Proceeding of the 7th International Symposium on Artificial Intelligence, Robotics and Automation in Space:
i-SAIRAS 2003, NARA, Japan, May 19-23, 2003

A MADM APPROACH TOWARDS SPACE SYSTEM DESIGN AUTOMATION BY A FUZZY LOGIC-BASED ANALYTIC HIERARCHICAL PROCESS

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Keywords: Space Systems, Design Process Automation, Multi-Criteria Decision-Making, Fuzzy Logic, Analytic Hierarchical Process (AHP)

Abstract

This paper proposes a method to support the space system preliminary design through a Multi-Criteria Decision Making approach based on the Analytic Hierarchical Process mixed with methodologies coming from the Approximate Reasoning domain.
The method here presented is focused on saving analysts' time and effort and in giving them an already pruned and ranked solution space for the preliminary space system configuration to be further analysed - consistently with the current trend of applying *collaborative* and *concurrent engineering* approaches to the space system design process too.
From a theoretical point of view, input data imprecision and qualitative dependencies among involved quantities, normally managed by the designers' expertise, have been modelled by applying the interval algebra rules and the Fuzzy Logic Theory (FL) respectively: in particular, the FL 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.
Moreover, a Multi-Attribute-Decision-Making approach has been select to deal with the discrete variable domain and numerous criteria to be considered to search for the final configuration. Specifically, the Analytic Hierarchical Process method is applied to decompose the complexity of the problem.
Simulation results have been carried out with good results: the algorithm gives an ordered set of possible preliminary configurations, the best always fitting with the real solution; moreover, the running time to obtain the solution set is definitely low ($O(10^3 s)$ for $O(10^2$ alternatives)).
A Multi-Objective Decision Making approach has been also implemented, in order to evaluate the proposed algorithm in terms of optimality. The ordered solutions obtained by applying the proposed method turned out to be sorted consistently to the distance from the optimum.

1. Introduction

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 stiffness, 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.

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.

To step forward the design process automation two main characteristics 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.

The first one is greatly answered by existing sophisticated software packages based on well-known mathematical models (e.g. NASTRAN, STK, IMAT, MEC, MINITAN, IGG, ADF, PCAT 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 first attempt device) rather than in an other one (i.e. communication device), by forcing the design direction.

In order to automate the subsystem selection that human inference method must be captured.

The pruning, changing and forcing processes can be classified, from a theoretical point of view, as a constrained Multi-Criteria Analysis: a balance between constrains 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.

A first step to improve the multi-disciplinary design efficiency is represented by the C*oncurrent Engineering* approach, already applied in several technical fields but space. A first successful attempt is on going at the European Space Research and Technology Center of the European Space Agency with the *Concurrent Design Facility* [1]. A CE approach is also assumed at JPL (Project Design Center Facilities). The CE 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.

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 [2,3,4].

Concerning with space system design applications, the Jet Propulsion Laboratory implemented OASIS (Optimization Assistant) [5, 6], 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.

The SCOUT, another spacecraft design tool, applies the Genetic Algorithms techniques to a fitness function that represent the whole cost of the mission [7].

In [8] the author devotes the selection of a space propulsion system to a fuzzy decision-maker through a multi-level architecture. Starting from that work the presented method selected the Fuzzy Logic Theory to capture the human knowledge and behaviour in taking decisions [3, 4, 9, 10]. Human reasoning is made of logic based on proposition relationships which involves qualitative *predicates* defined on sets with undefined boundaries: different qualitative propositions (e.g. "*x is low*", *x is high*") are admitted to be true at the same time, by giving them a sort of degree of truth, and the related final decisions (e.g. then "*y is bad"*, "*y is good"*) are driven by considering in parallel all the valid truth degrees of the *premises*. To simulate all that, the dycotomic concept *true-false* must be overcome.

The Fuzzy Logic permits to do that by managing qualitative relationships with a mathematical formulation: the truth level of a given assertion can be converted into any numerical value in the (0,1) range by a so called *membership function*; normally clashing propositions (e.g. "*x is low*", *x is high*"), are admitted to be contemporarily activated with different truth level represented by their related *membership function* values and logic relationships are managed by analytic settled formulations-

In the followings, the MCDM proposed method is clarified and the simulation results are discussed.

2. The proposed MADM approach

As already mentioned, the problem to simulate the human decisional behaviour is here faced by modelling it as a Multi-Criteria Decision-Making problem. The core of the presented method makes use of the FLC architecture to build a bridge between the spacecraft designers' ranking of the possible alternative configurations – based on approximate reasoning – and a rigorous mathematical formulation, needed to automate the process.

According to the Decision-Making branch, two different approaches are proposed: the Multi-Attribute (MADM) and the Multi-Objective

(MODM) Decision-Making depending on whether the number of options is finite and predetermined or not [11,12,13].

Here a Multi-Attribute approach is proposed as better fitting the spacecraft design process as actual solutions for each on board subsystem device are limited and a finite number of optional configurations can be settled to answer a space mission. The MODM approach could be useful to address improvements in each subsystem field as, by finding the optimum it suggests which technical parameters the researchers should change and how to obtain better device performance. A comparison between results from the two methods has been carried on to judge the proposed method solutions with respect to optimality.

Within the current work, the $\underline{Y}$ vector represents the feasible spacecraft configuration space generated by all possible combinations of each Z_j sub-space element (j=1,...,p=on-board subsystems); the generic Z_j sub-space represent the j^{th} on-board subsystem hyper-space of the related technical parameter sub-vector $\underline{x}_j \supset \underline{X}$.

In a MADM approach, the $\underline{Z}|_j(\underline{X},\underline{R})$ vector represents the set of actual devices to accomplish the j^{th} sub-system tasks. Hence, the $\underline{Y}(\underline{Z}(\underline{X}, \underline{R}))$ is a (qx1) vector with:

$$q = \prod_{i=1}^{p} n(i) \tag{1}$$

$n|_j(i)$=number of considered alternative devices for the j^{th} subsystem

As already highlighted, the overall goal of a space mission is the product return in a reliable context.

Hence, starting from a given set of requirements coming from the payload product return maximization, each $\underline{Y}(\underline{Z}(\underline{X}, \underline{R}))$ can be ranked according to the following sub-criteria vector elements:

$$\underline{G}=[M\ P\ C\ R] \tag{2}$$

Where:

M	=	S\c wet mass (Kg)
P	=	S\c power demand (W)
C	=	S\c cost (M$)
R	=	S\c reliability

In particular, low wet mass, low required power, low costs and high reliability are aimed.

The general architecture of a MADM approach sets a decisional matrix the elements of which represent the degree of satisfaction of each feasible option according to each selected criterion.

The available methods differ in the way those elements are computed and elaborated to obtain a global final index to rank the $\underline{Y}(\underline{Z}(\underline{X}, \underline{R}))$ elements.

As the current decisional problem is quite articulated and a multi-levelled criteria net has to be created to simulated the human reasoning, the so called Analytic Hierarchical Process (AHP) has been selected to be faithful to the real process as much as possible [12,14,15].

According to that theory, a hierarchical decomposition of the main criterion is performed by filling a Decisional Matrix. As it is shown in tab.1, the second criteria level can be further split into a third and a fourth level that collect several children-sub-criteria related to each i^{th} on-board subsystem (with p= no. of considered on-board subsystems). The last sets of q levels represent the options to be evaluated, that is, the spacecraft feasible configurations.

The decisional decomposition of tab.1 has been set in order to better simulate the human way of evaluating alternatives having a main general criterion: the problem is decomposed until the option space is reached. The q levels are filled by mapping preferences expressed by qualitative expressions into numbers through a selected scale [15]. A fixed weight vector is given to each of the four criteria levels to define the relative criteria importance with respect to their parent criterion and, by computing a pre-selected Utility Function; an index of global ranking is given to each option, finally obtaining the $\underline{L}_{glob}(\underline{Y})$ sorting vector.

The most common selected Utility Function is a simple weighted sum for each level of the former decisional matrix:

$$L_{s-1,j} = \left\{ \sum_{i=1}^{m} w_i L_{s,ij}(x_1,\dots,x_k,r_1,\dots,r_v) \right\} \tag{3}$$

with:

L	=	Preference index
s	=	Generic decisional matrix level
j	=	Generic feasible option j=1,…,$q=\prod_{ii=1}^{p} n(ii)$
n(ii)	=	Number of considered alternative device for the ii-th subsystem
p	=	Number of on board subsystems
m	=	s-th level criteria vector dimension
$\underline{w}$	=	Weight vector for the parent criteria current level
$\underline{L}_{s,j}$	=	Preference index vector for the s-th level according to the j-th option/criterion with respect to the upper level criteria vector

As to give an absolute evaluation of each option with respect to each parent criterion is quite hard, Saaty suggested to fill a matrix of pairwise comparison of the available options according to each parent criterion and to compute its right principal eigenvector to obtain a vector to be filled in the columns of the decisional matrix [13,14]:

$\underline{O|_i}$=eig(max(λ(B_i))

$$B_i = \begin{array}{c} \\ Y_1 \\ \dots \\ Y_j \\ \dots \\ Y_q \end{array} \begin{array}{c} \begin{array}{ccccc} Y_1 & \dots & Y_j & \dots & Y_q \end{array} \\ \begin{bmatrix} 1 & \dots & o_{1/j} & \dots & o_{1/q} \\ \dots & \dots & \dots & \dots & \dots \\ o_{j/1} & \dots & 1 & \dots & o_{j/q} \\ \dots & \dots & \dots & \dots & \dots \\ o_{q/1} & \dots & o_{q/j} & \dots & 1 \end{bmatrix} \end{array} \qquad i=1,...,m \qquad (4)$$

However, a user must give those matrix elements and this represents a gap to implement an autonomous decisional tool. To overcome the former problem, this work maintains an AHP approach till the last criterion decomposition level (fourth in tab.1); the remaining option level preference index is computed by dedicated Fuzzy Logic control (FCL) blocks in order to adaptively translate qualitative preference propositions in a mathematical formulation fundamental to compute the related Utility Function. The generation of the $\underline{w}$ and $\underline{L}_{s,j}$ vectors of eq.3 are explained separately in the following sections. In particular, the decisional matrix of tab.1 is differently interpreted from the weight and the preference index vector computation point of view.

2.1. The criteria weight vector

Usually, the user -as input -sets the w criteria weight vector related to each level that remains fixed throughout the process: hence, the ranking of the $\underline{G}$ elements according to their importance is stiff and highly user-dependent. This might be considered an adjoined degree of freedom as well as a constraint: some problems, in fact, could be better modelled with variable weights according to the related $\underline{G}$ element values. In spacecraft design, for example, an *a priori* fixed hierarchy between the gross mass and the required power criteria cannot be set as both can make a solution unfeasible; they also cannot be considered as *equal-weighted*: within each visited subsystem alternative combination both over-loaded and over-powered solutions should be highlighted: the worst criterion value should drive the combination position definition in the final global ranking of the whole feasible spacecraft configurations. On the contrary, it would not make sense to assume variable weights for the criteria related to no-strictly technical aspects, say the costs and the reliability: they are maintained *combination-free*, in the sense that their importance can correctly be considered to-be-defined by the spacecraft commissioner.

Tab.2 shows the further decomposition applied to tab.1 to obtain a variable weight vector for the criteria; the matrix is split in two different parts: the first one stops to the innermost criteria level decomposition, while the second part contains the feasible options too.

In particular, the criteria decisional sub-matrix of the technical criteria is decomposed until a fourth level that represents the single on-board subsystems mass and power criteria.

With the former architecture, the two following vectors are just asked to the user:

$$\underline{w}_{PR}=[\ w_{T'}\ \ w_{NT'}] \qquad \underline{w}_{NT}=[\ w_c\ \ w_R] \qquad (5a – 5b)$$

while the:

$$\underline{w}_{T}=[\ w_m\ \ w_p] \qquad (5c)$$

is automatically computed by the expert module of the algorithm.

The fourth level weight vector $\underline{w}_{AHP}$(2xp) is computed by applying the AHP; a matrix of pairwise comparison (one for each technical criterion) is filled by giving, within each technical criterion, the relative importance of each on-board subsystem (e.g. according to the mass criterion the thermal control subsystem mass is *less important* than the propulsion subsystem mass, etc).

After some simulations, the exponential scale [13, 15] revealed to be the best choice to map the qualitative space into the numerical one.

Actually, the matrices of pairwise comparison to be settled are more than two, as there exist particular alternative device combinations that invert the nominal subsystem relative importance according to a fixed criterion (e.g. while a photovoltaic solution for the power supply unit has a mass less important than a chemical propulsion module, the same power supply becomes relevant in terms of mass whenever correlated to an electric propulsion module). Moreover, dealing with the power criterion, its pairwise comparison matrix cannot have a fixed dimension as some on-board subsystems –in the currently visited combination- might not require any power supply.

The second part of the weight decisional matrix is strictly related to the possible combinations of the subsystem alternative devices and its element computation represents the core of the proposed method. The $\underline{w}$(2xpxq) matrix is computed by several Fuzzy Logic blocks, one for each on board subsystem, devoted to model the qualitative dependencies between some selected technical parameters of the visited device (a $\underline{X}$ and $\underline{R}$ sub-vector) and the related human score according to the current criterion (e.g. *“ IF the solar cell efficiency is high and the density is low THEN a photovoltaic power subsystem is light”; “ IF the antenna diameter is low and the transmission frequency is low THEN the TTC power demand is quite high”*, etc).

A Mamdani approach is applied, as no quantitative relationship is available between inputs and output to be mapped by a Sugeno scheme. The membership shapes and numbers, as well as the base of rules for the inference motor have been set trying to map both available data and system engineers' expertise. The outputs of each Fuzzy block are filled in the second decisional matrix that is variable depending on the visited y_i. A backward procedure is, then applied, for each visited $\underline{Y}$ element, to obtain the third level weight vector $[w_m \; w_p]$:

$$w_{T,i}(j) = \sum_{ii=1}^{p} w_{AHP,j}(i,ii) w(ii,i,j)$$

$$j=1,\dots,q \quad i=1,2 \quad ii=1,...,p \qquad (6)$$

By applying twice the eq.3, to the third level first and, consequently, to the second level of the matrix in tab.2 the final score is obtained:

- levels 3→2:

$$L_{2T}(y_j) = \sum_{i=1}^{2} w_{T,ij} \cdot L_i(y_j) \qquad (7a)$$

- levels 2→1:

$$L_{glob}(y_j) = \left\{ w_{NT'} \sum_{i=1}^{2} w_{NT,i} \cdot L_{NT,i+2}(y_j) + w_{T'} L_2(y_j) \right\}$$

$$j=1,..,q \qquad (7b)$$

2.2. The Criteria Preference Index

In the present paragraph, the fulfillment of the $\underline{\underline{L}}$(qxm) preference index matrix (see eqs.7) is clarified. The former matrix elements represent the goodness of a particular subsystem alternative device combination in satisfying the $\underline{G}$ criteria vector of eq.2, hence the decisional matrix of tab.1 is structured as presented in tab.3.

The former indexes are obtained by, firstly, sizing each q combination according to the $\underline{C}(\underline{X}, \underline{R})$ and the $\underline{h}(\underline{X}, \underline{R})$ vector expressions for equalities and inequality constraints and, consequently, by ranking them with respect to the obtained i^{th} criterion space. That last step is necessary whenever dealing with multi-dimensional problems that also present a greatly different order of magnitude both for the ranges they can vary in and with respect to the quantities themselves.

The sizing process has to manage, mainly two problems: the uncertainty intrinsic in the technical quantities related to each device that is not yet sized, and the definition of the most sizing phase within the whole mission horizon.

To answer the first problem, each $\underline{X}$ element has been represented by two intervals, defined by the most likely and by the largest likely values, respectively (MLV and LLV). A trapezoidal fuzzy membership has been associated to those intervals to represent the degree of satisfaction of each condition in between the two. That way of dealing has been already applied to the space component design – in particular the propulsion unit- with success by Hardy [11].

The introduced interval representation obliges to manage the whole sizing process with the interval analysis rules [16]. Therefore, the $\underline{G}$ vector becomes a (mx4) matrix as well as the final $\underline{L}_{glob}(\underline{Y})$ index vector and the last vector rows do not define directly the best subsystem alternative combination as they represent fuzzy sets that might overlap each other's, as shown in fig.3.

The fuzzy solution space is de-fuzzyfied by applying two triangular memberships that translate the closeness of each solution to the best and to the worst absolute score into a crisp ordering of the feasible configurations by giving a final $\underline{U}(\underline{Y})$ voting vector [8].

According to the second item, in order to define the most stringent conditions the spacecraft has to operate into, the whole mission is split in three main phases, Earth Escape, Transfer and Capture Phases. Actually this is a simplification as the operative modes for a probe are, usually, more numerous.

To effectively define the most stringent phase, too many information are needed unknown in a preliminary phase. As only qualitative notions are available, the automatic selection is obtained by configuring a dedicated block based on a Fuzzy Logic Control loop: the higher the output k parameter is the most sizing the current phase is; the highest k detects the dimensioning phase, hence the mission parameter values to be considered for the sizing.

That choice makes the computation light and robust, as a small variation in inputs does not produce a high deviation in the output. Phases are evaluated in terms of thermal and power stresses, thus inputs include quantities such as the heat generated by all active subsystems, the mean distance from the sun, the planet albedo and its IR emission, the required temperature range and precision. At the state of the art, the considered solution space comes from taking into account devices for five of the on-board subsystems plus the launcher.

Models applied to design each of them are simple and can be easily found in the related literature. [17, 18]

3. The MODM Approach

A Multi-Objective decision Making approach has been selected to analyze the proposed method behaviour in terms of optimality for a sub-space of the $\underline{G}$ vector given in eq.2.

The obtainable solution, as the $\underline{X}$ vector is no more discrete, can represent no actual feasible configuration because of an $\underline{X}$* optimal vector with no correspondence with existing devices. Then, depending on the goal of the decision making process, this could represent both a benefit and a drawback. From the technology improvement point of view, it represents an advantage as it suggest the technical parameters the research ahs to work on to improve subsystem devices; from the design point of view it requires a further computation to find the closest $\underline{X}$ set that can be correlated to real available subsystem devices.

The first guideline in selecting a method to be applied to the current problem was to apply the less user-dependent one. Moreover, as the problem is no convex the weighted sum has been immediately discharged. For reasons coming from several parameters to be set before running the optimization other methods, available in literature for continuous constrained multi-objective optimization, have been discharged but the distance method.

The distance method – with an Euclidean metric - has been selected as it gives directly a single solution without any more choice to be done by the user; obviously, the drawback stays in the utopic point definition that is the demand level [2, 11].

Again, in order to be user independent, the demand level vector is filled with each single criterion optimum; the preference function devoted to scalarize the problem is:

$$L(\underline{X},\underline{R})=\left\{\sum_{i=1}^{m}(g_i g_{i,u}^{-1}-1)^2\right\}^{1/2} \qquad (8)$$

Where: $g_{i,u}$= optimum point for the single i^{th} criterion = i^{th} coordinate of the utopic point in the criterion space

The $\underline{G}$ vector dimensions is restricted to two, as only the technical criteria have been considered in order to verify the proposed variable weight algorithm.

The optimization problem is identical to that one stated for the MADM approach with the preference function of eq.8. Lower and upper bounds for the $\underline{X}$ vector elements are consistent with the MADM approach that is the correspondent domains map only the real technical device parameter values. Results obtained by the MODM and the MADM approaches underlined that the proposed method actually detects, as suggested spacecraft configuration, the closest to the local optimum found with the classic multi-objective procedure .

4. Simulation Results

To evaluate the proposed method, several comparisons have been done between simulation results and already designed, in flight and flown missions –such as Viking, Magellan, Mars Global Surveyor, Mars Express missions - in terms of criteria and subsystem device set [19,20].

In the followings results from the comparison with the planned to be launched in February 2003 European Mars Express Mission are discussed [21].

Fig. 2 shows the final ranking, according to the $\underline{G}$ vector, for the feasible configurations, starting from the initial 360 possible combination; fig.3 shows the criteria fuzzy sets for the suggested twenty-first configuration. Tabs.7-8 give the criteria values and the subsystem devices for the twenty-first and the nineteenth combinations that are the first and the second configurations suggested by the code.

It is possible to notice that the suggested configuration is near the actual value in terms of mass, while it is penalized, with respect to the real one by an increased power demand and cost. This is clearly due to the selection of an electric thruster that has a high power demand to work, and to the nuclear generator for the power supply, quite expensive. That choice has been done by the expert module as the non-technical weight has been settled to 0.25, that is, preference is given to technical criteria. According to that, the electric propulsion lowers drastically the fuel mass, compared with a chemical thruster solution, highly increasing the power demand. The second suggested configuration just proposes a different power supply solution, cheaper but a little bit heavier.

According to the MODM simulations, the ranking identified by the proposed algorithm turned out to maintain the same cardinality in terms of distance from the obtained utopic point. Hence, configurations turned out to be ordered according to the optimum point.

5. Conclusions

The paper has presented a method to automatically manage the multi-criteria decision making of spacecraft design obtaining a very preliminary configuration .The fuzzy logic theory has been used to implement the inference motor of linguistic dependencies, which drive the human behaviour in making choices. The code drastically lowers the time dedicated to achieve a preliminary design (100-3600s), reduces the search space for refined configurations, and gives a preliminary ranking of the configurations that are consistent with the constraint manifold.

The method is based on a MADM approach with a revisited AHP for the criteria weight vector computation.

The comparison with the MODM approach for continuous problems gave good correspondence in a simplified architecture of the problem.

Several simulations have been run to compare the results with already designed probes and they highlighted a good mapping of the real solutions for both the criteria and the subsystem sets. Discrepancies can be ascribed to the simplified models used for the sizing procedure.

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1	Product return													
2	**Wet Mass**						**Power Demand**						**Cost**	**Reliability**
3	m_1		…		m_p		p_1		…		P_p			
4	m_{11}	m_{12}	…	…	m_{p1}	m_{p2}	p_{11}	p_{12}	…	…	p_{p1}	p_{p2}		
Y_1	o_{11}	o_{21}	...	...	o_{p1}	$o_{p+1,1}$	$o_{p+2,1}$	$o_{p+3,1}$	...	...	$o_{2p,1}$	$o_{2p+1,1}$	$o_{2p+2,1}$	$o_{2p+3,1}$
...														
Y_q	o_{1q}	o_{2q}	...	...	o_{pq}	$o_{p+1,q}$	$o_{p+2,q}$	$o_{p+3,q}$	...	...	$o_{2p,q}$	$o_{2p+1,q}$	$o_{2p+2,q}$	$o_{2p+3,q}$

tab.1 Decisional Matrix decomposition: possible criteria architecture

1	**Product return**							
2	**Technical (w_T)**						**No-technical (w_{NT})**	
3	**Wet Mass (w_m)**			**Power Demand (w_p)**			**Cost (w_c)**	**Reliability(w_r)**
4	$m_1(w_{m1})$	…	$m_p(w_{mp})$	$P_1(w_{P1})$	…	$P_p(w_{Pp})$		

4	$m_1(w_{m1})$	…	$m_p(w_{mp})$	$P_1(w_{P1})$	…	$P_p(w_{Pp})$
Y_1	$w_{1,1m}$	...	$w_{1,pm}$	$w_{1,p1}$	...	$w_{1,Pp}$
...	...	...	...	...	...	...
Y_1	$w_{q,1m}$	...	$w_{q,pm}$	$w_{q,p1}$	...	$w_{q,Pp}$

tab.2 Decisional Matrix decomposition for the weight vector computation

	Product return			
	Technical		**No-technical**	
	Wet mass	Power demand	Cost	reliability
Configuration1	L_{1m}	L_{1p}	L_{1c}	L_{1R}
…	**…**	**…**	**…**	**…**
Configuration i	L_{im}	L_{ip}	Li_c	L_{iR}
…	**…**	**…**	**…**	**…**
Configuration q	L_{qm}	L_{qp}	L_{qc}	L_{qR}

tab.3 Decisional Matrix decomposition for the preference index computation

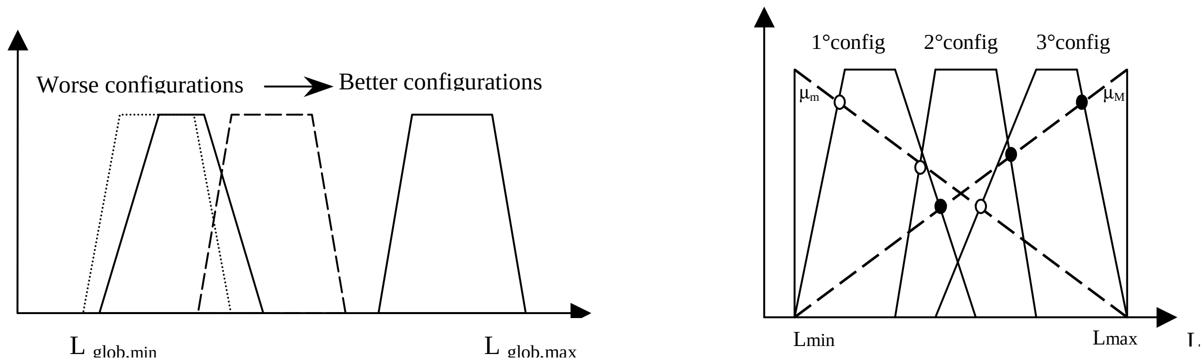

Fig.1 Uncertainty in the final solution ranking- final crisp score ordering memberships

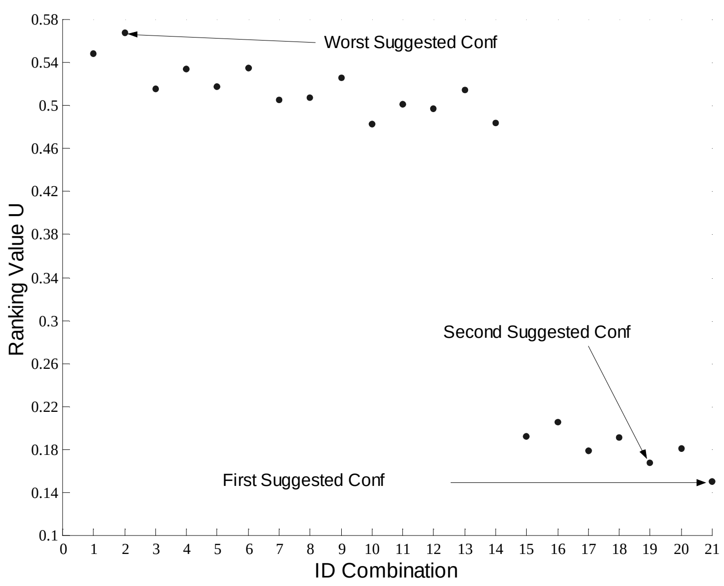

Fig.2 Final Configuration Ranking

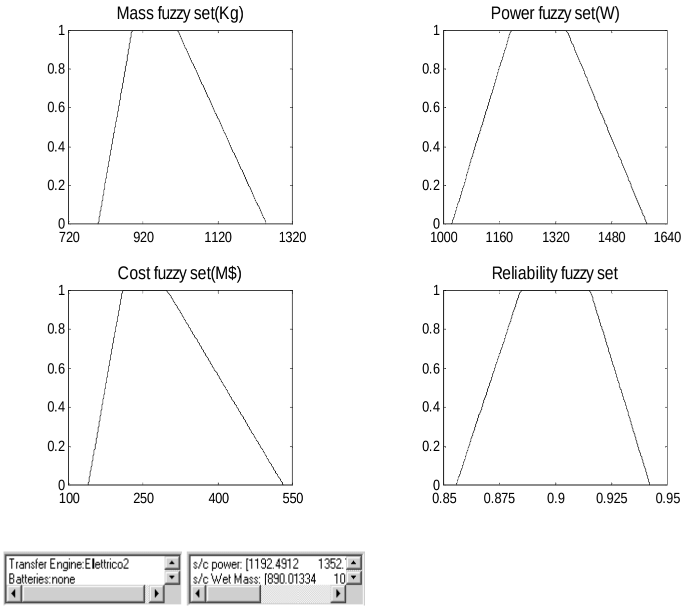

Fig.3 First Suggested Configuration: criteria values

Real Mars Express Mission			
Power	650W	**Propellant Mass**	427Kg
Wet Mass	927Kg	**Cost**	1M$
Reliability	-		

Tab.4 Real Mission Criteria Values

	Best Configuration (21st)		**19thConfiguration**	
	L.L.V.	M.L.V.	L.L.V.	M.L.V
Power	1023.48-1581.97W	1192.49-1352.74W	1026.17-1587.97W	1195.49-1357.23W
Wet Mass	799.22-1250.29Kg	890.01-1011.62Kg	860.39-1359.02Kg	945.29-1155.34Kg
Propellant Mass	435.85-730.13Kg	491.88-574.50Kg	469.21-793.63kg	522.43-656.12kg
Cost	139.21531.59M$	207.85-298.00M$	12.89-49.68M$	19.98-33.69M$
Reliability	0.852-0.945	0.881-0.922	0.8092-0.9128	0.8394-0.8841
$\mathbf{w_m}$		0.50986		0.49923
$\mathbf{w_P}$		0.57463		0.57288

Tab.5 Mars Express third level criteria: simulation results

Optimal Config.	**Optimal config. devices**	**Characteristics**		**19^{th} config. devices**	**Characteristics**	
		L.L.V	M.L.V		L.L.V	M.L.V
Passive Area	White Epoxy	$2m^2$		White Epoxy	$2m^2$	
Active Heat		0			-30J	
solar arrays Area		none	none	GaAs (Panels)	13.02-29.51(m^2)	16.25-23.48 (m^2)
Battery		None	none	Li-Ion	70-95Wh/Kg	80-90Wh/Kg
Other sources		15-18WKg^{-1}	10-22WKg^{-1}		none	none
Escape prop	Chemical	350-450N	300-500N	Chemical	500-600N	450-650N
Transfer Prop	Electric	0,09-.12 N	0.1-0.11 N	Electric	0,09-.12 N	0.1-0.11 N
TTC	Antenna3	2,9-3,2 m	3-3,1 m	Antenna3	2,9-3,2 m	3-3,1 m

Tab.6 Mars Express subsystem devices: simulation results