GAME THEORY AND CO-EVOLUTIVE ALGORITHMS FOR SPACE MISSIONS PRELIMINARY DESIGN

M. Lavagna(1), A. Mafficini(1)

(1)*Politecnico di Milano – Dipartimento di Ingegneria Aerospaziale*
Via La Masa 34, 20158 Milano, Italia
lavagna@aero.polimi.it

ABSTRACT

In this paper a method to select a set of preliminary space system configurations is proposed, based on a two-player multi-objective optimization. During the concept definition of a space system a key point stays in reducing the number of possible alternative paths to fasten the next feasibility study. The problem is here modelled as a multiobjective global optimization and managed by using The Evolutionary Programming techniques. The main issues related to the classical Evolutionary approach and the particular mixed search domain are overcome by means of the Game Theory combined with Possibilistic and Fuzzy theory. The simulation results, applied to the ESA Mars Express Mission scenario are offered.

1. INTRODUCTION

The so-called pre-phase A is devoted to accomplish a space mission feasibility study: within that phase a team of experts starts from the scratch the design, taking into account the requirements coming from the costumers, together with the mission objectives. Each team member sizes a particular aspect of the mission, constrained by the on going design of the other system parts. The information exchange among the team members depends on the approach selected to deal with the design process: surely the C*oncurrent Engineering* approach is currently turning out to be well suited to gain, quickly, effective solutions [4]. Nowadays space missions are growing in complexity in terms of available technologies and because of very ambitious scientific goals. The European Space Agency spacecraft to Mars, Mars Express, which is now orbiting around the red planet; the two Mars rovers Spirit and Opportunity from NASA, still operative; the joined NASA, ESA, ASI Cassini-Huygens mission to Saturn and Titan, completely successful as recently reported, are few examples on the great challenge the space mission design currently offers. Although efficient, the Concurrent Engineering approach cannot prevent the preliminary study to start from “first guess” configurations that could give rise to bottlenecks during the sizing process. Therefore, a tool that allows detecting good “first guess” high level configurations according to several criteria having as inputs qualitative information only such the mission objectives and requirements are, would represent a powerful help to speed up and efficiently address the pre-phase A sizing process. The scientific literature offers some works related to the space mission design automation, all of them related to the feasibility study process [2],[3].

This paper, on the contrary, proposes an algorithmic architecture, to perform a high-level configuration selection to be given to the pre-phase A study as an input. The process is here modelled as a multi-objective optimization and is faced by means of the Evolutionary methods, to both answer the global optimality requirements and to deal with the mixed nature of the treated quantities [15], [16], and [18]. To cope with the high degree of uncertainty that a very preliminary sizing phase intrinsically presents, a large number of optimization criteria are here taken into account to rank the admissible configurations. However, a large number of criteria make the traditional architecture of the Evolutionary Algorithms very heavy. Moreover, the criteria modelling can be hardly treated by applying the conventional algorithms because of the lack of quantitative information at the very beginning of the process. To cope with the highlighted issues, the Evolutionary Algorithms are here supported by methods coming from the Game Theory, the Possibilistic Theory and the Fuzzy Logic areas [20], [21]. In particular, the Game Theory is a fundamental part of the search algorithm. The Possibilistic Theory and the Fuzzy Logic support the modelling process, together with a statistical approach. The current paper will focus on the optimization algorithm, the criteria modelling is reported in [1]. A co-evolutive scheme is proposed with two populations/players in charge of different search areas, partially overlapped; communications and negotiation protocols are proposed to model a partial collaborative strategy. Populations are focused on a prefixed subset of the criteria vector and would optimize its own criteria if no collaboration between the players occured. A collaborative strategy makes the players look for the common utility, represented by the entire criteria set. According to the proposed scenario, the space system design, the selected criteria vector is six-dimensional. The proposed approach is anyhow, widely applicable.

Proc. of 'The 8th International Symposium on Artifical Intelligence, Robotics and Automation in Space - iSAIRAS', Munich, Germany. 5-8 September 2005, (ESA SP-603, August 2005)

2. THE THEORETICAL BACKGROUND

The theoretical background leans on the *Pareto Optimum* definition [6], [7]. The multiobjective optimization branch offers different techniques to succeed in catching the front, that differ depending on the search strategies and the solution ranking methodologies: among them the *Pareto-based ranking* sorts the solution according to a dominance metric; the *Aggregation function* reduces the criteria vector to a scalar function by summing/multiplying the criteria vector elements previously weighted [6]. The Game Theory is also applied to deal with multicriteria decision making, specifically whenever multiple decisioners are involved in the scenario [8]. The Game Theory focuses on the players' interaction strategies selection to visit different areas of the criteria space. The interactions among players define the applied protocol. The Game Protocols, strictly related to the presented work, are [9]:

Not-cooperative (Nash): The Nash equilibria are the solutions detected with a Not-cooperative Protocol strategy. The Nash optima turn out from a non-cooperative multiple objective optimisation. A Nash strategy asks for players who optimize his/her own criterion only, focusing on his/her own payoff; each player can move in a restricted search area, as he/her is in charge of a sub set of the $\underline{x}$ problem variable vector. While playing, each player assumes the subset of the $\underline{x}$ vector, different from his/hers, as fixed. As soon as no player can further improve his/her payoff, the game equilibrium is reached. Formally, given the criteria vector *f=[* $f_1(x_1, x_2)$, $f_2(x_1, x_2)$ *]*, by assuming a two-player scheme - p_1 on $f_1(x_1, \bar{x}_2)$, p_2 on $f_2(\bar{x}_1, x_2)$ - and by applying a not-cooperative strategy, the point (x^{1N}, x^{2N}) is a Nash equilibrium if [13]:

$$\begin{cases} f_1(x^{1N}, x^{2N}) = \min\limits_{x^1 \in X^1} f_1(x^1, x^{2N}) \\ f_2(x^{1N}, x^{2N}) = \min\limits_{x^2 \in X^2} f_2(x^{1N}, x^2) \end{cases} \quad (1)$$

Cooperative (Pareto): Whenever each player can search in the entire $\underline{x}$ space and the others choices are completely visible the players are said to be collaborative and better solutions than those detected with the not-cooperative strategy are expected. The cooperation entails that each step in the search space is globally approved to converge to common goal. The detected solutions belong to the Pareto front and the Pareto Optimum definition. The set of Pareto solutions ask for some additional sorting technique to rank them. On the other hand, the set of Nash solutions could be either small or even empty (the Nash equilibria are fixed points of a map and they may not exist without additional conditions). Generally speaking the Nash equilibria differ from the Pareto solutions [9].
According to the Game Theory approach, the protocol better suited for a given scenario depends on the application itself and, obviously, on the interaction to be modelled. In [13] an example is reported for a not-cooperative protocol application, connected with a Genetic Algorithm on a two-player scenario; a cooperative case is reported in [19].
As the global optimization is well managed by evolutionary algorithms and the presence of mixed domains is accepted they are the best candidate to connect with the Game Theory approach to deal with the distributed optimisation problems: by varying the game protocol, different solutions can be detected and several schemes of interaction among the decisioners involved in the real problem to face can be visited to highlight their effects on the final solutions. In the followings the Genetic Algorithm together with different game protocol is applied to the current problem.

3. THE CONFIGURATIONS PROBLEM IN SPACE MISSION DESIGN

A generic space mission scenario, with a discrete level of complexity, is here considered: an interplanetary mission with at least two modules, an orbiter and a lander, which can separate in a certain phase of the mission, to perform their own tasks is assumed to be the general framework. The Cassini Huygens mission could be a typical reference.
At the very beginning of a space mission design a very small set of data are available, coming from the given requirements, the mission objectives and some possible constraints coming from the customer. More specifically they are:

- The target planet
- The set of possible launchers
- The set of possible trajectories from the Mission Analysis
- The threshold on the maximum admissible wet mass
- The mission lifetime (included transfer)
- The time window devoted to science
- The number/type of on-board scientific instruments

A subset of the possible high level configurations is looked for, selected according to a certain criteria vector. Therefore, the $\underline{x}$ vector representative for the problem variables, that define a generic configuration includes:

- The phase in which the orbiter and the lander separate, and the split of mass

- The subsystems configuration for each modules (power system, propulsion type, ADCS architecture)
- The selected launcher/s
- The selected mission analysis (Trajectory)
- The planetary capture performed either by chemical propulsion or aerocapture at target planet
- The aerobraking strategy either applied or not

The set of final solutions is, obviously highly sensitive to the optimization criteria selection: the more multidisciplinary they are the more robust and reliable the results will be. Therefore the criteria vector includes the payload mass, the reliability the adequacy of the power and ADCS subsystems, the adequacy of the launch strategy and of the mission analysis (trajectory) maximisation, as listed hereinafter (2):

$$max\ \underline{G}=[1\ 2\ 3\ 4\ 5\ 6] \qquad (2)$$

1. Payload mass
2. System reliability
3. Adequacy of power subsystem
4. Adequacy of attitude subsystem
5. Adequacy of launch strategy
6. Adequacy of trajectory analysis

The mapping from the $\underline{x}$ hyperspace into the $\underline{G}$ 6D space opens the modelling issues raised from the particular treated scenario: no classical preliminary sizing analytical formula can be directly applied because of lack of inputs. The Possibilistic Theory is here applied to model the causal dependency of the power and ADCS adequacy from the $\underline{x}$ and the mission inputs [21]. Dedicated FLC have been implemented to connect the launch strategy and trajectory analysis adequacy to the $\underline{x}$ and scenario input vectors [18], [20]. The former set of criteria should be enlarged to better model the multicriteria real process: as example a criterion in charge of evaluating the scientific return level obtained with a selected $\underline{x}$ should be added. IN the current work a six-criterion global optimization is faced, solved with an Evolutionary approach: each genetic individual, made of numeric items and discrete/linguistic items (e.g. genes declaring which type of launchers are used) identifies a specific configuration. The aim is to find global optima with respect to all the six criteria; the global Pareto front is looked for. Although a simple cooperative strategy seems to be the choice to be done, the large number of criteria may suggest that a single-population Evolutionary Algorithm would probably encounter several issues in performing the search.

4. THE ALGORITHM

Three different Game Protocols can be selected in the proposed architecture:

- Two-players not-cooperative game
- One-player cooperative game
- Two players *semi-cooperative* game

The non-cooperative protocol makes the algorithm converging around the Nash Equilibrium. The final population is a “cloud” near the actual Nash Equilibrium because of the insertion of diversity operators, which maintain sparsity in the populations. Two populations communicate each other by means of genes exchange according to modalities similar to the aforementioned Nash Genetic Algorithm [3].

The Cooperative protocol is a classic multiobjective algorithm for Pareto front solutions identifications. The semi-cooperative protocol has been specifically implemented within the current work. It foresees two populations-players, having different, distinct criteria similarly to the not-cooperative protocol; however a sort of “links” between players is preserved. These links, called communication protocols, enhance the negotiation between players: therefore, the players not only try to optimize their own criteria while assuming the other players’ choices as fixed, but they partially take into account the other players’ criteria optimization. The final aim is to tend to Pareto solution, taking advantage from the search locally performed by each agent. The comparison between the cooperative and semi-cooperative are offered in the followings

The architecture of the proposed semi-cooperative algorithm is firstly reported. As already pointed out, a two populations-players scheme is adopted, and a communication channel for data exchange exists. The data flow on the channel is ruled by the negotiation mechanism, based on three tools:

- Elitism
- Genes exchange
- Criteria flip

Elitism: The Elitism is a classic technique to improve the Genetic Algorithm performances [14]. Anyhow, beyond its traditional goal, the Elitism has an important role in gaining a common goal in a multiple players’ scenario. The local populations evolve internally, each visiting a subset of the search space related to the criteria subset the player is in charge of: each population is called *Internal* population. A further *External* population, with no evolutionary mechanism, plays the role of attractor, being the basin for some elements coming from the two *Internal* populations selected according to their global dominance score; elements sampled from the *External* population seed the two *Internal* to partially lead the local search

process. The *Internal* population individuals evolve according to their own criteria; the more they belong to the complete $\underline{G}$ vector front, the more they are attracted into the *External* population. The frequency for the resource-consuming *External* attraction mechanism occurrence is less than one generation loop. The *External*→*Internal* genetic material reinsertion provokes, in the *Internal* search mechanism, the presence of a new attractive basin, representative for the entire $\underline{G}$ optimization success. The $\underline{x}$ subset, lead by the local criterion attraction, feels a sort of perturbing effects towards the global optimum area.
Gene Exchange: this kind of communication ensures that at the end of each generation each player's knowledge about the others is updated; given two individuals from population 1 and 2 respectively, correspondent genes values are exchanged according to the role each gene plays in the local criteria computation; fig.1 offers the sketch of the process [13].
Criteria flip: This mechanism is based on a specific concept of distance: the *distance among players*. The more the two populations are similar in the $\underline{x}$ configuration space the nearer the populations are.

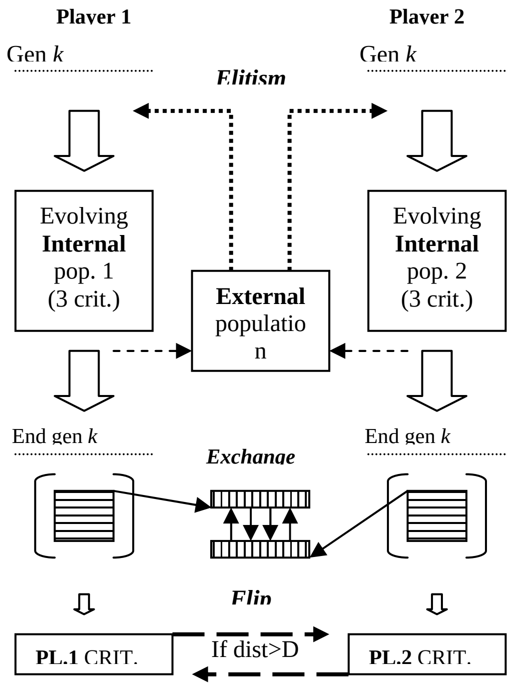

Fig. 1 General Architecture: communication mechanisms in the semi-cooperative protocol

Whenever a threshold is overcome the subset of criteria are flipped between the players: the flip frequency is upper bounded: the flip mechanism makes the local population been ranked from the other player point of view. The distance between players can be controlled, but this mechanism should be carefully tuned, being the algorithm convergence very sensitive to it.

According to each population evolution, the principal search operators are applied (e.g. mutation, crossover, genes exchange). The stop criterion is built to monitor quantities settled to evaluate the local player trends from a global point of view.

5. VALIDATION AND TESTING

The test functions are taken from [15], [16], and [17]. Here some significant examples are proposed, focused on convex and no convex Pareto fronts. In tab. 1 the main algorithm parameters are listed. It has to be noted that, for semi-cooperative protocol the active individuals are double with respect to the cooperative scheme, but the generation number is halved.

Tab. 1. Test 1/2 parameters

Test N.1/2 (Semi-cooperative)	
Evaluated generations	100
External population dimension	100
Internal pop. 1 and 2 dimensions	20 - 20
Test N.1/2 (Cooperative)	
Evaluated generations	200
External population dimension	100
Internal population dimension	20

The first two tests, propose the following optimization problem [15]:

$$
\begin{aligned}
&\mathrm{T}(\underline{x}) = [\, f_1(x_1),\, f_2(\underline{x})] \\
&f_2(\underline{x}) = g(x_2,.....,x_m)h(f_1(x_1), g(x_2,.....,x_m)) \\
&\underline{x} = [x_1, x_2, ..., x_m]
\end{aligned}
\qquad (3)
$$

The first test is built with:

$$f(x_1) = x_1\,,\;\; g(x_2,....,x_m) = 1 + 9\sum_{i=2}^{m} x_i \;\;,$$

and $$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} \qquad (4)$$

m=30, while the variables moves in the $x_i = [0,1]$ hyperspace. The Pareto front is *convex* and it is built with g=1. In fig. 2 the comparison between cooperative and semi-cooperative is presented, in the criteria space. The cooperative strategy clearly reveals to overcome the semi-cooperative approach; however, the semi-cooperative consistently approaches the Pareto front, with well-spread solutions.
The second test function is built with [16]:

$$f(x_1) = x_1$$

$$g(x_2,....,x_m) = 1 + 9\sum_{i=2}^{m} x_i \qquad (6)$$

$$h(f_1, g) = 1 - (f_1 / g)^2$$

Internal parameters assume the values: m=30, while the search hyperspace is $x_i = [0,1]$. The Pareto front is *non-convex* and it is built with g=1.

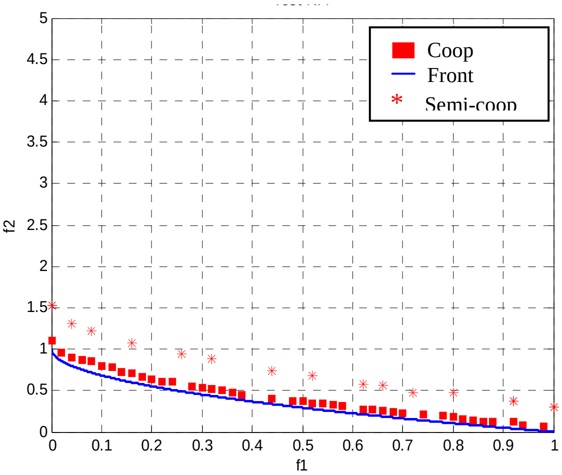

Fig. 2. Comparison between cooperative and semi-cooperative for a convex Pareto front

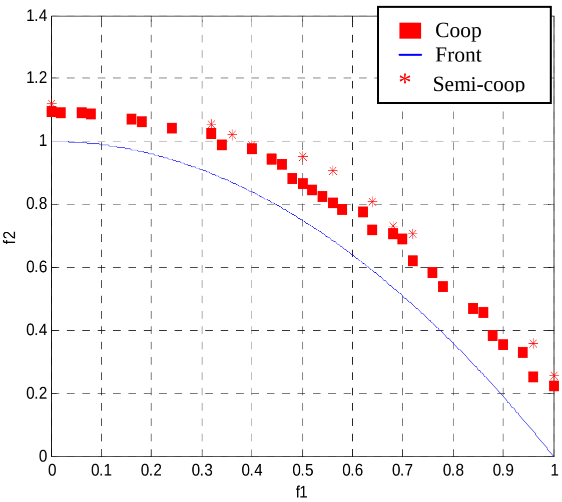

Fig. 3. Comparison between cooperative and semi-cooperative for a concave Pareto front

In fig. 3 the comparison between cooperative and semi-cooperative is offered, in the criteria space. The cooperative strategy reveals to overcome the semi-cooperative approach once more; however the semi-cooperative is almost coincident with the cooperative result, with respect to distance from Pareto Front of the best individuals. Still a definitely worse behaviour according to sparsity is experienced.

The next test highlights the difference between the Nash Equilibrium and the Pareto Front. It is really a simple test, but its Nash equilibrium is analytically known. The task is to minimize [13]:

$$\mathrm{T}(\underline{x}) = [\, f_1(x_1, x_2),\ f_2(x_1, x_2)] \qquad (7)$$

$$f_1(x_1, x_2) = (x_1 - 1)^2 + (x_1 - x_2)^2$$

$$f_2(x_1, x_2) = (x_2 - 3)^2 + (x_1 - x_2)^2$$

The Nash equilibrium is equal to:
$[\, f_1(5/3, 7/3),\ f_2(5/3, 7/3)]$ =[0.8840, 0.8849].

Tab. 2. Test 3 parameters

Test N.3 (Semi-cooperative)	
Evaluated generations	100
External population dimension	100
Internal pop. 1 dimension (f1)	20
Internal pop. 2 dimension (f2)	20
Test N.3 (Cooperative)	
Evaluated generations	200
External population dimension	100
Internal population dimension (f1,f2)	20

In tab. 2 the main parameters for each protocol are presented. Fig. 4 shows that the semi-cooperative strategy is definitely comparable to the cooperative approach.

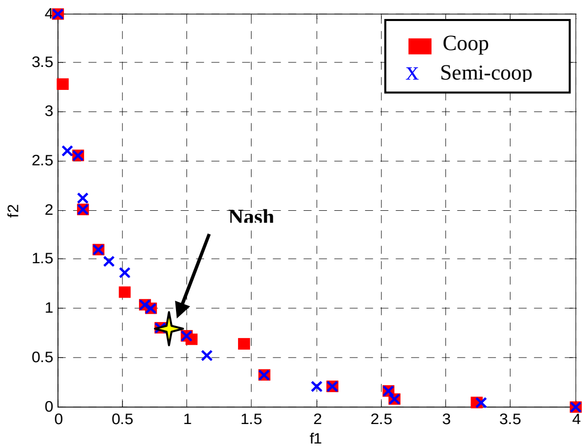

Fig. 4. Comparison between cooperative and semi-cooperative for test 3

As it can be seen, the Nash Equilibrium stays on the Pareto Front.
The test campaign showed that until the criteria vector dimension is small, the traditional single player architecture, corresponding to the cooperative strategy,

performs definitely well, and the semi-cooperative is hardly comparable. However, the semi-cooperative architecture reveals its benefit as soon as the criteria vector dimension increases, as the next paragraph highlights.

6. A CASE STUDY IN SPACE MISSION DESIGN

The Mars Express spacecraft, launched in June 2nd, 2003 is made of an orbiter and a little lander of about 71 kg. In tab. 3 the main MEX features are summarized:

Tab. 3. MEX features: real mission

Target Planet	Mars
Total wet mass (launch)	1120 kg
Orbiter mass - Lander mass	1049 – 71 kg
Payload mass	116+lander kg
Lifetime	3.08 years
Instruments for Operative phase (around Planet)	8
Launch Date	June 2nd , 2003
Launcher	Soyuz-Fregat
Capture and reaching of the final orbit	Impulsive chemical manoeuvres
Power plant based on	Solar array wing (SAW)
Propulsion	Chemical (CP)
Attitude during operative phase	3 axis
Separation	Before capture

Data specifically identifying the MEX scenario at the very beginning of its designing process are given in tab. 4. Those quantities correspond to the first list given in §3 to start the presented tool.

Tab. 4. MEX input scenario

Target planet	Mars
Max. admissible wet mass	1120 kg
Total maximum lifetime	3.08 years
N. instruments	8
Starting date for temporal scanning	January 1st, 2003

The simulation based on the semi-cooperative protocol detected 63 non dominated solutions; the dominant solutions ranking is performed according to the distance from the Utopian point, on an n Euclidean metric basis: the lower the score, the nearer the solution to the Utopian point. Among the others three dominant solutions are quite similar to the MEX both in the criteria and variable hyperspaces. The nearest is given in tab.5 (17th on 63). The payload mass approaches the MEX; although the selected launcher is different, its performance almost match the Soyuz ST features; the power plant and propulsion types correspond. The trajectory parameters are similar, although the transfer time is longer than the MEX which is of about 180 days. The tool selects a separation strategy completely different from the real mission: the MEX separation occurred before the planetary capture.

Tab. 5. The Nearest to real MEX (17th of 63 Pareto solutions)

Distance from utopia	0.62
Target Planet	Mars
Total wet mass (launch)	1120 kg
Orbiter mass - Lander mass	970.6 – 149 kg
Payload mass	206. 26 kg
Lifetime	3.08 years
Instruments for Operative phase (around Planet)	8
Launch Date	June 2003
Launcher	Soyuz ST-Fregat
Capture and reaching of the final orbit	Impulsive chemical manoeuvres
Power plant based on	Solar array wing (SAW)
Propulsion	Chemical (CP)
Attitude during cruise	Spinning
Attitude during operative phase	3 axis
Separation	On the final orbit
Intermediate ΔV	≈ 0 km/s
Departure C3	8.85 km^2/s^2
Arrival C3	7. 31 km^2/s^2
Transfer Time	201. 25 days

Those solutions with lower score according to the Utopia point distance (those placed before the former 17th solution) select the aerobraking as the main manoeuvre to lower the planetary orbit apoapsis: the aerobraking allows lowering the propellant masses, leaving a greater percentage to be exploited for payload accommodation. The aerocapture manoeuvre is selected too, but by solutions higher scored than the 17th: the aerocapture allows a propellant mass saving even larger than the aerobraking, but has the main drawbacks coming from the heat shield to be designed to protect the system from very high heat loads experienced during the atmospheric phase. Moreover, the aerocapture manoeuvre never occurred in a real mission, making the reliability index definitely low.

A simulation run with the cooperative protocol is reported too, to show the benefits of the proposed semi-cooperative strategy as soon as the criterion vector is enlarged. The population dimension is settled on 20 individuals (Semi-cooperative has obviously two populations-players), Elitism is activated, and the evolution stops at the generation number the stop criterion is satisfied whenever the semi-cooperative protocol is selected. Specifically the generation number is 101. The Elitism mechanism is active.

Tab. 6. Comparison between the Coop. and Semi-coop. protocols in MEX simulation scenario

Protocol	Coop.	SemiCoop
Number of selected solutions	50	63
Min distance from Utopia point in the final selection	0. 59	0. 53
Max distance from Utopia point in the final selection	1. 37	0. 99

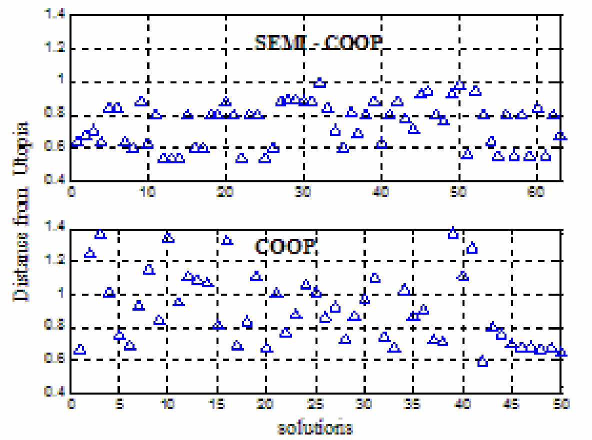

Fig. 5. Selected non-dominated individuals: distribution with respect to distance from Utopia

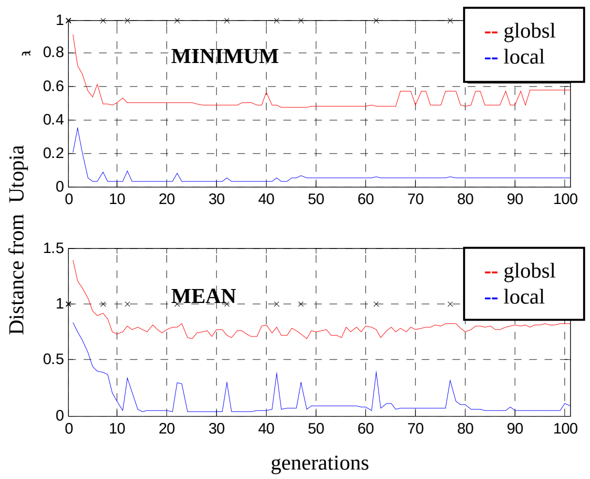

Fig. 6. Minimum and mean distance from Utopia for Player 1 in *semi-cooperative* simulation

Table 6 summarizes some interesting data coming from fig. 5: the cooperative strategy selects spread solutions but lightly worse than the semi-cooperative in terms of distance from the 6D Utopia point: the semi-cooperative shows smaller distances range (max-min), more shifted towards the Utopia point. However, it cannot be stated that the semi-cooperative finds better solution than the cooperative strategy, even though less spread. It means only that at the 101st generation the semi-cooperative seems behaving more efficiently: letting the cooperative search keeping running, the population possibly converges to the Utopia point. The semicooperative reveals to be faster in finding good solutions. A possible reason why, may be that the less numerous the criteria are the more effective the search is: the semi-cooperative by splitting the criteria into two players, focuses each player' effort on a restricted search hyperspace, better exploiting the evolutionary benefits. In fig. 6 the Mean and the Minimum distances from the Utopia point are reported, versus the generation number for Player 1, as example (player 2 one is almost analogous); red colour refers to distances calculated in the 6-dimensional criteria space, blue colour to distances calculated in the player criteria space (3-dimensional). Fig. 7 shows the same quantities according to the cooperative strategy (single-player scenario): the potential of the semi-cooperative approach with respect to the cooperative strategy is clearly evident.

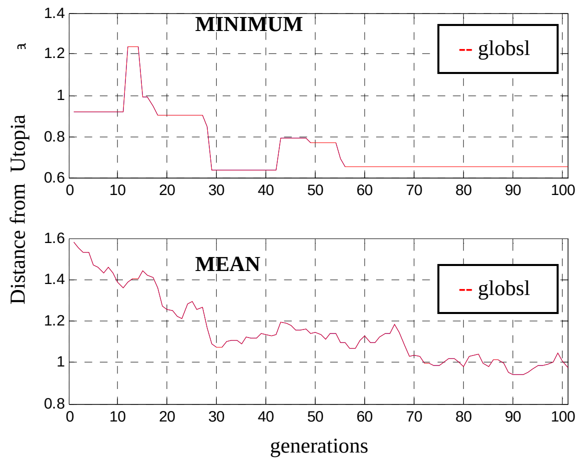

Fig. 7. Minimum and mean distance from Utopia in *cooperative* simulation

The semi-cooperative trends, however, show some nervous peaks in the minimum distance trend too: to correctly tune the communication mechanism among players is surely the most difficult task. It can be said that the semi-cooperative has surely the benefit of significantly simplifying the local evolution of each player's populations, letting the evolution speed increasing, but it asks for a smart and fine tuning of the communication operators.

7. CONCLUSIONS

The paper gives the theoretical background used to build the presented tool for preliminary high level configuration detection. The set of optimal configuration identification as input for the space mission feasibility study is introduced and formalized as a multi-objective optimization. Particular emphasis is given to the Game architecture selected to face the problem, focusing on the protocol selection. The proposed semi-cooperative protocol is described and some tests run on functions from literature are discussed. Simulation results obtained from a real space mission design problem are reported, to highlight the validity of the proposed architecture to deal with multiobjective optimisation problems with large criteria vectors. It has been underlined that the communication protocol tuning is the key element to obtain good results. Moreover, the logic for the criteria distribution among players seems to be another key point to be further analyzed. Although it has not been described in this paper, which almost focuses on the algorithm itself, a considerable modelling effort has be done, to characterize configurations in a very preliminary scenario, strongly affected by uncertainties and lack of data. The selected modelling techniques highlighted good performance in adequately manage scenarios with a discrete level of complexity. The modelling processes here implemented, based on the Possibilistic and Fuzzy Logic tools foresees for deeper investigation[18], [19], [20], [21].

8. ACKNOWLEDGEMENTS

The authors want to acknowledge Mr.Massimo Bandecchi, manager of the Concurrent Engineering Facility (CDF) at ESA-ESTEC and all ESA-ESTEC CDF team, for the provided data and support.

REFERENCES

1. A.Mafficini: Ricerca Ottima di configurazione di alto livello per sistemi spaziali: teoria dei giochi e logica possibilistica, master thesis in Aerospace engineering, Politecnico di Milano, October 2004
2. A. Fukunaga, A. Stechert: *An Evolutionary Optimization System for Spacecraft Design* International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, Atlanta-GA, 1997
3. T.Mosher: *Spacecraft Design Using a Genetic Algorithm Optimization Approach*, 0-7803-4311 IEEE Paper, May 1998
4. M.Bandecchi, B.Melton, F.Ongaro: Concurrent Engineering Applied to Space Mission Assessment and Design, ESA Bulletin, September 1999
5. A.Martelli, D.Tadino: *Collaborative and Distributed Engineering Applied to Design, Simulation And Verification in Space Projects*: The Distributed Systems Engineering (DSE) Project, DASIA 2001 Symposium, May 28th-June 1st 2001, Nice, France
6. C.A. Coello: *An updated survey of GA-based multiobjective optimization techniques,*Technical report, Laboratorio Nacional de Informatica Avanzada (LANIA), Xalapa, Veracruz, Mexico, 1998. Technical Report Lania-RD-98-08.
7. K.Deb: *Evolutionary Algorithms for Multi-Criterion Optimization in Engineering Design*, Proceedings of Evolutionary Algorithms in Engineering and Computer Science EUROGEN-99
8. S. Vannucci: *Elementi di teoria dei giochi*, April 1st, 2002
9. J.Rao, K. Badhrinath, R. Pakala, F. Mistree: *A study of optimal design under conflict using models of multi-player games*, Engineering Optimization, 28 (1997), pp. 63-94
10. R.L.Haupt, S.E.Haupt: *Practical Genetic Algorithms*, John Wiley & sons, Inc., 1997
11. X.Yao: *Global Optimisation by Evolutionary Algorithms*, Proceedings of the 2nd AIZU International Symposium on Parallel Algorithms/Architecture Synthesis, pp 282-291, Aizu-Wakamatsu-Japan, 17- 21 March 1997
12. C.M.Fonseca, P.J.Fleming: *Genetic Algorithms for Multi-Objective Optimization: Formulation, Discussion and Generalization, Genetic Algorithms*: Proceedings of the 5th International Conference, San Mateo –CA, Morgan Kaufmann, July 1993
13. M. Sefrioui, J. Periaux: *Nash Genetic Algorithm: examples and applications*, Proceedings of the 2000 Congress on Evolutionary Computation CEC00, July 16-19, 2000 LA Jolla-CA
14. K. Deb, S. Agrawal, A. Pratap, T. Meyarivan*: A fast-elitist Non-dominated Sorting Genetic Algorithm for multiobjective optimization*, Proceedings of the Parallel Problem Solving from Nature VI Conference, pp. 849-858, 16-20 September,2000,Paris-France
15. E. Zitzler, K. Deb, L. Thiele: *Comparison of Multiobjective Evolutionary Algorithms: Empirical Results*, Evolutionary Computation Journal,2000, 8(2), pp.173-195
16. E. Zitzler: *Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications*,Ph.D. Thesis, ETH-Zurig, Switzerland, November 11, 1999
17. K.Deb: *Multi-Objective Genetic Algorithms: Problem Difficulties and Construction of Test Problems*, Evolutionary Computation Journal 7(3), 205-230, 1999
18. S.Cammarata: *Sistemi a logica fuzzy – Come rendere intelligenti le macchine*, ETASLIBRI, 1997
19. K.Lewis, F.Mistree: *Collaborative, Sequential, Isolated decisions in design*, proceedings of DETC97
20. T.L.Hardy: *Fuzzy Logic Approaches to Multi-Objective Decision Making in Aerospace Applications*, in Proceedings of the 30th AIAA/ASME/SAE/ASEE joint Propulsion Conference (Indianapolis-IN), June 27-29, 1994
21. D. Cayrac, D. Dubois, H. Prade: *Handling uncertainity with Possibiliy Theory and Fuzzy sets in a Satellite Fault diagnosis Application*, IEEE Trans. on Fuzzy Systems, vol. 4, pp. 251-269,1996