be stuck on a plateau), an optimization method can adjust its parameters

(like mutation step size) to generate candidates that are further away from the current solutions.

In the following, we use two ways of characterizing the benchmarks. First, we sample uniformly-at-random around the best-known solutions in a way that is similar to those used by some local search algorithms, and we do so with the goal of simulating how a local search would perceive the area around the best solutions – we use parallel coordinate plots for the visualization due to the high dimensionality. Second, we use systematic grid searches for a holistic picture of the entire problem – we use 3D plots for the visualization.

First, we investigate the local sampling around the best trajectories known. We sample the neighborhood in a way similar to those employed by some local search approaches: (1) the mutation probability of each individual value is $\frac{1}{N}$, where N is the number of decision variables, (2) we sample from a normal distribution around the best-known solution with $\sigma_i = \frac{Ub_i - Lb_i}{3}$, where Ub and Lb are the upper and lower bounds of the i th variable, and (3) we do so one million times.

In Figs. 3 to 5 (for the eight single-objective problems), the columns represent the decision variables of the benchmarks, and colored lines connect the values that belong to a solution vector. The color denotes the respective solution quality: the most efficient solutions are dark blue. The primary observation of Fig. 4 is that some variables play an important role in optimizing the trajectory cost (ΔV), for instance $X1$ to $X8$ in Cassini2 (Fig. 5), where small changes result in the decision variable can result in large changes in the objective value. As another example, consider the variable $X3$ in Cassini1 or the variable $X5$ in GTOC1, which are highly sensitive. For practical approaches, this means that they need to be able to focus differently on the different decision variables.

² The best known integer sequence refers here to the value of the corresponding first objective function value.

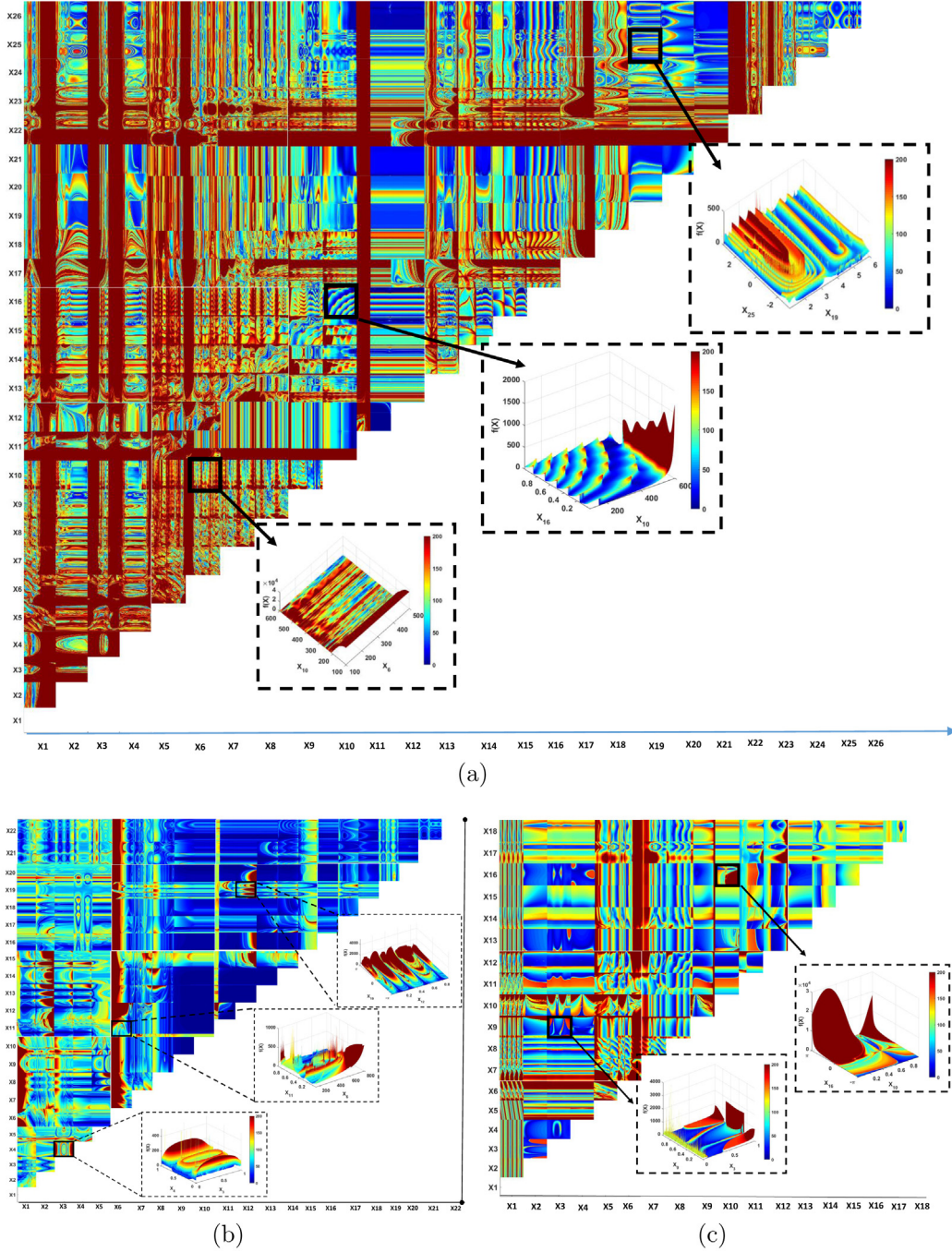


Fig. 6. Landscape analysis of GTOPIX benchmarks using grid search: (a) Messenger (full), (b) Rosetta, (c) Messenger (reduced).

Next, we use a grid search that is a systematic approach with a very small step (mesh) size ($\mu = (Ub - Lb) * 0.001$) as a sampling method across the entire search space. The grid search provides a uniform and discrete sampling of the landscape. While systematic, grid searches can be expensive landscape analysis methods where the number of decision variables is high (curse of dimensionality [26]) or the objective function is computationally expensive. Hence, we limit ourselves to pairs of grid searches, i.e. for each possible pair of decision variables.

Fig. 6 shows results for Messenger (full), Messenger (reduced) and Rosetta. We can see a high level of ruggedness and a large

number of spikes in the landscapes. Based on this observed multi-modality (i.e. multiple local optima), it might be worth considering optimization methods in the future such as niching techniques [27], crowding [28], fitness sharing [29], species conserving [30] and covariance matrix adaptation [31].

As a side-effect of our grid search and of the local sampling, we have found small improvements over the previously best known solutions for the Rosetta benchmark. A new solution with a percentage change improvement of 0.00075% was found. Note that in case of the GTOPIX benchmarks new solutions must traditionally hold a percentage change improvement of at least 0.1% to be considered significant. Nonetheless, other researchers (e.g. [7]) have published improvements below the 0.1% threshold and thus

Table 13
New solutions for Rosetta.

Rosetta	Previous Best	New solution (grid search)	New solution (local search)
x1	1542.802723	1542.802723	1542.802723
x2	4.478444171	4.478444171	4.478444171
x3	0.73169868	0.73169868	0.73169868
x4	0.878289696	0.878289696	0.878289696
x5	365.2423131	365.2423131	365.2423131
x6	707.7546444	707.7546444	707.7546444
x7	257.3238516	257.3238516	257.3238516
x8	730.4837236	730.4837236	730.4837236
x9	1850	1850	1850
x10	0.469187104	0.51018	0.512067
x11	0.810371727	0.810371727	0.810371727
x12	0.057240939	0.25119	0.2758878
x13	0.123333369	0.123333369	0.119192979
x14	0.436535683	0.436535683	0.43674223
x15	2.657626174	2.657626174	2.657626174
x16	1.05	1.05	1.05
x17	3.197806169	3.197806169	3.197806169
x18	1.056221792	1.056221792	1.056221792
x19	−1.253888118	−1.253888118	−1.253888118
x20	1.78760233	1.78760233	1.78760233
x21	−1.594671417	−1.594671417	−1.594671417
x22	−1.977325495	−1.977325495	−1.977325495
f(x)	1.34335206	1.34334453	1.34334419

such new solutions displayed here might be interesting to some (see Table 13).

4. Impact

We present the GTOPX space mission benchmark software package, available for C/C++, Matlab and Python. The benchmark problems in this package have been extensively tested in previous years, see for example [2–15]. See Code metadata table.

5. Conclusions

With this article, we introduce an extended and refurbished version of ESA's well-known GTOP database. The new version, called GTOPX, includes three new benchmark instances featuring mixed-integer and multi-objective properties. While the original Cassini1 benchmark is clearly the easiest instance, its extensions are more difficult to solve.

A simplified and user-friendly C/C++ source code base with efficient numerical gateways into Python and Matlab make the GTOPX database an attractive choice for researchers wishing to put advanced optimization algorithms to the test. The important feature of thread-safe function calls is provided for all GTOPX benchmarks, allowing the parallel execution of these benchmark functions which is a highly desired feature for modern optimization algorithms. We also provide a first fitness landscape analysis of the single-objective GTOPX benchmarks to visually characterize the relations among decision variables. Given the highly non-linear nature of interplanetary space mission trajectories, which translates into the difficulty to solve these benchmarks, the GTOPX collection provides a challenge for years to come.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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