CONCURRENT PROCESSES WITHIN PRELIMINARY SPACECRAFT DESIGN: > AN AUTONOMOUS DECISIONAL SUPPORT BASED ON GENETIC ALGORITHMS > AND ANALYTIC HIERARCHICAL PROCESS

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ABSTRACT – *This paper proposes a method to support decisions to be taken within a concurrent approach for the space system preliminary design: the defined architecture is based on a Multi-Criteria Decision Making approach mixed with methodologies coming from the Approximate Reasoning domain.*

The method here presented is focused on saving analysts' time and effort by addressing the decisions they have to make during the preliminary design process to solve inconsistency and bottlenecks risen from the parallel design of several subsystems
From a theoretical point of view, revisited Genetic Algorithms are applied, within each single subsystem design domain, in order to obtain a non-dominated solution set to be considered for solving conflicting design at system level; the Analytical Hierarchical Process – supported by dedicated blocks implemented by the Fuzzy Logic approach - has been selected as the fittest tool to simulate the causal relationships between variables and objectives, normally prerogative of the analysts' experience in the spacecraft design domain, within the system level point of view.

Simulations showed the ability of the algorithm to find conflicts and suggest a set of subsystem parameters to be tuned to converge – consistently with a user defined cost functions vectors – to a final spacecraft configuration; the tool runs in real-time with the on-going space system design process, in order to support the team leader in making decisions. A comparison with a completely transparent optimization process, implemented by applying a Multi-criteria optimization based on a revised Genetic Algorithm approach, highlighted the capability of the proposed approach to move towards the final Pareto front solution.

KEYWORDS: space system design process, concurrent design, decision making, multi-criteria optimization, genetic algorithms, approximate reasoning, AHP, Fuzzy Logic

INTRODUCTION ('HEADING 1' style)

To answer space mission requirements, that can be translate in then use of a particular set of scientific or technological instruments, a lot of subsystems must be designed - or selected among existing ones - to assure electrical power, thermal protection, data management, in orbit insertion instrument pointement control and telecommunication spacecraft-ground assurance; the growing complexity of the space systems and the rapidly increasing performance improvement of the spacecraft subsystems make the preliminary spacecraft design a very complicate goal. Not only does this complexity concern each single subsystem design but also the deep interaction among them; thus the choice of the fittest subsystem set for the planned mission is an articulated process. On the other end, the primary goal of a space mission is represented by the product return optimization: that normally leads to an increase in costs, mass and power of the whole spacecraft: the problem rises from the constraints that technology imposes on those aforementioned quantities.

Therefore, several iterative trade-off must be done to achieve a final compromise between real device performance (e.g. thrusters' specific impulse, battery capacity, solar cell efficiency, material tiffness, etc.) and desired payload data return.

As all the on-board subsystems heavily interact each other, their design and devoted device selection must proceed in parallel as several of them represent constrains for the others. That dynamic process, at the state of the art, is managed by different teams of engineers -expert in each subsystem field - with the contribute of the Principal Investigators (PI) who are scientists expert in the on board payload instruments. The process goes through sequential refined levels: engineers' teams interact each other to correct their unit partial design to answer constrains coming from the other unit partial design and reiterate their selection process.
By iteratively pruning existing as well as new solutions in each subsystem field to answer the mission requirements the teams converge to a first preliminary final spacecraft configuration in terms of on-board subsystem set, launcher, ground network, operation requirements.
As this way of managing takes a lot of time (about 6-9 months) to achieve a preliminary spacecraft configuration and obviously requires a great human effort, space agencies and companies started applying process methodologies coming from other design environments- such as the aeronautics; first of all the *concurrent* and *the collaborative engineering* approaches; the goals are, obviously, a pre-phase A design achievement reduction, a better engineers' effort addressing, a finer configuration alternatives domain mapping.

The European Space Agency at Noordwjik (ESA), the Jet Propulsion Laboratory at Pasadena (JPL), with the Project Design Center Facilities -and the Astrium company are, successfully applying a *Concurrent* approach to different space system design phases, while companies such as the Italian Alenia Spazio are working on defining a *Collaborative Engineering* with the DSE program.

The Concurrent Design Facility (CDF) at the European Space Research and Technology Center of the ESA has reduced the pre-phase A design process up to few weeks [1]. The *Concurrent Engineering* stresses the subsystem design interdependencies by intensifying the network among engineers' teams in order to make the design of each system module proceed in parallel, while maintaining humans in the loop without modelling their way of reasoning and their expertise [2].

Within those approaches to the design process optimization, two main features must be highlighted: a highly analytic aspect related to the lower level of designing each subsystem and simulating its performance; a heuristic aspect strictly related to the higher level of comparing intermediate solutions for each subsystem according to the overall system current configuration.
The first one is greatly answered by the existing sophisticated software packages based on well-known mathematical and numerical models (e.g. CATIA, NASTRAN, STK, ESATAN, ThermXL, etc). The second one is left to the system engineers' expertise, inventiveness, creativity, and intuition in addressing choices by pruning some solutions, by changing alternatives in one field (i.e. power supply device) rather than in an other one (i.e. communication device), by forcing the design direction.

While the first aspect is managed off-line, in between two consecutive concurrent sessions devoted to refine the design current status, the second aspect comes out to be determinant during a parallel session during which all designers work in parallel to converge and solve risen bottlenecks. Hence, a smart support in within this phase focused to address subsystem parameters choice to be rearranged in order to fast converge and solve the conflicts would represent a useful support to the team leader in making decisions in short time, devoted to optimize the final result.
The pruning, changing and forcing processes can be classified, from a theoretical point of view, as a constrained Multi-Criteria Analysis: a balance between constraints and performance optimization is driven by a deep domain knowledge and goes through several ranking processes of the possible solutions according to technological and financial criteria.

Automation would involve, mainly, the solution space reduction by driving the decision-making process, thanks to quasi-intelligent and knowledge-based systems. The area of intelligent and knowledge - based systems deals with a broad variety of ways in which the science and technology of Artificial Intelligence (AI) could contribute decisional process modellization [3], [4], [5], [6], [7], [8].

Concerning with space system design applications, the Jet Propulsion Laboratory implemented OASIS (Optimization Assistant) an adaptive problem solver tool which selects and adapts the appropriate global optimization technique depending on the current domain choosing between Genetic Algorithms and Simulated Annealing. One of the main goals of that tool stays in the minimization of the amount of customization required by the user. [9, 10]. That tool, however, is completely autonomous and istead fo supporting it substitutes the system engineer. The current work is focused on a design process simulator to support the team facing the numerous decisional nodes.

THE PROPOSED METHOD

The main aspect to be modelled by the proposed algorithm architecture deals with the multidisciplinary decisional process simulation, step by step, by a visible flow, as quick as possible, whenever required during the concurrent engineering sessions.

Hence, a classical optimization approach has been discarded as it would have been completely transparent to the user. It has conversely been applied to validate the proposed approach in terms of optimality. Particular attention has to be paid to the fact that the variable domains are not necessarily continuous but, often discrete. That means that classical approaches based on analytical function computation based on the constraints and cost functions continuity and, moreover derivability can no more by applied.

The core of the method is represented by a so called *Manager* module devoted to judge the current design process status in terms of constraint violations and criteria vector optimization, and to suggest a parameter vectors to be reinitialized, according to the current state variable domains.

At the time being only three on-board subsystems are involved in the preliminary configuration definitions but this does not imply loosing generality from the approach point of view.

Within a pre-processing phase, a set of state variables $\underline{X}$, of inequality and equality constraints $\underline{G}$, $\underline{h}$, and of criteria $\underline{C}$, have to be instantiated by the users, according to the current mission objectives, requirements and either financial or technological constraints imposed by the customer. Constraints coming from the design process are already part of the knowledge base of the system, but can be easily reconfigured.

In order to manage the deep interaction the subsystems design intrinsically has, the state variable $\underline{X}$ is made up of all technical parameters coming from the $\underline{S}$ vector of the p subsystems to be designed, no matter the subsystem they are related to. Moreover, they are selected according to a minimality principle that is only free technical parameters, within each subsystem are input in the state vector. Hence, according to the current development, the $\underline{X}$ vector is a (15 x1) array, while the $\underline{C}$ internal constraint vector is a (29x1) matrix, as follows:

$\underline{S}$=[TT&C Propulsion Power Mission Analysis] p=4

$\underline{X}$= [f, D, EbN0, η_{SA}, ρ_{SA}, α_{SA}, $E_{batt,spec}$, $\rho_{E,batt}$, η_{batt},T, I_{sp}, $P_{prop,spec}$, m_{prop}, $t_{transfer}$]

$\underline{V}$=[Beamwidth, $P_{TT\&C}$;$M_{TT\&C}$; $C_{TT\&C}$; $R_{TT\&C}$;, $P_{Supplied}$; Energy Capacity; T_{SA}; A_{SA};M_{SA};C_{SA}; R_{SA}; M_{Batt}; V_{Batt}; C_{Batt}; R_{Batt}; $M_{powers\backslash s}$; $P_{powers\backslash s}$; $C_{powers\backslash s}$; $R_{powers\backslash s}$; M_{Fuel}, $M_{Propulsion}$; $P_{Propulsion}$,$C_{Propulsion}$, $R_{Propulsion}$, M_{gross}, $P_{req,global}$; C_{global}, R_{global}, $t_{Transfer}$]

(1)

Where :

M(Kg) = s\s mass

P(W) = s\s required power

C(M$) = s\s cost

R = s\s reliability

Actually, the cost and the reliability modellization are on going and they are not presented in the current paper.

Each of the $\underline{V}$ element is implemented by making use of simplified sizing models available in literature [11], [12]..

Each of the $\underline{V}$ elements can be settled as an element of the criterion vector $\underline{C}$ for the decision-making process, according to the current mission requirements and objectives. The $\underline{h}$ and the $\underline{G}$ vectors take into account possible thresholds on each $\underline{X}$ element.

While the design relationships among parameters of the first three elements of the $\underline{S}$ vector can be easily represented and managed, the fourth introduces several issues; the mission analysis in the loop means a trajectory optimal control problem solving in the loop, to be done in a very reduced time window to be useful for a concurrent section. At the time being, different MA scenarios are run off-line and stored. To the smart decisional support is devoted the definition of the weight vector variation in the multi-objective optimization process of the MA, whenever the stored solutions turned out not to be sufficient to consistently solve the design current bottleneck.

The first guess settlement

In order to initialize the process, a first guess in terms of $\underline{X}$ element values must be given. According to the actual design process, alternatives in terms of devices within each s\s domain belong to a finite and known domain of existing technological solutions. Those single solutions can be combined in a first space system possible configuration either by the designers' team, by a random generation, or by a quasi-Pareto front element subset, in within each s\s domain according to the same criteria vector $\underline{C}$ settled for the overall system. In that way, the *Manager* starts evaluating the criteria and constraint status from an already refined solution. Alternatively, the user can input a preferred configuration as a starting guess.

The *Manager*

The Manager is the 'agent' of the process: it is devoted to simulate the system engineer's reasoning, according to the current multidisciplinary system scenario. As a lot of parameters as well as a large number of constraints can be involved in the design process, the so-called Analytic Hierarchical Process technique has been selected to manage the current judgment of the system design status [7].

As the process to be modelled and supported is, obviously dynamics, the ranking of possible alternatives has to be made on decisions to be made to converge, according to particular relevant aspects of the current scenario. That is why three decisions have been settled as criteria for the decisional matrix, as reported in (1):

$$\underline{A}=[\text{to increase to decrease to do nothing}] \tag{2}$$

The $\underline{X}$ free technical parameters have been settled as alternatives to be ranked. Hence, no matter of the s\s to be reconsidered in the design process, the decisional matrix $\underline{\underline{M}}$, at each running step, suggests, throughout the ranking vector, on which parameters to intervene on by doing what:

Tab. 1 Decisional Matrix

	To increase	To decrease	nothing
	W_i	W_d	W_n

$\underline{\underline{M}}$=

X_1	L_{i1}	L_{d1}	L_{n1}
…	…	…	…
X_m	L_{im}	L_{dm}	L_{nm}

The $\underline{W}$ weight vector is assumed to be unitary.

The novelty of the proposed method stays in the $\underline{\underline{M}}$ matrix fulfilment. Each L_{kj} index is obtained by strictly applying the AHP: three (mxm) matrices of pairwise comparison are created to deal with each $\underline{\underline{M}}$ column computation. According to the multi-criteria decisional method selected, to compare alternatives in pair is definitely easier than giving – directly- their absolute ranking according to a specified aspect. Hence each alternative is compared in pair with the others and a final absolute ranking is obtained by the following procedure [13], [14]:

Tab. 2 Matrix of pairwise comparison

$\underline{\underline{P}}$=

	X_1	**…**	**X_m**
X_1	$p_{1/1}$	$p_{1/\ldots}$	$p_{1/m}$
…	…	…	…
X_m	$P_{m/1}$	$p_{m/\ldots}$	$p_{m/m}$

$$\mathrm{Eig}(\max \lambda(\underline{\underline{P}}))= \underline{L}_j \qquad j=1,\ldots,3 \tag{3}$$

Each of the three $\underline{\underline{P}}$ matrices, in the classic AHP approach, is filled by the experts thanks to their expertise, by giving qualitative rankings. In order to automate the matrices filling, in the current work dedicated control blocks have been implemented to obtain the generic $L_{kj\ \mathrm{index}}$. As the control variables can be identified in the process goals, they have been assumed as inputs to judge the action to be applied to consistently converge. Hence, constraints satisfaction and criteria optimization are the control variables of the matrices of pairwise comparison fulfilment.
Each parameter couple, according to a fixed intervention in (1) is evaluated in terms of (Tab. 3):

Tab. 3 control variables for the $\underline{\underline{P}}$ matrix elements generation

$\Delta\underline{C}$	=	Sum of ratios of criteria improving versus no of criteria the two parameter is involved in
$\Delta\underline{V}$	=	Sum of ratio of no. of violated constraints versus no of constraints the two parameter is involved in
N_c	=	Ratio of no. of improved criteria versus criteria involved by each parameter
N_v	=	Ratio of no. of violated constraints versus constraints involved by each parameter
N_p	=	Ratio of no. of parameters involved in the violated constraints by each parameter versus no. of parameters
N_i	=	Ratio of no. of interventions already suggested on the two parameters

The control law is implemented by applying techniques from the approximate reasoning domain; in particular, the Fuzzy Logic theory turned out to be well suited to translate qualitative causal dependencies into a numerical formulation, without loosing the multivariate features the human reasoning naturally has. The $\underline{\underline{P}}$ matrix, in fact, is the core of the modellization of the system engineer's reasoning behaviour to lead the project to converge [15], [16].
By applying such an approach, the decisional process is completely visible and tuneable whenever desired by the user.

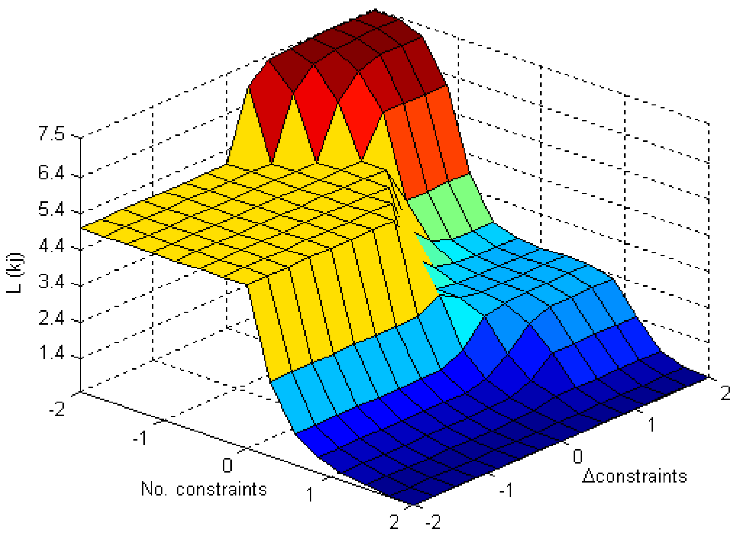

Fig. 1 Control law model for the L_{kj} definition in a bi-variate domain

Fig. 1 shows the trend of the L_{kj} controlled index according to two inputs of the input set in Tab. 3. Given a fixed action of (1), the more negative the no. of constraints is the more the selected intervention on the jth-parameter would worsen the constraint violation scenario; the more positive the Δconstraints is, the more the action on the kth-parameter would increase the margin for the whole constraint set satisfaction is high with respect to the jth-parameter.
By applying the (2) to each element of (1) the $\underline{\underline{M}}$ decisional matrix is obtained: the higher the L_{kj} index is the stronger the jth-action on the kth-parameter is suggested, to optimize the $\underline{C}$ set consistently with the $\underline{h}$, $\underline{G}$, $\underline{V}$ constraint sets.
Hence, the system engineer has a user-friendly tool to evaluate whether to apply the suggested action-parameter couple or not. As each parameter value is strictly related to an actual device, that implies specific values for some other related $\underline{X}$ elements, the suggested action is, actually a suggested device type change.
A further enhancement is available, in terms of simultaneous actions to be done on different parameters.
In the former process, each possible action is evaluated by reducing the multivariate space of variables to those directly involved with the visited parameters. The remaining $\underline{X}$ elements are considered fixed at the starting configuration values.
That means that, by the inputs of the control box represent, somehow, the component of Jacobian of the $\underline{C}$ and $\underline{V}$ vectors, in the currently visited parameter dimension.
According to a minimization process, the more the following relationships are satisfied, the more the search direction to consistently converge is valid:

$$\underline{J}_C<0$$
$$\underline{J}_G=0 \qquad (4)$$

According to (3), a pool of maximum simultaneous action is obtained by identifying, among the $\underline{\underline{M}}$ elements possible combinations, those that best satisfy the (3).
A stop criterion is imposed as, if the user does not stop the manager at each decisional step, the manager keeps solving the decisional nodes assuming the suggested parameter-actions suggested couples being applied. Two criteria are checked: the relative convergence in terms of criteria vector optimization between two consecutive decisional steps, according to a prefixed threshold, and some already visited decisional loop further activation.
At the time being, the *Manager* keeps track of decisions within five former steps and check for that action patterns in the process evolution: whenever such a pattern has been already applied to the same system configuration, the Manager stops tracking the process, as it fell in a decisional loop.
The current development is focused on solve the decisional tree such an event opens in terms of:

- some constraints relaxation
- some new alternatives (in terms of devices) insertion

The Evolutionary Algorithms approach

In order to validate the proposed approach, a comparison has been done with a completely transparent approach, based on the Evolutionary Algorithms [17].
A Multi Objective Genetic Algorithms (MOGA) as been assumed and the fitness has been based on the number of dominated chromosomes:

$$f = d - \alpha(\Delta c) \tag{5}$$

where:

d	=	No. of dominated individuals in the criterion space
α	=	Penalty
Δc	=	Normalized sum of margin of violated constraints

Both binary and real encoding have been applied [5].
The population size is maintained fixed and the mating for the mutation and the crossover operations is based on the fitness value.
Crossover operator is not completely random has parents are forced to belongs either both to the current Paretian subset, or to the Paretian subset and to the no-Paretian subset respectively. This is done in order to preserve the goodness of the current population and to spread out the next population to maintain the global variable domain mapping. Moreover, the current Paretian individuals are maintained in the final pool for the selection of the next population.
The criterion for stopping the population generation is based on a threshold for the relative variation of the Euclidean distance of the best individual in the current and the former generation from the utopic point:

$$D = \frac{\left|\underline{x}_i - \underline{x}_{i-1}\right|}{\left|\underline{x}_{i-1}\right|} \le Thr \tag{6}$$

SIMULATIONS RESULTS

As an example, results obtained by applying both the proposed method and the MOGA approach are presented. In particular a mission to Mars is assumed to be preliminarily designed with the following added constraints and selected criteria:

$$\begin{array}{lll} \theta & > & 7^\circ \\ T_{sa} & < & 400^\circ K \\ M_{gross} & < & 1000\ Kg \\ P_{required} & < & 1000\ W \end{array}$$

$$\min \begin{cases} M_{gross} \\ P_{required} \end{cases} \tag{7}$$

Further fixed inputs are:

- p\l characteristics (mass=200Kg, Power demand=100W)
- Thermal, AOCS, structural, operations s\s design
- Final Mars orbit parameters

Alternatives considered at the system levels are related only to the propulsion subsystem options as both the chemical and electric solution for the transfer are taken into account.

According to (1), the following alternatives in terms of possible devices have been considered:

Tab. 4 Alternative device considered

Solar Cells	8
Batteries	21
Antennas	16
Chemical Thrusters	13
Electric Thrusters	16

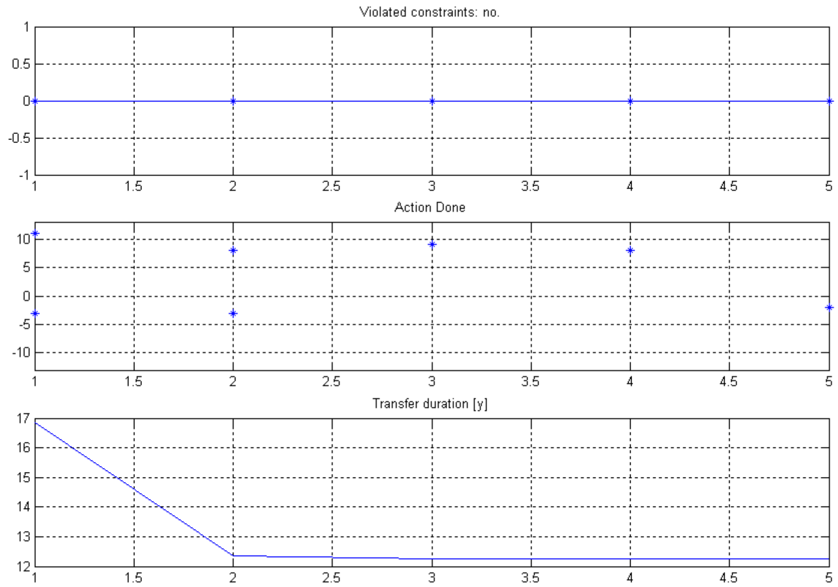

Fig. 2 Manager behaviour: Constraints violation, action done and transfer time versus decisional steps

Fig. 2 shows the Manager decisional behaviour: the first guess configuration has been selected from a randomly generated pool, based on the best behaviour in terms of consistency and criteria satisfaction. Actions suggested and applied by the manager, according to the given parameter domain are reported in the second plot of the figure. Up to five simultaneously actions can be applied. As no violations are present, the Manager is focused on optimizing the configuration according to the criteria vector <u>C</u>, hence the parameters reported in the third graph of Fig. 2 are managed as follows:

Step1:

ACTIONS: 1. INCREASE Frequency (TT&C) From: 2.50 [GHz] To: 2.54 [GHz]
2. INCREASE SA Degradation (SA) From: 1.20 [%/y] To: 1.61 [%/y]
3. INCREASE Battery Spec En (Batt) From: 42.00 [Wh/Kg] To: 43.39 [Wh/Kg]

Step: 2

ACTIONS: 1. DECREASE EbN0 (TTC) From: 4.00 [dB] To: 2.70 [dB]
2. DECREASE Battery En Den (Batt) From: 76.89 [Wh/L] To: 74.65 [Wh/L]

Step: 3

ACTIONS: 1. INCREASE Battery Spec En (Batt) From: 50.40 [Wh/Kg] To: 50.90

[Wh/Kg]

Step: 4

ACTIONS: 1. INCREASE Battery Spec En(Batt) From: 50.90 [Wh/Kg] To: 52.00 [Wh/Kg]

Step: 5

ACTIONS: 1. INCREASE Battery Spec En (Batt) From: 52.00 [Wh/Kg] To: 52.80 [Wh/Kg]

Step: 6

ACTIONS: 1. INCREASE Battery En Dens (Batt) From: 78.80 [Wh/L] To: 82.80 [Wh/L]

The first step is focused on lowering as far as possible the power demand because of the electric propulsion. Moreover, by intervening on the battery cells a mass reduction is looked for, balanced by the annual degradation increase of the SA, that involve a SA efficiency increase. As clearly visible in Fig. 3, Fig. 6, Fig. 7, the power demand drastically lowers in within the first two steps from 850W to 693.2W, while the mass slightly increases from 751Kg to 765 Kg. The next steps focus both on mass and power reduction, by mainly intervening on the power storage s\s, as depicted in Fig. 4, Fig. 5.

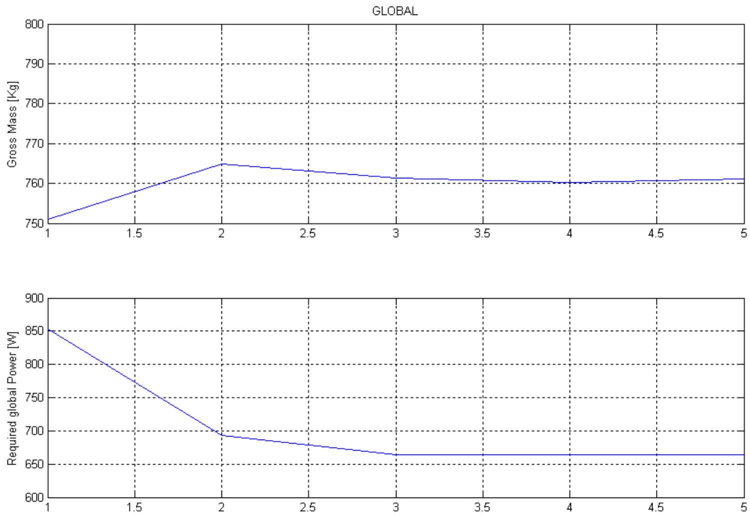

Fig. 3 Criteria trends versus decisional steps

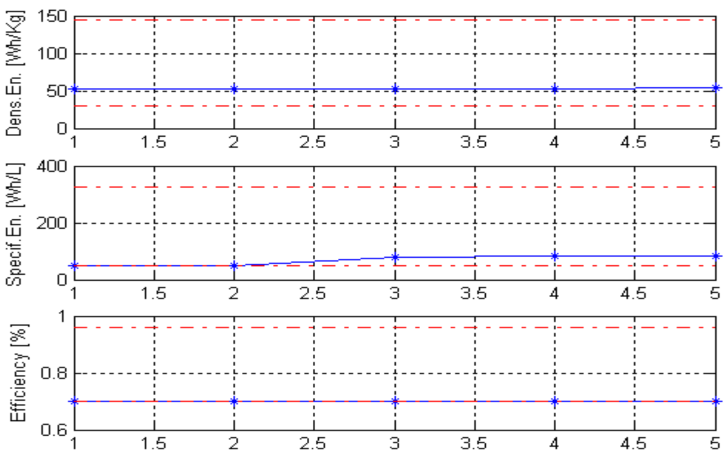

Fig. 4 Battery X free parameters management versus decisional steps: (in red: min-max thresholds)

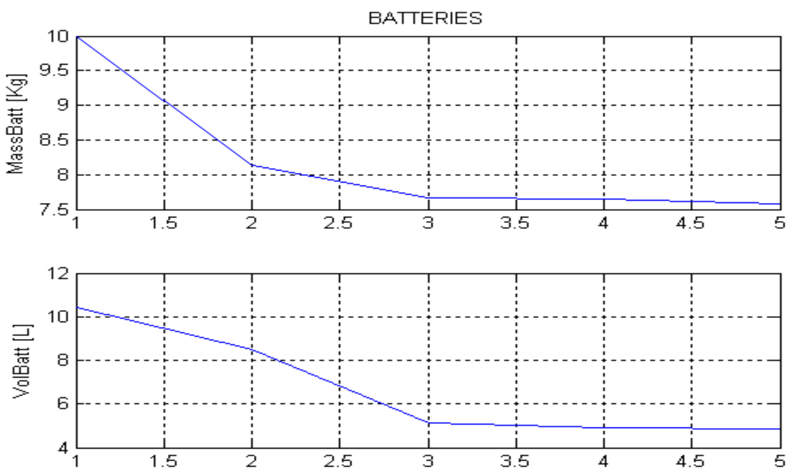

Fig. 5 Battery s\s design constraints trends versus decisional steps

Fig. 6, Fig. 7 show the comparisons between the proposed step-by step approach and the GAs applied to the same multi-criteria decisional process, by assuming a discrete and a continuous variable domain, respectively. In the given simulation results, the binary coding has been applied.
It is possible to notice from Fig. 6, that the proposed approach definitely converge towards the Pareto optimum, towards the utopic point. Moreover, while the GA needed 25 generation before converging, the Manager required only 5 steps. The deviation from the Pareto optimum is:

ΔM	12.8Kg	1.71%
ΔP	28.5 W	4.48%

(8)

That results are obviously preliminary and to be surely refined. At the time being the manager stops searching whenever the ratio between benefits and drawbacks within two consecutive steps in criteria optimization is lower than one, according to a consistent scenario. The work on going is focused on augmenting the convergence towards the Pareto front, by maintaining the step number low.

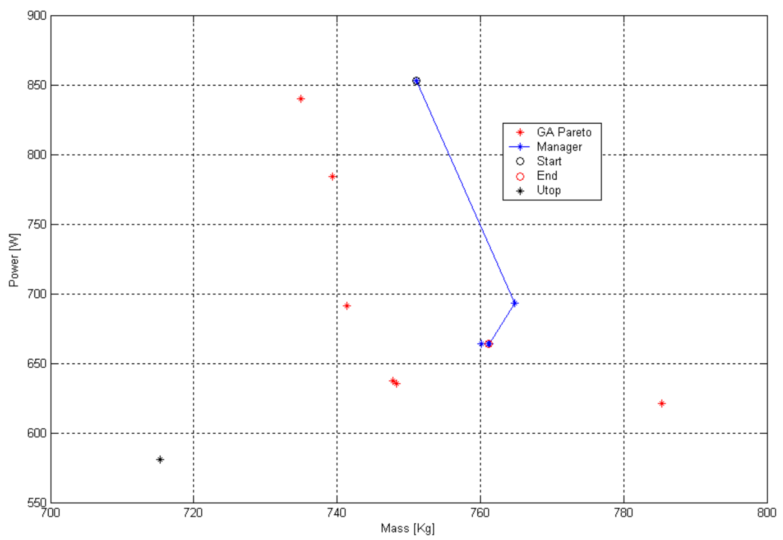

Fig. 6 Manager decisional step and discrete GAs Pareto front in the criterion space comparison

Fig. 7 highlights the high dependence of the final configuration from the variable domain width. The GA on a continuous domain definitely improves the final Pareto front in terms of final preliminary configuration.

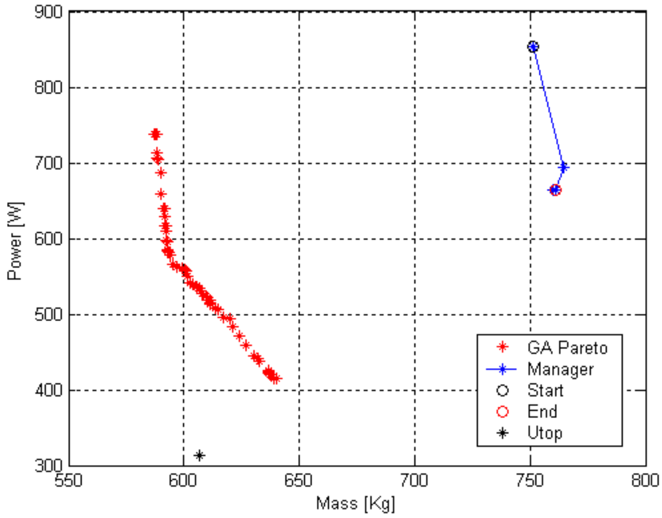

Fig. 7 Manager decisional step and continuous GAs Pareto front in the criterion space comparison

CONCLUSIONS

The paper proposes a method to lead the decisional process towards a consistent optimized solution, in a concurrent design environment, specifically applied to the space system design. The main aim, to reduce time dedicated to iterations and to support the system engineer in solving designing bottlenecks while keeping improving the system design, is achieved. The main tools applied come from the multi-criteria decision, making field together with the approximate reasoning.

The approach is definitely domain independent and can be easily configured, off-line by the user. In order to validate the method, comparisons have been done by applying different Evolutionary Algorithms approaches. Results show the method correctly moves towards the Pareto front, consistently with the constraints scenario, definitely quick to be run in a concurrent design session. .

REFERENCES

[1] M.Bandecchi, S.Melton, F.Ongaro,"*Concurrent Engineering Applied to Space Mission Assessment and Design*", ESA Bulletin 99,1999

[2] http://www.cc.gatech.edu/computing/SW_Eng/people/Phd/ce.html

[3] R.Fuller, C.Carlsson," Fuzzy Multiple Criteria Decision-Making: Recent Developments", *Fuzzy Sets and Fuzzy Systems*, 78, pp.139-153, 1996

[4] R.R.Yager, "Multiple Objective Decision-Making Using Fuzzy Sets", *International Journal of Man-Machine Studies*, nr.9, pp.375-382, 1977

[5] C.Coello,A.D. Christiansen, "An Approach to Multi-Objective Optimization Using Genetic Algorithms", *Intelligent Engineering Systems Through Artificial Neural Networks*, vol.5, pp.411-416, November 1995

[6] H.Eschenauer J.Koski A. Osyczka, "Multi-criteria Design Optimization", *Springer-Verlag*, 1990

[7] E.Triantophyllou "Multi Criteria Decision-Making: An operations Research Approach", *Encyclopedia of Electrical and Electronics Engineering*,J.G.Webster, John Wiley & Sons Ed., N.Y. vol 15 pp.175-186, 1998

[8] A.De Monti, P.de Toro, B.Franke, I.Omann, S.Stagl, "Criteria for quality assessment of MCDA Methods", *Third biannual Conference of the European Society for Ecological Economics*,Vienna May 3-6, 2000

[9] A.Fukunaga, S.Chien,D.Mutz, R.Sherwood, A.Stechert,"Automating the Process of Optimization in Spacecraft Design", *Proceedings of IEEE Aerospace Conference*, Snowmass,CO,1997

[10] A.Fukunaga, A.Stechert,S.Chien "Towards a self-configuring Optimization System for Spacecraft Design ", *Proceedings of the I-Sairas Conference*, Tokyo,Japan,1997

[11] W.J.Larson J.R.Wertz, "Space Mission Analysis and Design" *Space Technology Library*,1996

[12] P.Fortescue, J.Stark, " Spacecraft Systems Engineering", *John Wiley & Sons*, 1990

[13] T.L.Saaty, "A Scaling Method for Priorities in Hierarchical Structures" *Journal of Mathematical Psychology*, 15(3), pgg.234-281,1977

[14] E.Triantophyllou, F.A.Lootsma, "On the evaluation and application of different scales for quantifying pairwise comparisons in fuzzy sets", *Journal of Multi-Criteria Decision Analysis*, vol.3 no.3 pp.133-155,1994

[15] G.J.Klir, B.Yuan, "Fuzzy Sets and Fuzzy Logic", *Prentice Hall PTR*,New Jersey, 1995

[16] L.A.Zadeh, "Fuzzy Sets", *Information and Control*, no.8, pp.338-353, 1965

[17] Zbigniew Michalewicz, "*Genetic Algorithm+Data Structure=Evolutionary Programs*", Springer-Verlag 1992