

On the generation and evolution of multiple debris removal missions

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The team

Team &
Resources

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approach

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models

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search

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the solutions

Global
optimisation

Solution
refinement

Results

Future ideas

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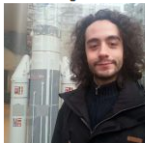
Prof Mx Vasile



Dr. Romain Serra



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Lorenzo Ricciardi



Marilena Di Carlo



Mateusz Polnik



Cristian Greco



Aram Vroom



- **Slack** - instant messages, creation of discussion channels (#combinatorial_optimisation, #impulsive_transfer, #the_bakery, ...)
- **GitHub** - code developing
- **Wikispace** - sharing of information (problem considerations, plots, tutorials on parallel computing)
- **GDrive** - sharing of data (solution files, databases)



- Archie-West: teaching cluster for the West of Scotland \sim 12400 core/hours used
- Torque resource manager: 11 heterogeneous commodity hardware \sim 60 cores

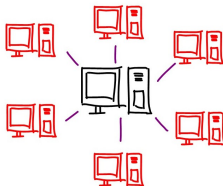


Table 1: Solution Rankings for the Kessler Run (GTOC9)

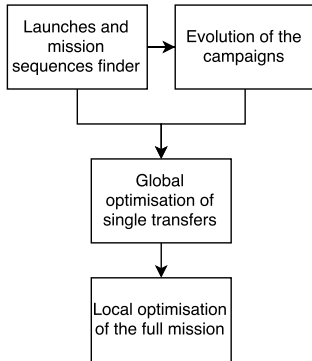
Rank	Team Name	Missions	Removed	<i>J</i> in MEUR
1	Jet Propulsion Laboratory	10	123	731.2756
2	NUDT Team	12	123	786.21452
3	XSCC-ADL	12	123	821.37966
4	Tsinghua-LAD	12	123	829.57987
5	NPU	13	123	878.99821
6	Strathclyde++	14	123	918.9808
7	DLR	14	123	949.85389
8	Missions Learners	14	123	964.51134
9	The Aerospace Corporation	14	123	1004.4860
10	Team Jena	15	123	1022.9063
11	UT Austin	15	122	1044.1787
12	NJU Team	16	123	1047.9685
13	EFLMAN TEAM	14	119	1107.6936
14	CU Boulder	17	123	1150.8439
15	CAS-NUAA	14	123	1182.0632
16	MTU-UoM	16	122	1192.7433
17	NSSC-THU	16	122	1210.3333
18	Brute WORHP	18	123	1229.5475
19	The Goonies	15	122	1238.6396
20	NablaZeroLabs	16	123	1267.7501
21	TYSE	16	123	1336.8590
22	TM	18	123	1490.9659
23	Occitania	22	120	1493.8567
24	ARGoPS	20	123	1512.6017
25	Personal team	23	123	1588.5770
26	GO to space	20	112	1819.1391
27	UoM and Goddard	23	123	1951.6797
28	LSPirates	20	105	2164.2321
29	Astro-ASAP-UC3M	13	85	3141.1951
30	Cal Poly SLO	39	84	4467.8746
31	Team STAR Lab	12	57	4481.7781
32	Nicolas RAVE	13	18	6453.0254
33	National University of Colombia	2	7	6511.5471
34	MeltedCode	1	5	6594.1105
35	AMSS_GTOC	1	4	6619.3569
36	Bremen optimizers	1	2	6760.20

Solution approach

Three-step process involving:

- Low & high fidelity models
- Global & local optimisers

- ① Beam search & sequence patching method
- ② Global evolutionary optimisation
- ③ Local optimisation



Dynamical models

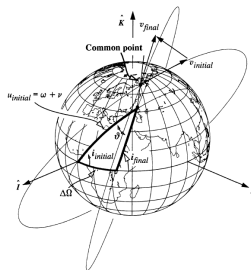
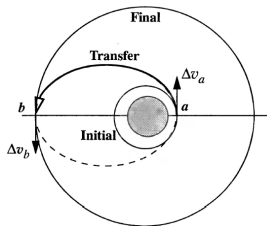
Low-fidelity cost estimation of a transfer

Assumptions:

- Keplerian motion
- Circular orbits
- No phasing

Combination of two parts:

- Hohmann transfer (2 in-plane maneuvers)
- Change of orbital plane (i and Ω simultaneously)



The cheapest combination of the two is chosen as the predicted cost.

Dynamical models

Trajectory design for rendezvous

Ideas:

- 5 maneuvers (including 3 'deep-space' ones)
- Incremental complexity of the model

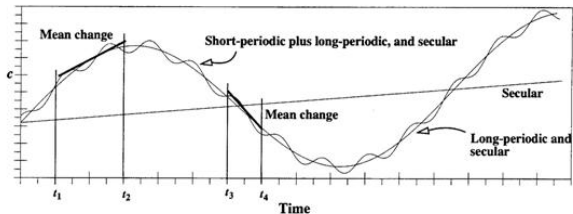
1st model: J_2 secular perturbations only

- ΔV s applied on velocity obtained from osculating elements
- Propagation performed analytically with mean elements after conversion (same model as debris except for M)

$$\dot{M} = n \left[1 + \frac{3}{2} J_2 \left(\frac{R_{\oplus}}{p} \right)^2 \sqrt{1 - e^2} \left(1 - \frac{3}{2} \sin^2 i \right) \right]$$

2nd model: J_2 complete model

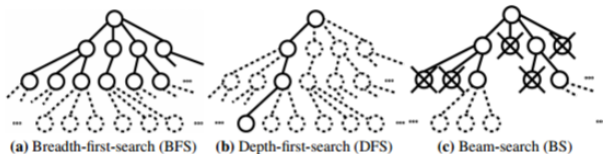
- Numerical integration (predictor-corrector and Runge-Kutta)



Combinatorial search

Incremental construction of launch campaigns

- Itinerary $\{(D_j, t_j)\}$
- At level k , extend with either:
 - transfer to new target in active mission
 - **new launch** in available mission time intervals
- Base algorithm: *Beam Search*
 - easy to control memory and runtime (Br, Be)
 - heuristics to avoid **excess of permutations**

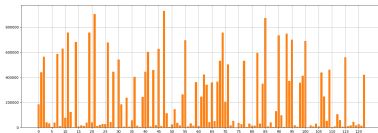
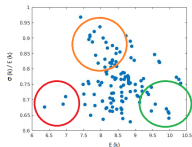


- J estimated with low-fidelity ΔV model (precomputed).
- Various additional heuristics, corrections to the cost function, etc. gave **solutions with different properties**.

Combinatorial search

Incremental construction of launch campaigns

- New launch heuristics:
 - **Cyclic exploration** of mission timeline ($>95\%$ solutions).
 - Other used: concurrent search, cheap transfer density, etc.
- **Naïve initialisation:**
 - Each search from all 123 debris.
 - Total ~ 150 searches in a grid of launch times t_0 .
 - Keep a database, give priority to promising t_0 values.
- Additional heuristics:
 - Maximise length of shorter mission ($\rightarrow 13$ launches!).
 - Per-debris **rarity bonus**, based on:
 - Cluster size first and second statistical moments.
 - Debris frequency in database of unexpensive missions.



- **Input** Feasible sequences
- **Output** Launch campaign
- **Algorithm**
Find a clique in the
undirected graph (N, A)
 - N sequences
 - A pairs of compatible
sequences
- Extracted campaigns
covering up to 116 debris
from a database
of 2.2 mln samples
without single launches

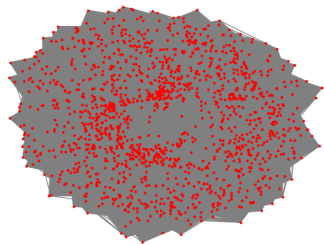


Figure: Partial graph of
1500 compatible sequences

Evolution of the solutions

The Time-shuffler encoding

Idea 1

- each debris associated to a (free) departure time
- times are then sorted in ascending order \rightarrow ID sequence
- $\Delta t \leq 30$ between sorted times define missions
- within each mission, $5 \leq \Delta t \leq 30$ is imposed
- between missions $\Delta t \geq 43$ is imposed (3 days safety margin, 10 days for removal of first and last)

t_{deb}	69.2	4.4	41.6	17	3.1
ID	1	2	3	4	5

	<5		>5, <30		>30, <43		>5, <30	
t_{sort}	3.1	4.4	17	41.6	69.2			
ID	5	2	4	3	1			

t_{corr}	3.1	8.1	17	60	69.2
ID	5	2	4	3	1
	└─ M1 ─┘			└─ M2 ─┘	

Evolution of the solutions

Reformulation of the problem

Idea 2

- The Time-shuffler encoding allows working only on continuous variables → timings are treated explicitly, combinatorial problem is treated implicitly, gradient based refinement possible
- Debris sequence, visit times and mission lengths are optimised concurrently → holistic global optimisation of the whole campaign (transfers evaluated with low fidelity model)
- To reduce number of missions, promising mass-unfeasible solutions should be retained → multi-objective problem, with mass constraint violation as second objective

$$\min_{\mathbf{L}_t \leq \mathbf{t} \leq \mathbf{U}_t} \mathbf{J}^*(\mathbf{t}), \quad \mathbf{t} = (t_1, \dots, t_j, \dots, t_{123})$$

s.t.

$$5 \leq t_{s_j+1} - t_{s_j} \leq 30 \quad \forall s_j \in M_i, \forall M_i$$

$$t_{s_1, M_{i+1}} - t_{s_{\text{end}}, M_i} \geq 43 \quad \forall M_i$$

- solved with MACS, initialised with solutions from Beam Search

Global optimisation

Minimisation of the cost of the debris-debris transfer

- Objective: $\min \sum_{i=1}^5 \Delta V_i$
- Optimisation variables: **times of application and magnitude and direction of impulsive ΔV s**
- Population-based algorithm **MP-AIDEA** (Multi-Population Adaptive Inflationary Differential Evolution Algorithm):

<https://github.com/strath-ace/smart-o2c>

1st GLOBAL OPTIMISATION

Model: J_2 secular perturbation

Solver: MP-AIDEA



2nd GLOBAL OPTIMISATION

Model: J_2 complete model

Solver: MP-AIDEA



LOCAL OPTIMISATION

Model: J_2 complete model

Solver: Matlab fmincon active-set

Solution refinement

Local optimization and tolerance matching

Direct multiple-shooting transcription scheme

- Initial guess: solution from local single-shooting
- J_2 complete dynamical model
- Runge-Kutta 4 integration scheme
- WORHP as NLP solver

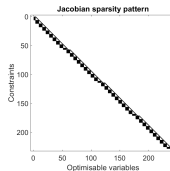
Accuracy and computational efficiency enhancement

- Augmented variational dynamics to compute first and second-order derivative information

$$\frac{\partial \mathbf{G}_x(t, \mathbf{x})}{\partial t} = \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \cdot \mathbf{G}_x, \quad \mathbf{G}_x(t_0, \mathbf{x}_0) = \mathbf{I}$$

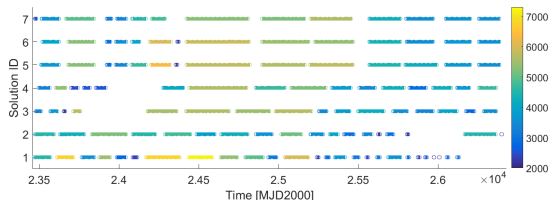
where $\mathbf{G}_x = \frac{\partial \mathbf{x}(t)}{\partial \mathbf{x}_0}$ is the first-order sensitivity matrix.

- Sparsity patterns exploited
 - Constraints' Jacobian and Hessian non-zero elements: $< 0.1\%$



Solution ID	N. Launches	\hat{J}	Improvements in solution process
7 (The Mystery)	14	918.98	Larger population including diverse features.
6 (The One)	14	945.15	Multi-objective formulation of evolution
5 (Ghostbuster)	14	967.49	Added evolution algorithm to solution process, Small population of best submitted solutions.
4 (Anibal)	16	1028.72	Further relaxation of search overconstraints.
3 (Donald)	16	1059.54	Improved Cyclic Beam Search heuristics.
<i>"Make Strathclyde great again"</i>			Improved low-fidelity model. Improved global optimisation on high-fidelity model.
2 (Wrappy)	18	1133.94	Cyclic Beam Search. Improved high-fidelity model.
1 (Wary)	26	1713.07	Added single and multiple-shooting refinement. Beam Search in the first 100 mission days. No thorough trajectory refinement.

Time and mass distribution of the missions of the submitted campaigns:

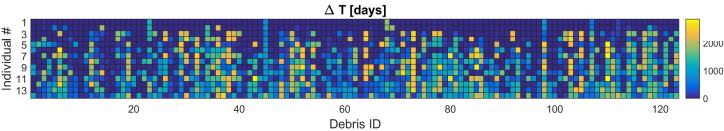


Results

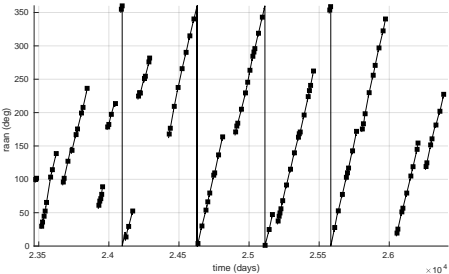
Final solution



Difference in departure time from each debris between final solution and the initial 14 individuals used by MACS:



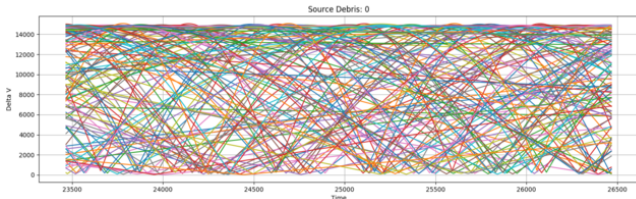
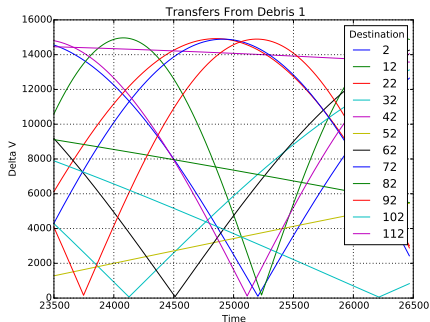
RAAN evolution of the spacecraft:



Results

Low-fidelity estimation of the ΔV for debris-to-debris transfer

Cost of the transfer from debris 1 to other debris in the database:

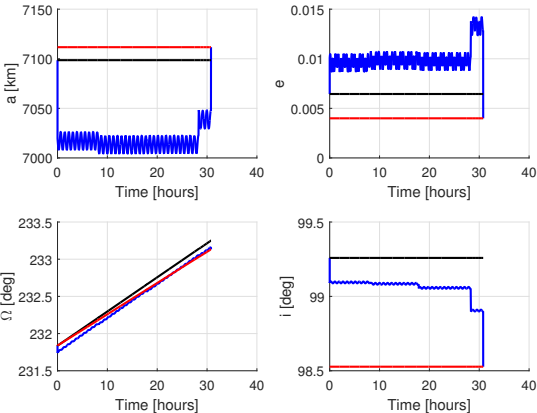


Results

Example of transfer between debris

- Black: departure orbital element
- Red: arrival orbital element
- Blue: High-fidelity orbital elements variation during transfer between debris

The optimiser reduces the semi-major axis to exploit the natural J_2 drift



- Complete the construction of the **surrogate model** for the low fidelity transfer estimation → Multi-layer Perceptron Neural Network with 12 inputs (6 departure orbital elements, 6 arrival orbital elements), 2 outputs: time of transfer and ΔV
- Solve the problem as an integer/mixed integer programming problem: example **bin-packing** problem formulation
- Study the best generation of **sequences** for sequence patching: allow the best variety of sequences
- Study the evolutionary **(non-) combinatorial** approach and its possible applications
- Investigate further the best **number of impulses** for the problem
- Win GTOC next year :)

while continuing pickling solutions...

```
80 self.occurrence = np.array([185045, 4408
81 self.rarity_bonus = 0.05*(1.0 - self.oc
82
83 self.verbosity = verbosity
84
85 def branch_objfun(self,x):
86     f = x.Jfinal + random()*|
87     return f
88
89 def beam_objfun(self,x):
90     f = x.Jfinal + random()*|
91     return
92
93
94
95 # def objfun(x):
96 #     dv_launch = 0.5e3
97 #     minlen = 100
98 #     thislen = 100
99 #     for i in x.dvs:
100 #         if x<=0.0 or x>= dv_launch:
101 #             minlen = min(minlen,thislen)
```

Part of the GTOC team enjoying some space debris art... and wine, the day after



by Dr Stuart Grey

