Application of a New Hybrid Evolutionary Strategy to Spacecraft Thermal Design

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Abstract. In this paper, a new hybrid evolutionary strategy is used to the inverse design of a spacecraft thermal control system. This hybrid strategy comprises one step of global, stochastic search, using the Generalized Extremal Optimization (GEO) algorithm, followed by a local, deterministic refinement minimization step with the EXTREM optimization routine. The GEO algorithm is a novel global search meta-heuristic, based on a model of natural evolution, while EXTREM uses Powell's method of conjugate directions. This approach is applied to the inverse design of a spacecraft thermal control system, considering different critical, on-orbit operational conditions. Numerical results show that the hybrid approach improves the design solution in terms of the value of the objective function, while GEO yields non-intuitive efficient solutions in the sense they were unlikely to come out through the classical, "manual" design procedure.

1 Introduction

Many numeric techniques have been developed to address optimization problems in science and engineering [1-3]. The existence of many types of optimization methods is the consequence of a practical and theoretic observation: the efficiency of a given optimization algorithm is dependent on the kind of problem is being tackled. Traditionally, due to their computational efficiency, the most popular methods are based on local search algorithms, frequently using the gradient of the objective function as a "guide" in the design space.

Gradient-based methods are very efficient when applied to problems with relatively simple and smooth design space. However, many relevant engineering problems have complex design spaces, that may be non-convex, disjoint, have severe non-linearities in the objective function and its constraints or contain a mix of continuous, discrete and integer design variables. These characteristics often decrease considerably the efficiency of the gradient-based methods, making them converge to suboptimal designs. An alternative approach in this case is to use a global search algorithm so as to reduce the probability of being trapped in a local minimum.

In the last twenty years, a considerable number of global methods have been developed. Most of them are based on natural phenomena analogies, trying to copy the efficiency and simplicity of observed self-optimized processes in nature. Algorithms based on the evolution of species [4,5], on the annealing of metals [6], on the functioning of the brain [7], on the immune system [8] and even on the social behavior of ants [9] have been developed and used to get optimized solutions for many science and engineering problems. Among them, perhaps the most commonly used are the Simulated Annealing (SA) [6], Genetic Algorithms (GAs) [4] and their derivatives.

Recently, a new global search metaheuristic was proposed. Called Generalized Extremal Optimization (GEO) [10-12], it is a stochastic algorithm specially devised to be used in complex optimization problems. It has been shown to be competitive to other popular metaheuristics [10,11] and has proved to be a very useful design tool [11-13].

Although the use of global search strategies increases significantly the probability of finding the best solution in a multimodal design space, these methods usually require a great number of function evaluations to be effective. Hence, in problems where the calculation of the objective function is very time consuming, they may become impracticable. Computation costly objective function evaluation is common in the aerospace field, where frequently numerical expensive routines or software packages are used for the calculation of the design parameters. One approach that has been used for tackling these problems with global search metaheuristics is to hybridize them with a local search algorithm [14-17].

Another interesting feature of coupling a local search deterministic algorithm to a global stochastic one, is that while the global explores the entire design space searching for candidate regions where to find the optimum, the local one can make a more refined search on those regions.

In this paper, first results of the application of the GEO algorithm, hybridized with a local search deterministic method (EXTREM, [18]), to a complex aerospace design problem is presented. The GEO and hybrid GEO/EXTREM algorithms were applied to the optimum design of a spacecraft thermal control subsystem - the Multi-Mission Platform (in Portuguese, Plataforma Multi-Missão - PMM) -, considering different critical, on-orbit operational conditions. The main objective of this first study on the hybridization of GEO, was to verify if the introduction of the local search routine would improve significantly the results obtained with GEO for this problem.

2 Global Search: The GEO Algorithm

The Generalized Extremal Optimization (GEO) algorithm is a global search metaheuristic [10-12], based on a model of natural evolution [19], and specially devised to be used in complex optimization problems. It has its fundaments on the Self-Organized Criticality (SOC) theory, which has been used to explain the power law signatures that emerge from many complex systems [20].

In the GEO algorithm the species are represented by bits that forms a string which encodes the design variables of the optimization problem, and each bit corresponds to one species. This string is similar to a chromosome in the canonical GA. But different from the GA, in the GEO there is not a population of strings (or solutions), but a population of bits represented by one string (see Fig. 1). Moreover, there is not mating between individuals, as in the GA, but each bit (species) is forced to "evolve" (or "mutate") with a probability that is proportional to its fitness. The fitness is a number assigned to each bit of this string that indicates the level of adaptability of each bit on the population, according to the gain or loss that one would have on the value of the objective function, if the bit is mutated (flipped).

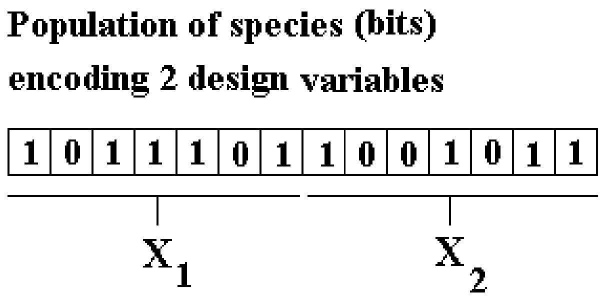

Fig. 1. Population of bits on the GEO algorithm. In this example the population encodes 2 design variables.

A flowchart for GEO and its variant GEO_{var} (see next paragraph) is presented in Fig. 2. In the flowchart, F(X) is the objective function, k is the ranking value of the bit and L_j is the number of bits of the design variable "j".

The GEO algorithm, as the SA and the GA, is a stochastic method, does not make use of derivatives and can be applied to non-convex or disjoint problems. It can also deal with any kind of variables, either continuous, discrete or integer. The only one τ free parameter allows the user to set up the determinism degree of the search, from a random walk ($\tau = 0$) to a deterministic search ($\tau \to \infty$). It has been observed that there is a τ best value for each problem, denoted τ^*, such that the global search efficiency is maximal. For most problems, τ^* remains in the rage of $1 < \tau < 5$. A slightly different implementation of the GEO algorithm can be obtained by changing the way the bits are ranked and mutated (see Fig. 2). Instead of ranking all the bits together, we rank them separately for each variable. In this way the bits of each variable will have a rank ranging from 1 to L_j. Then, one bit of each variable is chosen and mutated in the same way as described before. Hence, at each iteration, N bits are mutated. The idea behind this implementation, called GEO_{var}, is to improve all variables simultaneously, at each algorithm iteration, as an attempt to speed up the process of searching the global minimum. A detailed explanation of both implementations, including a real world application can be found in [11]. In this work the GEO_{var} implementation (called here, for simplicity, GEO) was used.

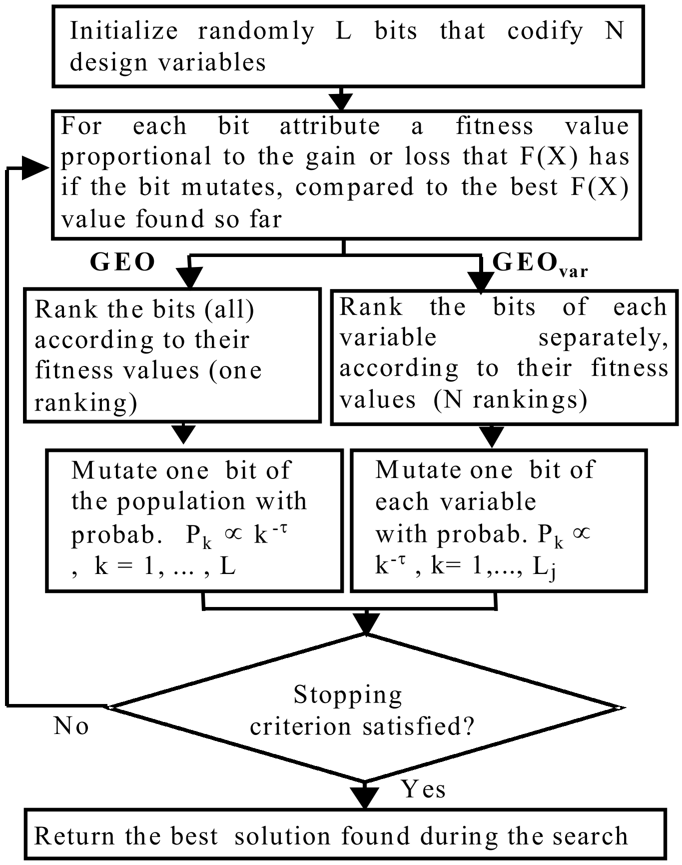

Fig. 2. Flowchart for GEO and GEO$_{var}$.

3 Local Search: The EXTREM Algorithm

The local search algorithm coupled to GEO was the EXTREM routine [18], which uses Powell's method of conjugate directions approach [1]. Its working principles are very simple: i) a set of perpendicular directions is given and the objective function along one of them is approximated by a polynomial through three points; ii) along this direction, the minimum of the approximate objective function is searched; iii) from this minimum a new search is performed in a direction perpendicular to the previous one until the perpendicular set of directions is covered; iv) then, a new direction is created by the line that connects the starting point and the last found minimum; v) a new set of perpendicular directions is created from this new direction and steps ii to v repeated until a given convergence criteria is met.

4 The PMM Spacecraft

The Multi-Mission Platform is a multi-purpose space platform being developed at the brazilian National Institute for Space Research (INPE) to be used in different types of tasks such as Earth observation, scientific or meteorological missions. Its main physical characteristics are depicted in Fig. 3.

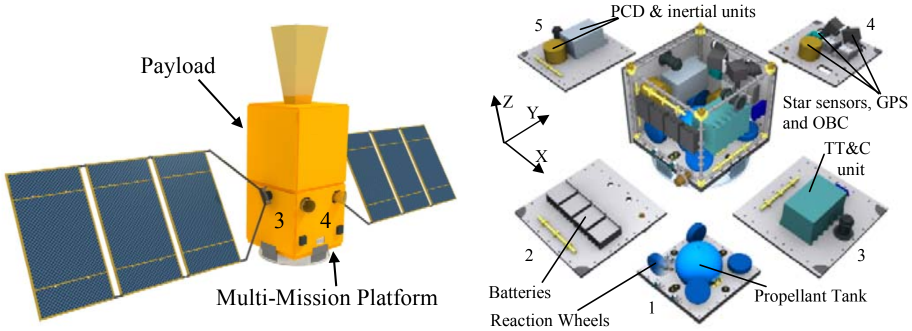

Fig. 3. Simplified views of the Multi-Mission Platform.

The PMM architecture concept consists of assembling in one platform, all the necessary equipment essential to the satellite in a way that different types of payloads can be mounted on the same basic bus. In this concept, there is a physical separation between platform and payload modules, which can be developed, constructed and tested separately, before the integration and final test. Its main advantage is the possibility of reusing the same platform project, what reduces the development cost of new satellites.

The main goal of the thermal design of a spacecraft is to keep the temperature of the elements of the vehicle within their required ranges [21]. One of the most important issues the satellite thermal engineer has to address is the definition of the size and position of the radiators. Radiators are areas of the satellite covered with high emissivity coating. Their goal is to reject heat into space so as to keep the equipment temperature at the appropriate design ranges, during periods of high internal heat dissipation and/or of high external thermal loads. On the other hand, these areas must not be excessively large so that, during periods of low heat loads, the temperatures do not go below the allowed minima. In the case of the PMM, radiators can be positioned in 5 of the 6 sides of the platform body, since the top side does not “see” the space due to the payload mounted on it (see Fig. 3).

In satellite thermal design two critical situations are usually identified, where minimum and maximum temperatures are expected to occur: i) The Cold Case (CC), when the external heat loads (solar radiation, earth radiation and albedo) are minimal, the satellite is operating with the lowest heat dissipation in the electronic equipment, and the thermal optical properties of its coatings are non-degraded and; ii) The Hot Case (HC), when the external heat irradiation is maximal, the satellite is in operational mode with the highest heat dissipation and the optical properties of the coatings are degraded. The thermal design shall manage the heat flow in a way that, in both situations, the temperatures of all elements remain within the required range of temperature. There are many variables, such as the size of radiators, that affect the temperature distribution, and the thermal engineer has to find a combination of these variables to reach a satisfactory design. This task needs a lot of simulations and analysis, considering the large numbers of variables involved.

In equipment where a strict control of the temperature is required, such as in the batteries of the PMM (panel 2), heaters are frequently used to warm the equipment during the CC. On the other hand, as the electrical power supply is very limited in a satellite, the power spent on the heaters must be the least possible.

In this study a specific mission of the PMM was analyzed, defined by equatorial orbit with altitude of 600 km and having the battery panel always pointing to Earth along the orbit.

5 Formulation of the Inverse Design Problem

The overall goal of using the optimization tool in the thermal design process is to obtain an automatic procedure to test different design options and find (hopefully) the one(s) that best fit the design requirements. This process is usually done "manually" by the thermal engineer, heavily relying in his/her design experience and frequently stops as soon as a feasible design is found.

The optimization problem consists of finding the areas of five thermal radiators and the power dissipated by the battery heater, in order to minimize the difference between operational temperatures, at given locations, during the CC and HC, and a set of corresponding target temperatures. As usual, minimization of the power dissipated by the heater during operation is also required.

As the satellite is still in the early stages of development, a simplified numerical model was made only considering the six PMM sides, with the equipment simulated as heat sources over their respective panels. Panels 1 to 5 exchange heat with each other, by conduction and/or radiation, and with the space environment, by radiation, through the radiators placed on them. The top panel (not shown in Figure 3) makes the interface with the payload and is thermally isolated from it, but exchange heat with the other panels of the PMM.

Using the lumped parameter representation [21] (that is, the spacecraft numerical thermal model is made of discrete isothermal nodes) and assuming steady state conditions with orbit average heat loads, the heat balance at each one of the six panels leads to a set of nonlinear algebraic equations, with the design variables (5 areas and 1 heat dissipation power) as parameters. For a given vector of parameters **X**, the solution results in two set of temperatures: $\mathbf{T_{CC}(X)}[1:6]$, if CC conditions are applied (minimum values of Q_{int} , q_{ext} and α); and $\mathbf{T_{HC}(X)}[1:6]$, if HC conditions are considered (maximum values of Q_{int} , q_{ext} and α). Q_{int} , q_{ext} and α are, respectively, the heat dissipated by equipment on panels 1 to 5, the incident external radiation flux on panels 1 to 5, and the absortivity of the radiators coating. The pertinent coupling coefficients and the solution of the system of equations are obtained using INPE´s PCTER thermal software package [22], which was coupled to the optimization algorithm.

Constraints are posed to the panels' temperatures, which must lie inside required design intervals. The target temperature and allowed range for each panel are defined from reliability requirements of the instruments and other equipment mounted on each panel. Table 1 summarizes the limits on the design variables, the operational temperature limits, as well as the internal heat dissipation from the electronic devices applied to the panels.

Table 1. Design variable limits, operational limits and panel heat dissipation.

Parameter		Panel					
		1	2	3	4	5	6
Radiator area limits (m^2)	Xmin	0.0	0.0	0.0	0.0	0.0	-
	Xmax	0.902	0.952	0.952	0.952	0.952	-
Temperature limits (°C)	Tmin	-5.0	-10.0	-20.0	-20.0	-10.0	-20.0
	Tmax	+50.0	+20.0	+50.0	+45.0	+45.0	+50.0
Target temperature	T_T (°C)	+22.5	+15.0	+15.0	+12.5	+17.5	+15.0
Internal heat dissipation (W)	CC	15.0	13.0	8.6	40.0	20.0	0.0
	HC	40.0	47.5	27.2	55.0	90.5	0.0

Mathematically, the multi-objective inverse design problem described above is formulated as a mono-objective optimization problem, assuming unitary weighting factors [23] before each term of the objective function:

$$\text{Minimize } F(\mathbf{X}) = \|\mathbf{T}_{CC}(\mathbf{X})-\mathbf{T}_T\|_2 + \|\mathbf{T}_{HC}(\mathbf{X})-\mathbf{T}_T\|_2 + \|\mathbf{X}[6]\|_2 \tag{1}$$

$$\begin{aligned} \text{Subj. to: } \mathbf{X}_{MIN} &\leq \mathbf{X} \leq \mathbf{X}_{MAX} \\ \mathbf{T}_{MIN} &\leq \mathbf{T}_{CC}(\mathbf{X}) \leq \mathbf{T}_{MAX} \\ \mathbf{T}_{MIN} &\leq \mathbf{T}_{HC}(\mathbf{X}) \leq \mathbf{T}_{MAX} \end{aligned}$$

$\mathbf{T}_T$ denotes the vector of target temperatures and $\mathbf{X}[6]$, the power dissipated by the battery heater. Hereafter, the complete optimization problem will be referred to as the Cold and Hot Case (CHC). Additionally, the CC and the HC are formulated and solved as optimization problems separately. The idea is to get some insight by comparing these separated CC and HC solutions with the combined CHC one. It is important to note that there is no battery heater being used in the CC and HC stand-alone cases.

6 Results

The optimization strategy comprised a step of global search with GEO followed by a local refinement with EXTREM. In running GEO, each design variable was encoded in 7 bits, what means a resolution better than 0.01 m^2 and 1.0 W for the radiator areas and the heater dissipation, respectively. The search for optimal τ was made for different values of τ within the range [0.0, 5.0], using a 0.5 step size. After that, 25 runs were performed for each design case; simulations were stopped after 10^5 function evaluations. The best results are summarized in Table 2, with and without a local refinement step with EXTREM algorithm. Figure 4 presents the radiator areas obtained for CC, HC and CHC (with the EXTREM step). The lower and upper area limits, for each panel, are also indicated. Figures 5, 6 and 7 display the corresponding temperatures, in panels 1 through 6, for CC, HC and CHC.

Table 2. Best designs for CC, HC and CHC.

Case	Algorithm	F[X]	X[1]	X[2]	X[3]	X[4]	X[5]	X[6]
CC	GEO	4.360	0.008	0.062	0.035	0.271	0.022	-
	GEO/EXTR	4.101	0.001	0.059	0.037	0.269	0.029	-
HC	GEO	1.789	0.028	0.433	0.129	0.372	0.457	-
	GEO/EXTR	1.448	0.028	0.435	0.145	0.364	0.450	-
CHC	GEO	142.5	0.676	0.460	0.089	0.008	0.072	49.7
	GEO/EXTR	141.7	0.679	0.455	0.085	0.016	0.077	49.7

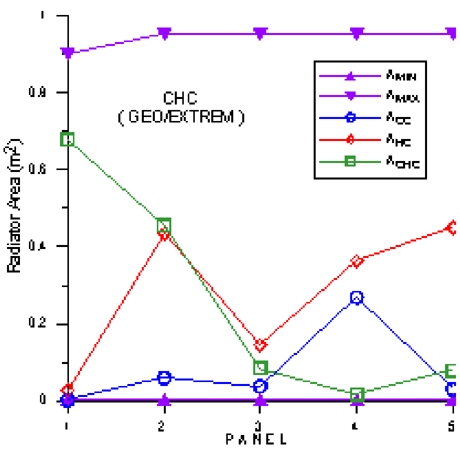

Fig. 4. Radiator areas for CC, HC and CHC

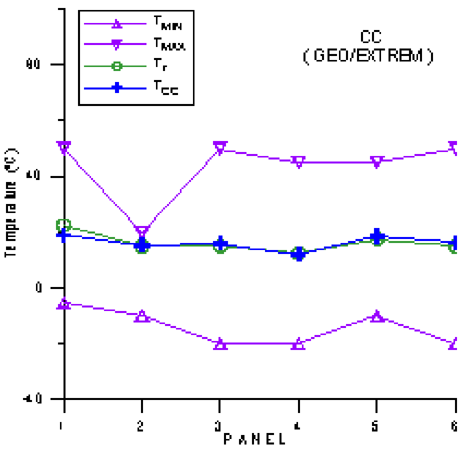

Fig. 5. Resulting temperatures for CC

ition based on a simple linear interpolation between the CC and HC solutions did not lead to the best CHC solution. From a engineering point of view, this result highlights the relevance of introducing optimization tools into the design process as way, not only to reduce the time (and cost) during the project phase, but also to generate innovative design solutions and to check new design paths. We also remark that the use of a hybrid strategy, with a final deterministic search step, had a positive impact in the design process. In the present case, our gains (in terms of objective function value; see Table 2) ranged from less than 1%, for the CHC, to almost 20%, for the CC.

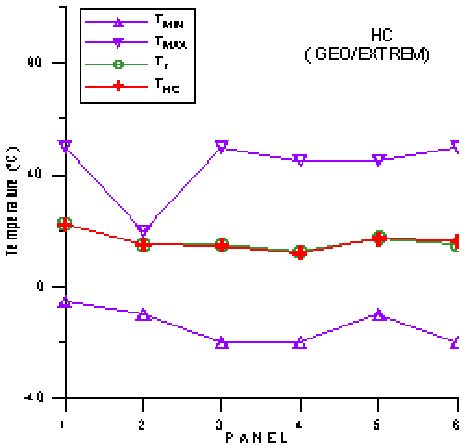

Fig. 6. Resulting temperatures for HC

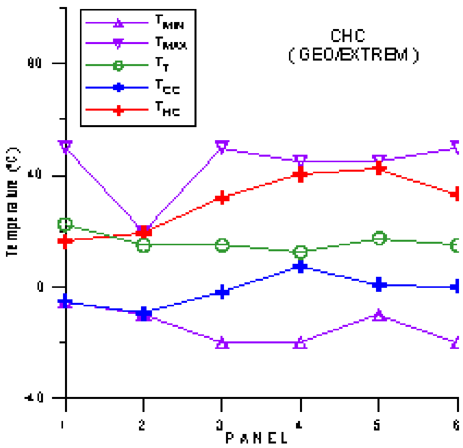

Fig. 7. Resulting temperatures for CHC

A quick look at the temperatures computed for CC and HC, show that the panels have been brought very close to their target temperatures. As expected, this is not the case for CHC, which represents much more challenging task, with diverging engineering requirements having to be met simultaneously. All this results in a CHC design solution which includes panels operating at their (higher or lower) operational limits. For example, panels 1 and 2 almost cross their lower temperature limits, during the cold phase (Figure 7). We observe the same feature with panel 2 (and to a lesser extent with panels 4 and 5), during HC.

It is important to note that, in such a complex problem, the existence of other (possibly better) design solutions is not ruled out. However, having at hand an iterative design tool, such as the one used in this work, allows designers and engineers to easily perform a systematic exploration of the design space in search of new, better solutions. Moreover, additional project constrains or changing project requirements can readily be incorporated into the design process.

7 Conclusions

In this paper, a hybrid evolutionary strategy was presented and applied to the inverse design of a spacecraft thermal control system. The results show that combining the newly developed GEO global search metaheuristic with a local deterministic method was advantageous, since while the global search performed with GEO provided efficient, even non-intuitive, design solutions, the local search yielded refinements to them.

In a further development of this study, different strategies of combining GEO with the local search algorithm and with gradient based methods are envisioned.

Acknowledgements

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