ON THE OPTIMAL POSITIONING OF ELECTRONIC EQUIPMENT IN SPACE PLATFORMS

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Abstract. *In this paper a framework for the optimal distribution of electronic equipment in a space platform is presented. The task of defining the position of electronic equipment inside a spacecraft is a complex problem that is usually done "manually" by a team of system engineers. In the approach proposed here, this task is posed as a multiobjective design optimization problem, so that the position of the equipment can be automatically found, while optimizing the performance requirements of the entire system. For this study, a preliminary assessment of the efficacy of the proposed approach is presented through a simplified numerical experiment: the optimal distribution of electronic boxes over a flat plate, with two objectives: target temperatures for the boxes and a desired position for the system´s (boxes and plate) center of mass. The mass, power dissipation and required operation temperatures for the boxes, the mass of the plate and the desired position of the system center of mass are the input parameters. The position of each box over the panel are the design variables. A recently proposed evolutionary algorithm, Generalized Extremal Optimization (GEO), is used as the optimization tool.*

Keywords*: satellite, layout optimization, evolutionary algorithm, generalized extremal optimization.*

1. INTRODUCTION

Space platforms, satellites or spacecrafts, are composed of many interacting subsystems, each of which made of many components, and the design of these kinds of vehicles is a complex multidisciplinary task. One of the first tasks taken in the design process of a new space platform is the definition of a mechanical architecture for the system. This includes not only the creation of a baseline for the structure but also a preliminary positionning of the platform´s equipment. The conceptual mechanical architecture of a satellite is usually based on previous designs of platforms that have similar missions. Hence, for example, if a new Earth observation satellite is being developed, early designs of previous vehicles with the same mission and size are reviewed and, frequently, the new design is an adaptation of old solutions. The rationale behind this approach is that the new design should profit from the heritage of proven ones, so that the risks of project failures, time delays or cost overuns could be avoided or minimized. On the other hand, the process of conceptual design is traditionaly made "manually" by a team of system engineers, and is stopped as soon as a viable solution is achieved. This solution is further refined as the design matures and also if required by results of specific analysis, such as thermal or structural.

Hence, the process of conceptual design of space platforms usually relies heavily on two main sources: i) the heritage from previous designs and ii) the past design experience of the system engineer team that works it out. Although this is surely a good way to follow in order to come up early with a promissing good solution for the new mission, it is also a way to sub-optimal designs, since few alternatives are tried in the process and better solutions could be missed. It has been argued that automatizing the conceptual design process of satellites and spacecraft, using optimization methods, in a way such that multiple candidate solutions could be generated and compared, is a very interesting approach to come up with better initial designs (Taylor, 2000; Jilla and Miller, 2004; McManus et al., 2004). Because this problem has a complex design space, frequently with mixed types of variables, metaheuristics are natural candidates as optimization tools, and methods such as the Simulated Annealing (SA) and Evolutionary Algortithms (AEs) have been used recently for this purpose (Mosher, 1999; Jilla and Miller, 2004; Hassan and Crossley, 2003, Pühlhofer et al., 2004).

As mentioned previously, one of the first tasks that must be tackled during the conceptual phase of a space platform is how to distribute over its structure the electronic equipment. This task can become very hard if there are a lot of equipment on the platform, such as in the case of the China-Brazil Earth Resoucers Satellite (CBERS), that has more than 100 electronic boxes to be positioned. Posed as an optimization problem, the positioning of the equipment can be classified as a 3-D NP-hard layout problem (Cagan et al., 2002), that becomes computionaly prohibitive as the size of the system grows. In this case the use of heuristics can provide good solutions in acceptable computation time. Sun and Teng (2003) and Junzhou et al. (2006) have used evolutionary algorithms to address the satellite layout problem considering the inertia performance of the system subjected to dimensional constraints.

In this work investigates the conceptual satellite layout problem taking into account not only the mass properties and mechanical characteristics of the equipments, but also their thermal behaviour. Specifically, we propose a methodology to find the optimal positioning of equipment inside a space platform taking as objectives a desired center of mass for the system and target temperatures for its electronic boxes. This is a multi-objetive multidisciplinary problem and is tackled here using a Pareto approach. That is, after optimization, is obtained a set of non-dominated solutions, and the Pareto frontier that characterizes the best objective functions trade-offs. A multi-objective version of the Generalized Extremal Optimization (GEO) (Sousa et al, 2003) algorithm called M-GEO (Galski et al., 2005) was used as the optimization tool. In this work, the methodology is applied to design the layout of the equipment positioned over two panels of the Brazilian Multi-Mission Platform (In Portuguese, Plataforma Multi-Missão - PMM), now under development at the Brazilian National Institute for Space Research (INPE). The results are compared to the actual spacecraft layout.

In Section 2 the layout problem under analysis is described. In Section 3 the optimization tool is presented and the multiobjective optimization problem stated. In Section 4 the results are presented and commented, followed by the conclusions in Section 5.

2. LAYOUT PROBLEM DEFINITION

The layout problem can be stated as to find the position of a set of components on a given available space, so that one or more objectives are optimized under a set of constraints (Cagan et al., 2002). In the case of the PMM, the available space for placement of the electronic boxes is on the inner surfaces of its lateral panels, as shown in Fig. 1.

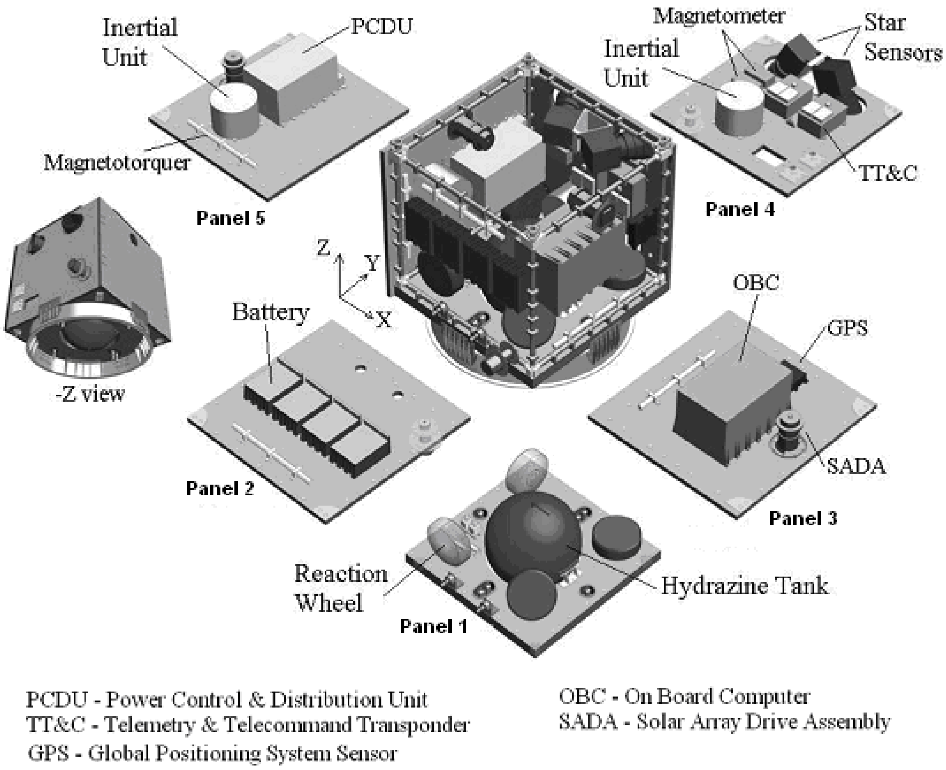

Figure 1. Exploded view of the main components of the Multi-Mission Platform.

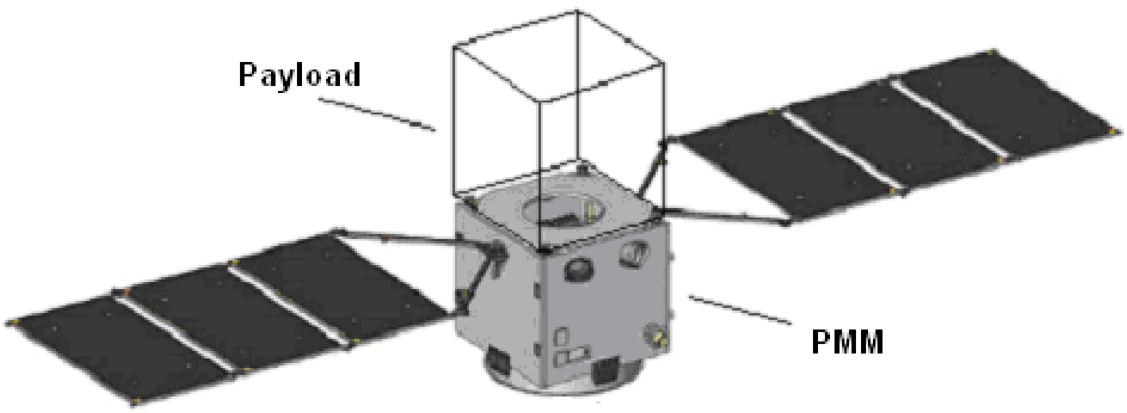

Figure 2. Representation of the PMM at flight configuration.

The Multi-Mission Platform (in Portuguese, Plataforma Multi-Missão - PMM) is a multi-purpose space platform to be used in different types of missions such as Earth observation, scientific or meteorological (Schroder et al., 2005). The PMM is a concept of satellite architecture that consists of assembling in a platform all the necessary equipment essential to the satellite, independent of the orbit or pointing mode. In this kind of architecture, there is a physical separation between platform and payload modules, which can be developed, constructed and tested separately, before the integration and final test. There is also the advantage of reuse of the platform design and reduction of the cost for the development of new satellites. The PMM has an overall envelop of 1m x 1m x 1m, 250 kg of mass and total power generation of 420 W. In Figure 2 is shown the PMM in a flight configurion with the envelope for a generic payload.

The PMM has 25 main pieces of equipment to be positioned. The configuration shown in Fig. 1 shows the layout obtained for the distribution of the electronic boxes on the platform using the tradional way. That is, it was done "manually" based on the experience of the design team, following some design "rules of thumb", such as positioning the equipment of the same sub-system close to each other, and only regarding dimensional constraints. No thermal performance and constraints considerations were taken into account. The thermal design was performed *a posteriori*, by the definition of the area and position of the radiators and the thermal coatings of the equipment.

For a preliminary proof of concept of the optimal layout design approach proposed here, we applied the method to find the position of the equipment on panels 2 and 4 of the PMM. The equipment on each panel was kept the same as on the traditional design, only their position was allowed to be relocated. Hence, on panel 2 the method was used to place the batteries while on panel 4 it worked on the placement of the star sensors, the magnetometers, the inertial unit and the transponders. We choose these two panels because we wanted to test the approach on problems with incremental levels of complexity. Panel 2 has 4 pieces of equipment with the same physical characteristics and power dissipation while panel 4 has 7 pieces of equipment, some of them with different power, dimensional and mass properties. They represent two different levels of challenge for the method, from the “simple” panel 2 to the more complex panel 4. The main objectives were i) to verify the efficacy of the method on producing viable designs and ii) check out if a better layout could be obtained, from the point of view of the system´s mass distribution and thermal conditioning, compared to the existing one.

The pieces of equipment were modeled as square boxes with the same footprint, mass and heat dissipation as the real ones. For this work only translational movements were allowed to the equipment. The values for these quantities are given in Table 1.

Table 1. Physical properties of the equipment.

Equipment	Mass (kg)	Footprint		Heat dissipation (W)
		Length in X (m)	Length in Y (m)	
Battery pack - bat	4.0	0.166	0.211	2.8
Inertial unit - iu	4.5	0.235	0.235	31.0
Star sensors* - ss	6.2	0.520	0.121	15.2
Magnetometer - mag	0.5	0.143	0.077	1.0
Transponder - trans	2.0	0.156	0.210	16.8

*Due to functional and mechanical requirements, the star sensors shared the same attachment support, and were considered as a single unit.

The layout problem was posed as: find the position of the equipment on the given panel, such that the center of mass of the equipment is as close as possible to a given desired center of mass for the system (panel and equipment). Moreover, the temperatures of the equipment must be as close as possible to a given target temperature specified for each of them. Note that the problem is two dimensional, hence only the coordinates on the plane of the panels are taken into account. Each panel is 0.899 m x 0.882 m rectangle with uniform mass properties so that only the mass centers of the equipment must be taken into account on defining the mass center for the whole system.

Formulated as an optimization problem, the task of finding each panel layout is then written as:

Minimize:

$$F_1 = \left\| \overrightarrow{CG}_{sys} - \overrightarrow{CG}_{target} \right\| = \sqrt{(XCG_{sys} - XCG_{target})^2 + (YCG_{sys} - YCG_{target})^2} \tag{1}$$

$$F_2 = \left\| \vec{T} - \vec{T}_{target} \right\| = \sqrt{\sum_{i=1}^{N} (T_i - T_{i\_target})^2} \tag{2}$$

Subject to:

i) All equipment lies inside the panel´s area;
ii) There is no mechanical interference among the equipment;
iii) $T_{i\_min} <= T_i <= T_{i\_max}$.

Equation 1 gives the distance between the systems CG and the target CG position, considered here in the center of the panel ($\overrightarrow{CG}_{target}$ = [0.4495, 0.441]). The coordinates of $\overrightarrow{CG}_{sys}$ are given by:

$$XCG_{sys} = \frac{\sum_{i=1}^{N} x_i \cdot m_i}{\sum_{i=1}^{N} m_i} \tag{3}$$

$$YCG_{sys} = \frac{\sum_{i=1}^{N} y_i \cdot m_i}{\sum_{i=1}^{N} m_i} \tag{4}$$

where x_i and y_i are the coordinates of the mass center of equipment i, m_i is its mass and N the total number of equipment on a given panel.

Objective function (2) gives the difference between the calculated temperature for each piece of equipment (T_i) and its desired (target) temperature of operation.

Constraint (i) was taken into account limiting the total area available on the panel for placement of a given equipment i. This was done simply imposing that each equipment could not be positioned within a distance from the panel´s edges lesser than half the equipment length over X and Y.

Constraints (ii) and (iii) were taken into account incorporating them to the objective functions 1 and 2 respectively, using the external penalty function method (Vanderplaats, 1998). F1 and F2 were then re-written as:

$$F_{1\_\mathrm{mod}} = F_1 + p \cdot \sqrt{(\max(0, A_{\mathrm{int}}))} \tag{5}$$

$$F_{2\_\mathrm{mod}} = F_2 + p \cdot (\max(0, \sum_{i=1}^{N} (T_i - T_{ref})^2) \tag{6}$$

In Equations (5) and (6), p is the penalty parameter, which was set to 1000. A_{int} is the total area of interference of the equipment on a given panel. Note that for $A_{int} > 0.0$ we have an infeasible design. T_{i_min} and T_{i_max} are, respectively, the minimum and maximum operational temperatures allowed for each equipment i. In Table 2 these limits are presented, together with the target temperatures. In (6), if $T_i < T_{i\_min}$, then $T_{ref} = T_{i\_min}$. If $T_i > T_{i\_max}$, then $T_{ref} = T_{i\_max}$. If $T_{i\_min} <= T_i <= T_{i\_max}$, $T_{ref} = T_i$.

Table 2. Limits and target temperatures for the equipment.

Equipment	T_{min} (°C)	T_{max} (°C)	T_{target} (°C)
Battery pack	-10.0	20.0	5.0
Inertial unit	-30.0	70.0	20.0
Star sensors	-30.0	45.0	7.5
Magnetometer	-30.0	75.0	22.5
Transponder	-20.0	50.0	15.0

The multi-objective optimization problem was solved numerically using the M-GEO algorithm, described in the next Section.

3. THE M-GEO ALGORITHM

A multi-objective implementation of the Generalized Extremal Optimization was used as the optimization tool. In the following, GEO algorithm is described, being followed by an explanation about M-GEO. GEO is a recently proposed evolutionary algorithm (Sousa et al., 2003; Sousa et al., 2005) that has been succesfully applied to complex optimal design problems (Galski et al., 2005, Vlassov et al., 2006, Muraoka et al., 2006). In GEO a string of L bits encodes N design variables. For each of them is associated a fitness number that is proportional to the gain (or loss) the objective function value has in mutating (flipping) the bit. All bits are then ranked from 1, for the least adapted bit, to L for the best adapted. A bit is then mutated according to the probability distribution $P(k) \propto k^{-\tau}$, where k is the rank of a selected bit candidate to mutate, and τ is a free control parameter. For $\tau \rightarrow 0$, any bit of the string has the same probability to be mutated, while for $\tau \rightarrow \infty$, only the least adapted bit can be mutated. The meaning of this is that for $\tau \rightarrow 0$, GEO performs a random walk in the binary discretized search space, whereas for $\tau \rightarrow \infty$, GEO performs only deterministic (best choice) movements. In practice, due to the exponential character of the distribution of P(k), for values of k > 10 the probability that other bit than the least adapted be mutated is very low. In fact, it has been observed that the best value of τ, i.e., the one that yields the best performance of the algorithm for a given application, generally lies within the range [0.75, 5.0]. This, added to GEO having only one free parameter, makes the algorithm easily settable to give its best performance on the problem that is being tackled. After the bit is mutated, the procedure is repeated until a given stopping criterion is reached, and the best configuration of bits (the one that gives the best value for the objective function) found is returned. The main steps of GEO are shown in Fig. 3.

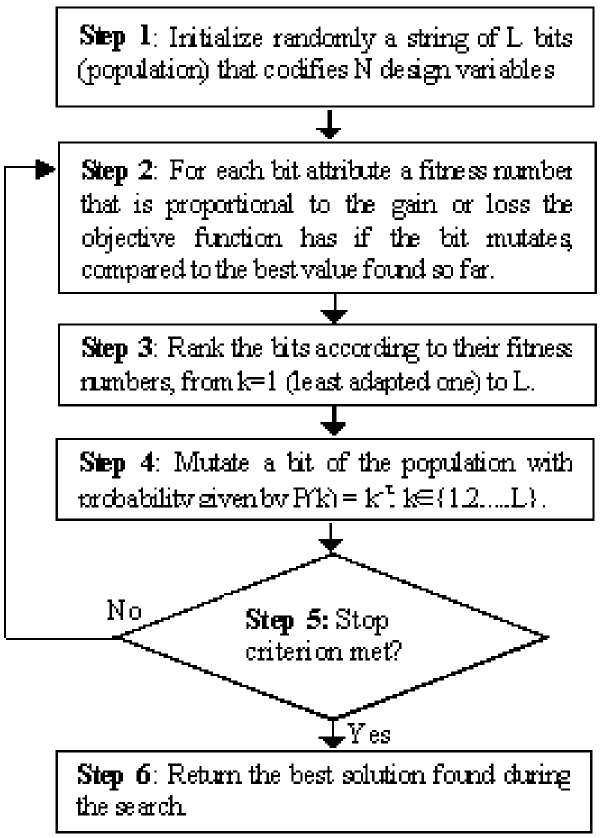

Figure 3. The canonical GEO algorithm.

New developments of GEO´s canonical implementation have been proposed in order to extend its applicability and improve its performance (Galski, 2006). One of these developments was a multi-objective version for it, M-GEO, whose main steps are described in Fig. 4. M-GEO has the same basic functioning as GEO. The differences are that i) in M-GEO the bits are ranked based on one of the objective functions that is chosen randomly at each iteration; ii) each new solution created during the search is compared to the ones in the set of non-dominated solutions and incorporated to it if it is also a new non-dominated solution. If it dominates previous solutions contained in the set, these are deleted from the set; iii) M-GEO can be re-started during an execution. The restarting time (rt) is an additional adjustable parameter and represents the number of times the algorithm is re-initiated during a single execution. It is important to note that the population of bits can be re-initiated during a run, but the set of non-dominated solutions is kept in a separated file and preserved during the complete run of M-GEO.

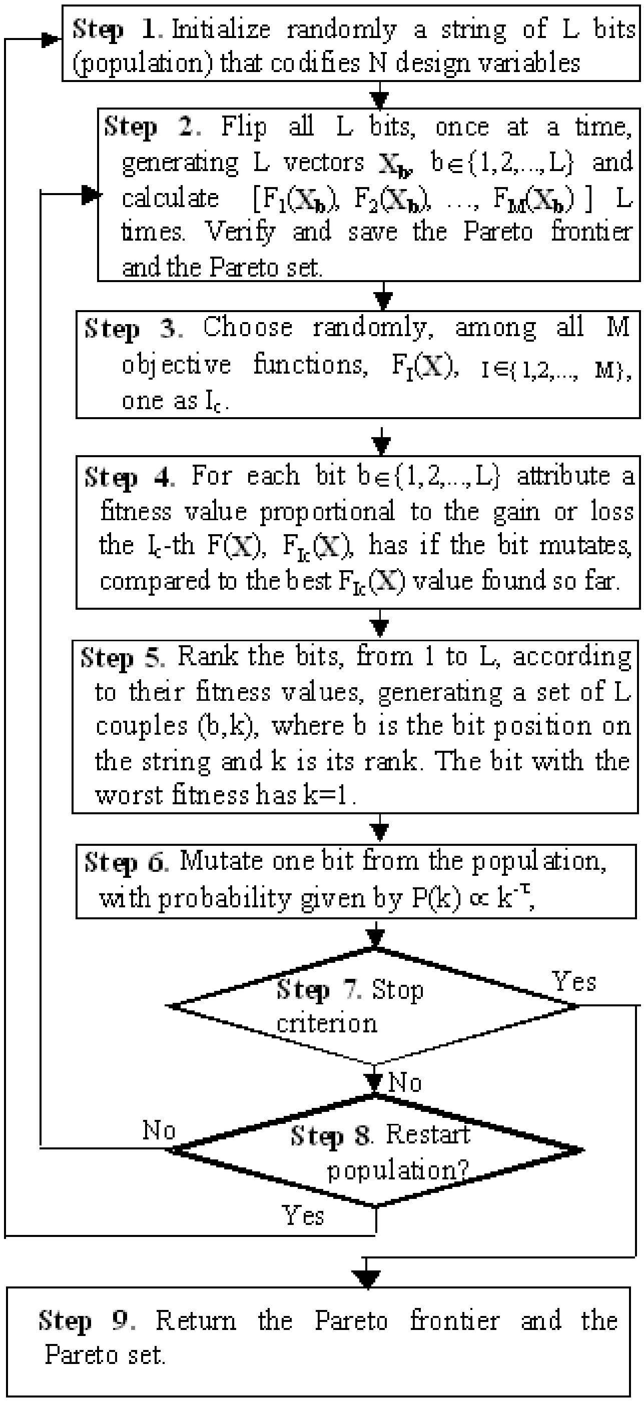

Figure 4. The M-GEO algorithm.

In the layout problem treated here M-GEO searched the design space for non-dominated (best trade-off) solutions which represented different possible configurations for the distribution of the equipment on the panels. The results are presented in the next Section.

4. RESULTS

In the present layout problem, the design variables are the coordinates of the center of mass of each piece of equipment on the platform panels. The center of mass of each electronic box was considered on the center of its footprint, and the origin of the system on the lower left corner of each panel. In the numerical implementation, the dimensions of the panels and equipment were normalized to the range [0, 1].

Each panel was discretized in 100 nodes and boundary conditions were set to simulate the heat loads on the external surfaces of the panels, in addition to the heat loads dissipated by each piece of equipment. It was also considered a boundary temperature on the edges of the panels, in order to simulate heat conduction from other parts of the PMM. For the present study it was considered a hot environmental, that is, maximum external heat loads from Solar, albedo and Earth thermal radiations, and a hot boundary temperature of 45 ^{o}C. Thermal radiators of fixed size were present on the external surfaces of each panel. No heat radiation exchange was considered between the equipment and the panels or between the equipment themselves, only conduction through the panel. Moreover, the pieces of equipment were merged to the panels so that they were represented by their heat dissipation spread over the panel´s nodes that contact each equipment´s footprint. The temperature of each piece of equipment was represented by the average of these nodes temperature. The temperature of the panels´ nodes were calculated, for each new layout created, by the PCTER thermal analyzer (Cardoso et al., 1990), that was called as a sub-routine of M-GEO.

Eight bits were used to discretize each design variable, hence each equipment could be positioned with a resolution of 0.004 m. The free parameters of M-GEO were set to τ = 1.00 and rt = 50. One execution of M-GEO was performed for each panel, starting from randomly generated layouts. In each execution, 2.5 x 10^6 function evaluations were performed. Each run took aproximately 15 hours on an AMD Athlon 64 3500 (2.2GHz) PC computer with 512MB of RAM memory.

For comparison purposes, the layout configurations obtained with the traditional approach for panels 2 and 4 are shown in Fig. 5. The shadowed areas represent the radiators on the external surface of the panel.

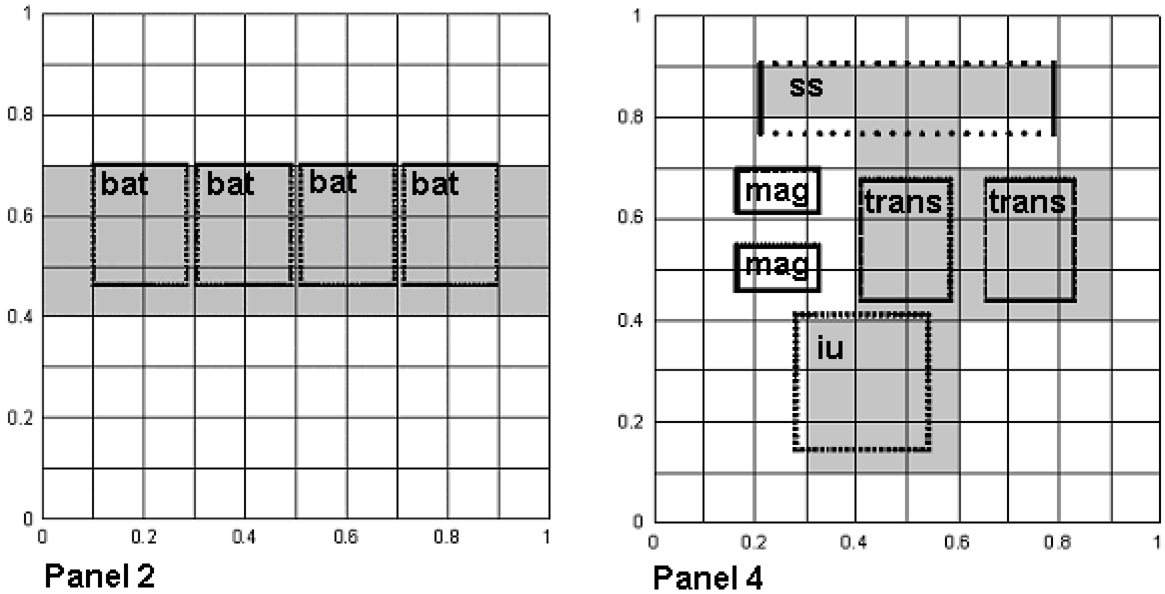

Figure 5. Layouts for panels 2 and 4 using the traditional approach.

The pair of values for the objective functions (F1,F2), for panels 2 and 4 in Fig. 5 are, respectively, (0.073,7.67) and (0.080,15.50).

In Figure 6 the Pareto frontiers obtained using the optimal design approach for the two panels are shown. All solutions on the frontiers represent feasible designs.

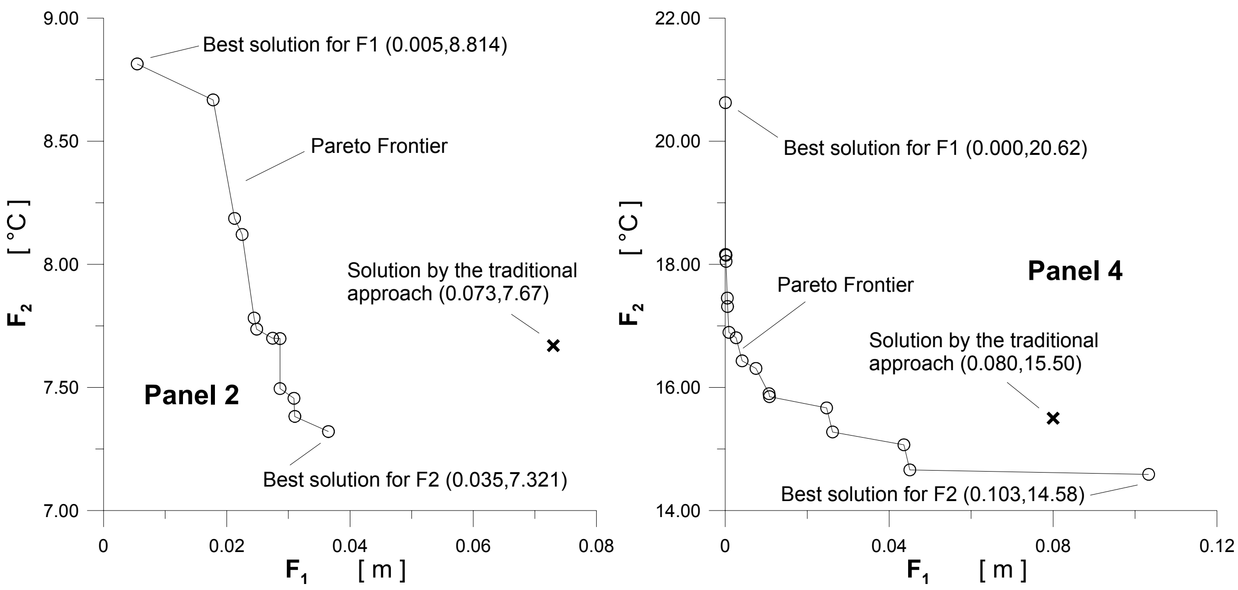

Figure 6. Pareto frontiers for panels 2 and 4.

From the results shown in Fig. 6, it can be seen that the layouts obtained by the traditional approach (Fig. 5) are dominated ones. In fact, they are dominated both in F1 and F2. That is, there are solutions on the Pareto frontier that are better than the traditional solutions in both F1 and F2. Hence, the traditional solutions represent sub-optimal designs. It can also be seen from Fig. 6 that a big gain can be obtained for F2 with a relatively small increase in F1. This means that re-arrengements in the layout can improve significantly the thermal design, with little loss for the system´s mass property.

In Figure 7 are presented the best layouts found for panels 2 and 4 in respect to F1. They are the physical representation for the points with minimum values for F1 in Fig. 6.

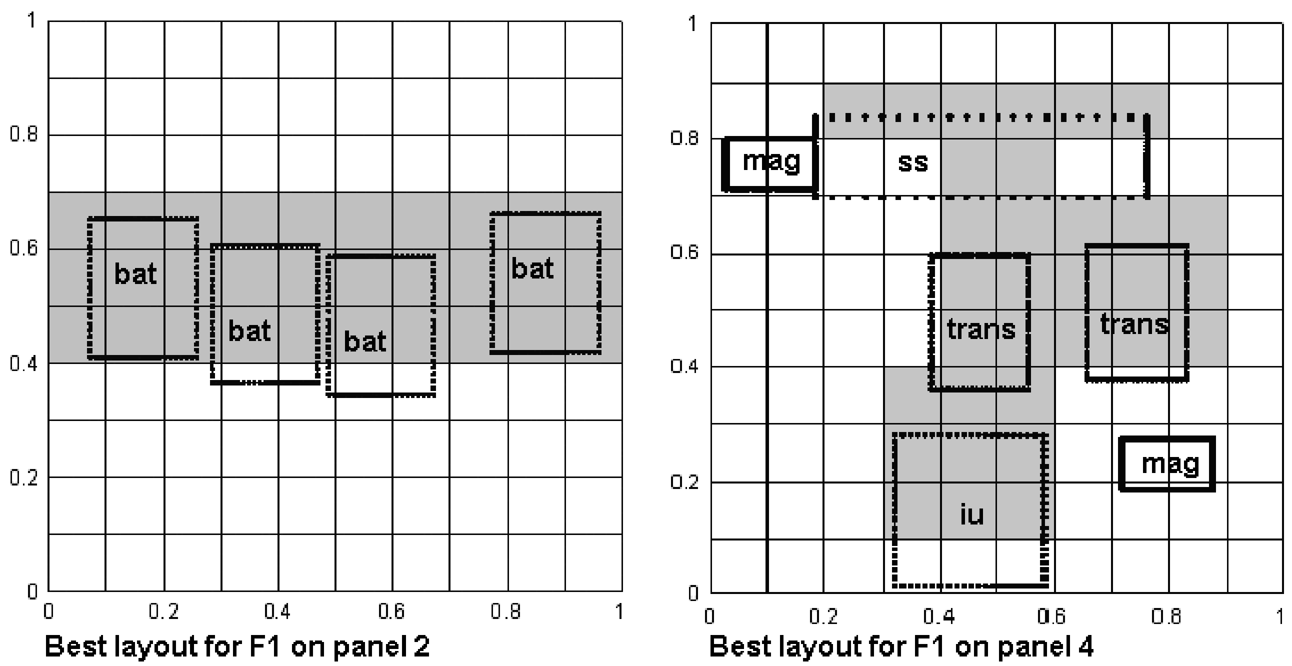

Figure 7. Best layouts representations for F1 on panels 2 and 4.

The solutions shown in Fig. 7 represent the best non-dominated solutions on the Pareto set that minimizes the distance from the obtained CG to the desired CG position of each system (panel). Comparing the solutions obtained for panel 2 by the traditional (Fig. 5) and optimal (Fig. 7) approachs, it can be clearly seen that in the latter case the batteries were displaced so that they where positioned close to the panels centerline in the Y axis. This minimized the value of F1 but maximized the value of F2, since the baterries were moved off the radiator area. The same happened on panel 4.

In Figure 8 the best layouts found for panels 2 and 4 in respect to F2 are shown.

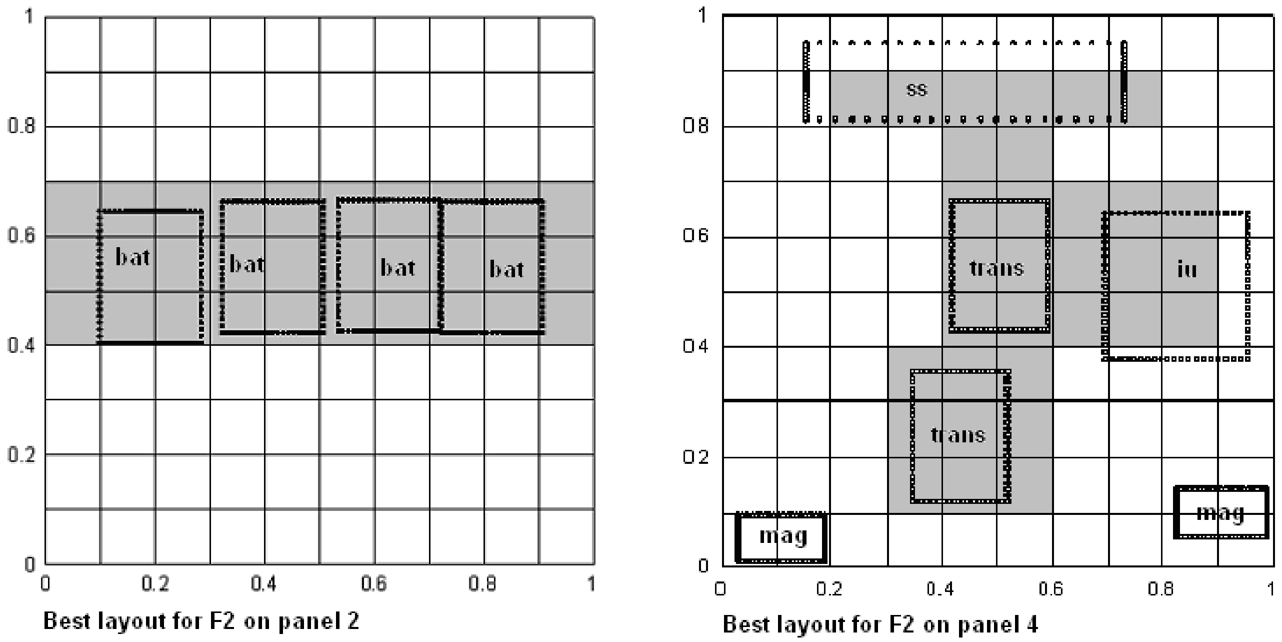

Figure 8. Best layouts representations for F2 on panels 2 and 4.

The layouts in Fig. 8 represent configurations that privilege the optimization of the thermal aspects of the design. As can be clearly seen on the batteries´ panel, the pieces of equipment were positioned preferentialy over the radiator areas.

The results shown in Figs. 7 and 8 are the extremal solutions of the Pareto set. That is, they represent the limit trade-off solutions between F1 and F2, where the best of one represents the worst of the other. But the complete solution for the problem is represented by the Pareto sets associated to the Pareto frontiers shown in Fig. 6. This is the essence of the multi-objective Pareto optimization, that is, the solution is not unique but a set containing the best trade-off configurations. It is left for the designer to choose the one that best fits his/her needs.

5. CONCLUSIONS

In this paper a new approach to the conceptual layout design of equipments for space platforms was presented. The task was set as a multi-objective multidisciplinary optimization problem, taking in consideration thermal and mechanical requirements. A multi-objective implementation of the Generalized Extremal Optimization algorithm, M-GEO, was used as the optimization tool. In the present study, the approach was applied to a simplified layout problem. Namely, the positioning of equipment on two panels of the Brazilian multi-mission space platform. The results show that the approach was successful on finding a set of optimized trade-off solutions for the problem. It is noteworthy that the solution found by the traditional approach does not take part on the set of non-dominated solutions found by the approach proposed here. That is, better solutions than the traditional one (for all objective functions) were found using the optimal design approach. The objectives of the present work were then fully realized, not only the approach proposed showed to be viable, but also valuable on finding better solutions. In fact, the results foresee a very promising future for the proposed methodology.

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