Geometric Deep Learning for rapid prototyping of satellites. ID 232

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ABSTRACT

A satellite layout optimization design (SLOD) approach to automatically generate effective and efficient layout configurations is here proposed. The optimal position of the Centre of Gravity of satellites components and their orientation is determined. The analysis combines layers and position optimization, approaching the problem as a multi-objective optimization accounting for behavioral and technical constraints. Results show high impact of the adopted Design Of Experiments (DoE) approach on the optimal layout.

INTRODUCTION

Layout definition is key step in satellites design as it determines whether the aggregation of functional components from different subsystems will operate normally and smoothly in the space environment. So far SLOD has been addressed as a single-objective optimization problem, aiming at minimizing the moment of inertia of the entire satellite. Main objective of this work is demonstrating that better results can be obtained by approaching the problem as a multi-objective optimization combining both layers and position optimization.

METHODOLOGY

The optimal position of the Centre of Gravity of N satellite components and their orientation is determined by using two sequential optimization steps (layers and position), thus transforming the three-dimensional layout design problem into two two-dimensional problems: to solve the position optimization, three design variables (x_i, y_i, α_i) are defined for each component, where (x_i, y_i) is the position of the Center of Gravity in the xy-plane of the Global Reference Frame, and α_i is the angle between the x and x_i'' axis (see Figure 1). z_i, (third position of the Center of Gravity of the component) is evaluated by solving the layers optimization.

All the objects are regarded as rigid cuboids or cylinders with a uniform mass distribution and regular shapes.

In details, the **position optimization** problem definition where three behavioural constraints are considered:

- non-overlap constraints: all components must be installed within the satellite module. There must be no overlap between all components and between any component and the structure of the satellite.
- CMA (compatibility, maintainability and accessibility) constraints: enough space among components should be considered for laying cables, assembling operations and ground test. To improve the CMA, all objects must keep a certain distance from each other.
- Static stability constraints: for the mass balance of the system, the centroid offset of the satellite should be limited within the permissible range.

The sum of principal moment of inertia of satellite in the Satellite Reference Frame is the objective function that is minimized.

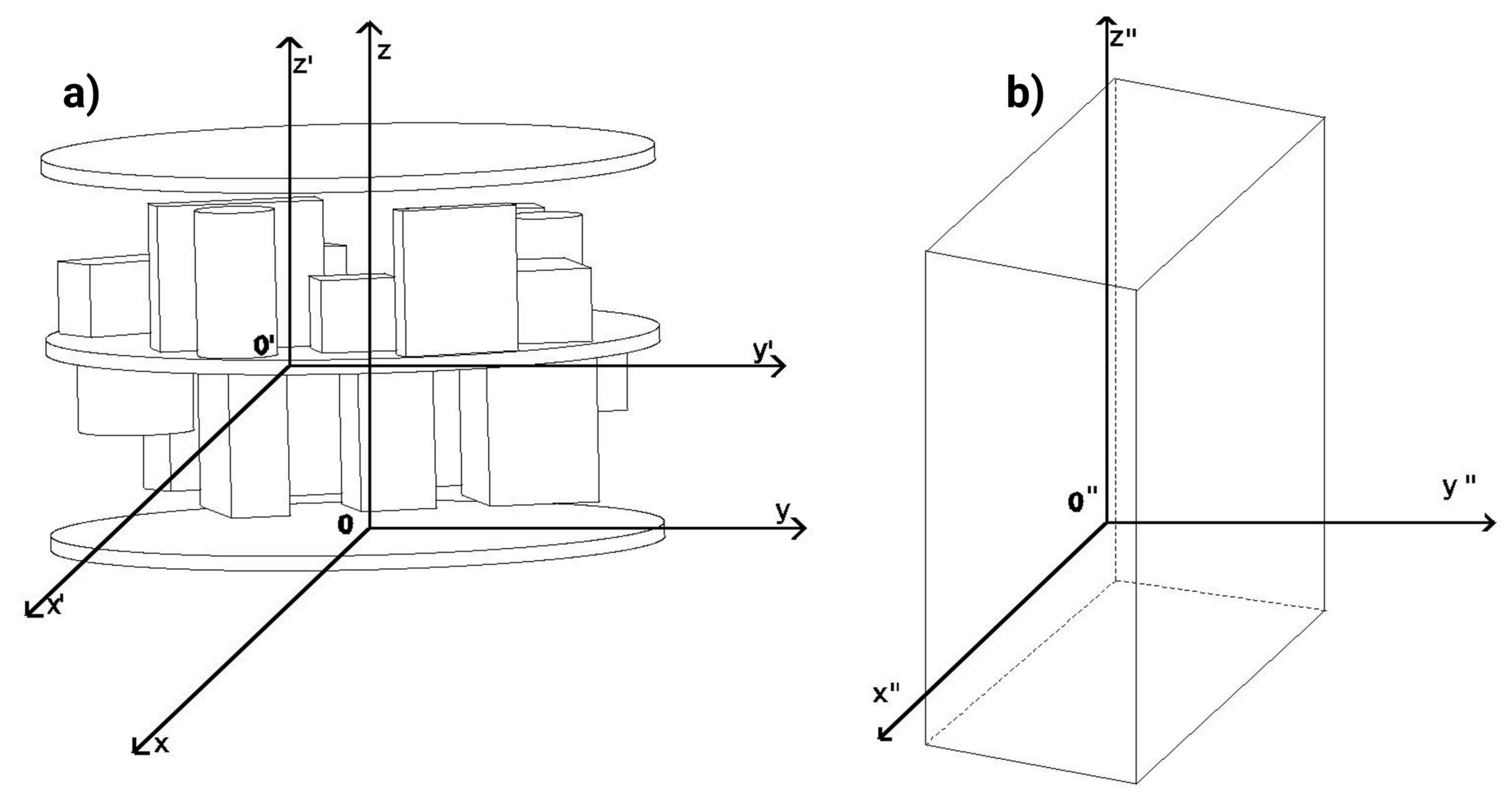

Fig.1. Example of satellite layout. For computational convenience, three left-handed Cartesian coordinate systems are defined:

a) Global Reference Frame (O−xyz): O is the geometric center of the lower surface of the satellite. z-axis is the vertical axis. Satellite Reference Frame (O′− x′y′z′): O′ is the Center of Gravity of the satellite, with x′y′z′ parallel to xyz.

b) Reference Frame for single component (O″−x″y″z″): O″ is the center of gravity of the component. z″ is parallel to the satellite z axis, and x″ is normal to the length of the component.

DoE has been applied at first: it positions the centroid of the components within the structure by providing a position and an orientation angle sampled from a uniform distribution.

Then, two optimization models have been compared: Multi-Objective Genetic Algorithm II (MOGA-II) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II). They are both genetic algorithms and utilize a population-based approach. The substantial difference between them lies in the calculation of the solution's cost: after computing the Pareto front, NSGA-II evaluates the solution's cost based on the number of fronts that must be removed to obtain a non-dominated solution. In MOGA-II, the solution's cost is determined by the number of solutions that dominate it (i.e., if many solutions dominate the considered solution, its cost will be higher).

RESULTS

5040 evaluations were performed. MOGA-II has 140 optimization results with an elapsed time of ~7 minutes, and the optimal value of the objective function is $0.171 \cdot 10^{-6}$ kgm^2. NSGA-II has 2144 results with an elapsed time of ~8 minutes, and the optimal value of the objective function is $0.158 \cdot 10^{-6}$ kgm^2.

As a result, NSGA-II is more performing than MOGA-II. Figure 2 shows the optimized position of components according to the two algorithms.

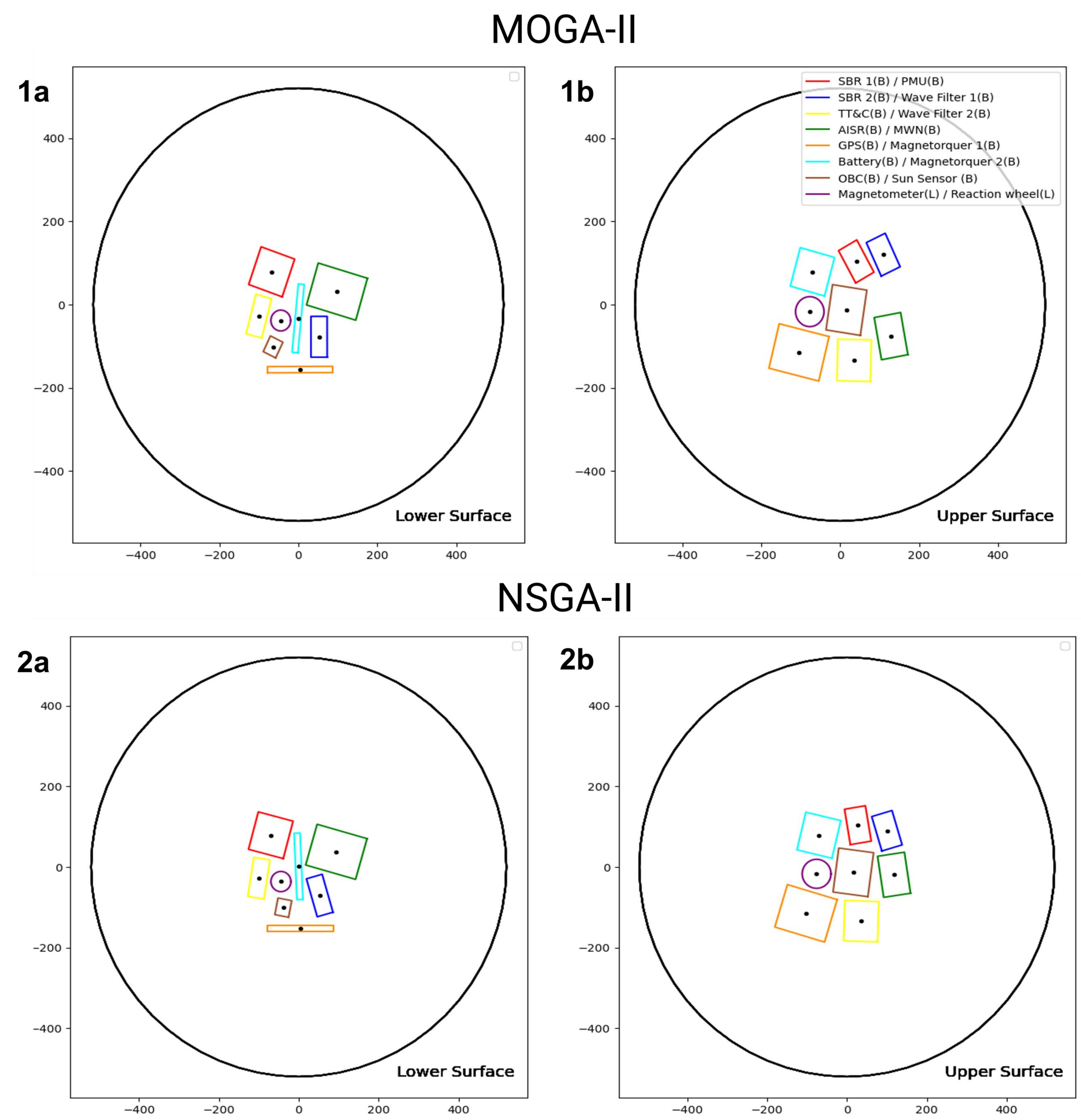

Fig.2. Examples of optimal layouts obtained using **modeFrontier** (ESTECO's optimization software):

1a) satellite lower layer optimal layout (MOGA-II)
1b) satellite upper layer optimal layout (MOGA-II)
2a) satellite lower layer optimal layout (NSGA-II)
2b) satellite upper layer optimal layout (NSGA-II)

CONCLUSIONS AND FUTURE WORK

There is a strong dependency between the objective function and the used state vector: small differences in solutions correspond to very different objective functions values.

Both optimization algorithms here tested resulted to be strongly influenced by the applied DoE technique. We believe better results might be obtained by testing different initial positions distributions.

Our next goal is to solve a multi-objective optimization problem, accounting for conditions such as uniformity of thermal and magnetic fields: thermal and magnetic models will be built, ranging from low to high-fidelity, trying to strike a balance between accuracy and computational cost. High-fidelity models will be used to train surrogate models, with the aim of rapidly prototyping satellites designs, maintaining a reasonable level of predictions accuracy. A particular focus will be given to Geometric Deep Learning techniques, which allow to train AI algorithms using the 'real' shape of components.

We believe that the process described will result in more performing satellite designs and in their rapid prototyping, allowing to tackle the complexity associated with the optimization of such systems.

REFERENCES

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