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GENERATION OF DESIGN SPACES AND TRADE OFF BETWEEN FEASIBLE EMBODIMENTS : THE BOOTSTRAP DESIGN PROBLEM

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ABSTRACT

The embodiment design of a Joule-Brayton cycle based air-conditioning system for aircrafts (bootstrap) proves to be a difficult design problem. This difficulty is due to the variability in the system environment. For instance, atmospheric conditions are very different according to the flight phases. This difficulty is also inherent to the complexity of the system. Therefore, the design space appears to be very broad and quite difficult to explore. Design choices are relating to continuous and discrete design variables while the Bootstrap effectiveness is extremely sensitive to most of these design variables. Designers investigate the design exploration space by considering several criteria and there is a lack of tools to support designer decisions at early stages of the design process. In this paper, a method is proposed to manage the compromise between various requirements.
A design digital tool based on the meta-heuristic of Genetic Algorithms has been developed to investigate the design problem. An exploration of the feasible design configurations is also proposed. The selection of Pareto optimal solutions is used to optimize choices among the design solutions of an air conditioning system.

Keywords: Design space exploration, embodiment design, trade off, decision support, genetic algorithm, Pareto optimal solutions, aeronautics

1 EMBODIMENT DESIGN OF COMPLEX SYSTEMS

1.1 Research context

Before the detail design phase, the embodiment design phase leads to the expression of a design configuration (product architecture) where main dimensions and components are chosen [1]. This design phase remains challenging in the context of industrial design departments. Indeed, at a stage where the knowledge is uncertain, most of existing computer aided tools are not suitable because they are based on models requiring the complete geometrical definition of the product. Designers do not have the tools to help them make decisions with regard to the choice of concepts whose performances they have to assess [2]. Therefore, many a priori choices are performed according to the expertise of the designer or of the company; these choices hide a great part of the potential solution space.

Embodiment design problem can be naturally expressed as mixed Constraint Satisfaction Problems [3] [4] which cannot be solved using classical mechanical simulation tools. In order to overcome this difficulty, embodiment design problems are tackled using several solving strategies.
An overview of these solving strategies is presented by Antonsson and Cagan [5]. Existing tools are mainly concerned with genetic algorithm, evolutionary programming, agent based systems and ensemblist methods [6]. These tools are developed for application relating to structural configuration in mechanics, micro system and robotic synthesis and chemical processes [7].

1.2 Application: air conditioning system design

Air conditioning systems for aircrafts are made of several complex components which interact to regulate air temperature and pressure in the aircraft cabin [8]. The air-conditioning system considered in this paper (see figure 1) is mainly made of two cross-flow plate-type heat exchangers (main and pre-cooling exchangers), one turbine and one compressor coupled together. Nozzles, valves and pipes are used to manage the air flow between these elements.

The air flowing through the cabin comes from the main compressor of one of the turbo reactors of the aircraft. This air flow (main air flow) goes through a precooling heat exchanger, a turbo machine (compressor, turbine, coupling shaft) and the main heat exchanger. Heat extracted from the main air flow is transferred to a ram air flow taken from the frontal surface of the aircraft. Due to the aircraft velocity, the ram air flows through the precooling and main heat exchangers. The temperature of the main air flow is regulated by taking cool air -from the outlet of the precooling heat exchanger (secondary air flow) and mixing it with cold air flow from the outlet of the turbine. The secondary air flow regulation is performed by a valve.

The two circuits (main air and ram air) cross each other in alternate layers inside the exchangers. Exchange surfaces are made of stacked fins. For each air circuit, the fins have to be chosen among 48 different standard shapes [9]. Since there are two exchangers, and two air circuit per exchanger, there are 5.3 millions (48^4) possible alternatives according to the choice of heat-transfer surfaces types.

Thanks to the discrete nature of some design variables and to the discernment precision of the others, the number of solution principles of the design problem can be assessed. For example, the dimensions of the precooling heat exchanger along “x” and “z” axes, which define the ram air inlet section. In order to facilitate the ram air flowing through the two exchangers, the equivalent dimensions of both heat exchangers are identical. The domains of the Lx and Ly dimensions range from one 0.01m to 0.5m. Their discernment precision has been defined by designers at 0.01m. Thus, the number of combinations of possible value domains is equal to 2,500.

The size of the global Bootstrap design problem has been assessed to approximately 10^{15} design configurations when considering all of the possible value combinations of the design variables. However, every design configuration does not correspond to a design solution. Every design configuration does not fit the design requirements and some design configurations do not work for some system environment configurations.

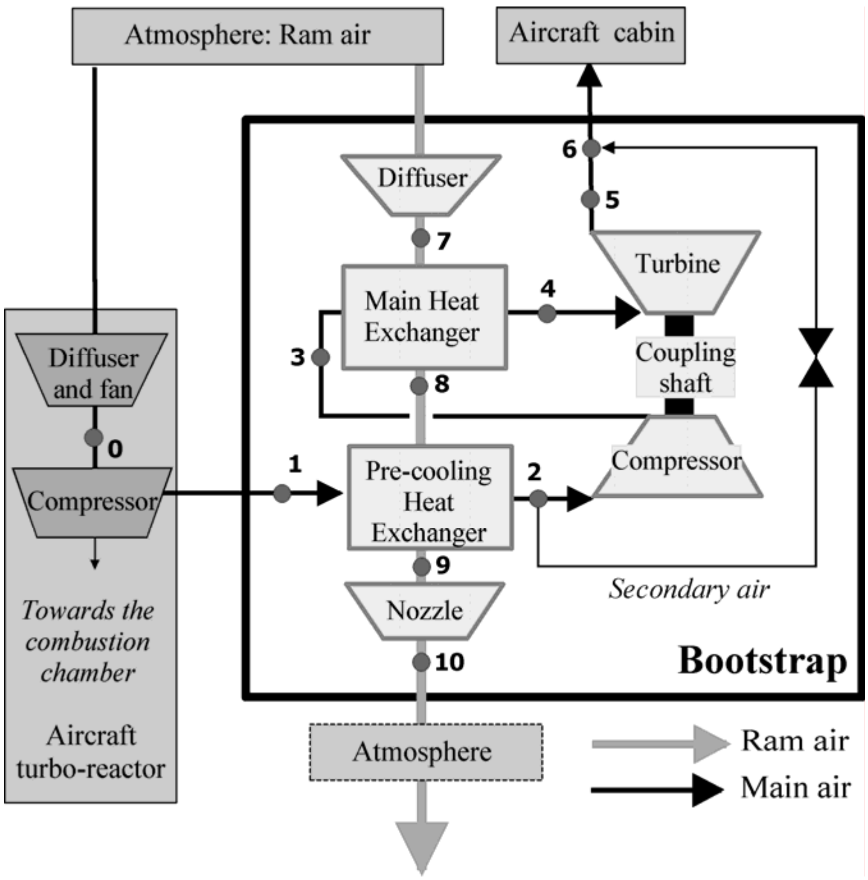

Figure1. Air conditioning system components and environment

The air conditioning system has to produce air at constant temperature and pressure inside the aircraft cabin. Therefore, the design of the Bootstrap must take into account different flight phases corresponding to different altitudes and relative speed of the aircraft. The temperature, pressure and relative speed of the air strongly vary between these flight points.

1.3 Embodiment design difficulties and proposal

Due to the complex interactions of the components, air conditioning designers have no support to guide them in the process of determining the more efficient fin types inside heat exchangers. Manual (as opposed to digital) solving processes require the setting of values of some design variables. Therefore, bootstrap designers usually fix a priori values for the heat exchanger efficiencies, which is equivalent to considering one configuration of heat exchanger without considering the variability of the design problem.

No tool is available to assist the designer during this design phase, especially because the product behaviour modelling has to take into account complex combinations of physical phenomena. Moreover, design solution validation is performed as soon as all of the architectural choices are made. It is usually processed by developing a digital simulation code of air conditioning system and by testing and comparing the performances of a small number of configurations.

Finally, the dimensioning of the system is performed for the most critical life-cycle stage, the prevailing situation. Using trial and error mode, the designer converges towards a solution which is not necessarily the most powerful one, or, which doesn't necessarily corresponds to the best trade off between the various flight phases.

The approach proposed in this paper leads to the identification of the best design compromises between various design objectives, whatever the life cycle stage. It consists in :

- the expression of the design problem as a set of constraints,
- the exploration of the whole design space using Genetic Algorithms,
- the assessment of their performances using criteria relating to the design objectives,
- the reduction of the solution space using the Pareto front : it allows identifying solutions which are the best compromise in simultaneously satisfying the design objectives, without privileging one.

Until the end of the embodiment design phase, no potential solutions have been dismissed by a designer choice. The results of the proposed approach allow decision support at this stage of the design process.

2 DESIGN PROBLEM MODELLING

2.1 Constraint modelling

In order to avoid the usual trial and error iterative design process and not to dismiss a solution because of a priori choices, we propose to take all the constraints into account simultaneously, without any hierarchy or preliminary choices, by modelling the problem as being as set of constraints.

Relations between variables (equalities, inequalities, logical rules) and variable domains constitute the constraints. Variables can be real numbers, integers, enumerated values. Parameter values of standard components can be described using discrete variables. Domain using is well adapted to the uncertain knowledge inherent to the embodiment design phase.

The variables which define the product architecture to be designed (dimension, standard component characteristics, materials, mass, number of elements, etc.) are called design variables (DV). The assessment of a solution is performed by using criteria relating to the design objectives [10]: the resolution allows the evaluation of various working structures -meeting the working conditions of the system. These solutions may be numerous and may thus require to be classified. In order to objectify choices among these solutions, criteria which express the performance of each design configuration are used.

So, a design problem is described by a set of DV, criteria and constraints. A solution corresponds to a set of values -for all DV and criteria- which meet all the stated constraints: these values define a particular design configuration.

2.2 Air conditioning system modelling

The knowledge base of the air-conditioning system consists of:

- 23 thermodynamic state variables (pressures, mass flow rates, temperatures),
- 14 geometric and structural variables: lengths, surface types, pass number;
- 8 criteria (outputs, efficiencies, etc.) which define the performance or which are used to qualify the quality of a design configuration;
- 24 auxiliary variables which are defined as functions which correlate their definitions with the 45 preceding variables.

A methodology has been proposed to identify the structuring characteristics of the embodiment design problem, which must be translated into constraints [11]. The global model is constituted by 69 constraints. Constraints relating tophysics have been derived from energy, momentum or mass flow conservation laws. Due to the complexity of the physical models which indicate strongly-coupled physical phenomena, model reduction methods have been applied [10]. The model of the design problem also includes the functional performance specifications and the description of standard components. The aircraft manufacturer expresses technical skills and manufacturing rules.

The Design Variables are:

- the type of fin (integer value ranging from 1 to 48),
- the dimensions of each exchanger (from 0.1m to 0.5m),
- the diameter of the bypass pipes.

The performance criteria are:

- the mass of the heat exchangers,
- the total volume of the 2 exchangers,
- the drag force induced by the air flowing through the heat exchangers.

Table 1. Flight phase characteristics

Aircraft speed	Altitude		Atmosphere pressure	Atmosphere temperature
Mach number	ft	m	Pa (10^4)	K
0,8	36080	11000	2.27	216.7
0,3	9840	3000	7.03	268.7

The system has to deliver air at constant temperature and pressure to the cabin whatever the flight phase (ground, lift, economic cruise, economic cruise for long haul flights, descent, etc). For the sake of simplicity, only the main two flight phases have been investigated in this paper (see table 1).

3 GENERATION OF DESIGN SPACES

A first investigation of the design search space has been carried out by using a Constraint Satisfaction Problem solver [12]. Only one flight point was investigated at this stage. More to the point, the Bootstrap design problem was solved by considering only 6 kinds of fins inside the heat exchangers, whereas, in this paper, 48 different types of fins and two different flight points have been considered. The design exploration space is therefore much wider in this case.

In the following paragraphs, the computing times of every exploration job have been limited to one hour in order to facilitate comparison of the results.

3.1 Genetic algorithm based solving

A Genetic Algorithm (GA) based design code has been developed to improve the solving performance of the Bootstrap design problem process. The Genetic Algorithm heuristic is a meta-heuristic having a large scope of interest and applications (see [13] and [7]). It is based on the mutation, crossover and selection of individuals among an evolving population. Evolving generations tend to improve optimization criteria (fitness function) by mixing individual genes and generating random individuals to search the complete exploration space of solutions. This heuristic method is involved in many different types of mechanical design tools. However, in industrial conditions, it is mainly used as an optimization tool for the management of several simulation codes. Simulation codes simulate the behaviour of different parts of the mechanical system, whereas the GA based optimization tool supervises the system architecture and the design performance criteria.

The design code proposed in this paper is used to solve a design Constraint Satisfaction Problem, rather than optimizing a design problem. This means that the design code conducts a search for sets of solutions rather than optimized solutions. This is performed using an optimization criterion guaranteeing the satisfaction of every constraint of the design problem. Every constraint "Ci" of the problem is relating to a value "SAT(Ci)": If Ci is satisfied, SAT(Ci)=1, else SAT(Ci)=0.

The fitness function optimized by the genetic algorithm is described in (1) :

$$SAT = \prod_{i=1}^{n} \frac{SAT(C_i)+1}{2} \quad (1)$$

Three different mutation probabilities (Pm equals 0.1, 0.3 or 0.5) are considered in the following paragraphs. Figure 2 displays all the solutions obtained for the two flight points and the three values of the mutation probability. Every solution is represented according to three performance criteria: the global masses and volumes of the heat exchangers, and the drag forces induced by the air flowing through the heat exchangers.

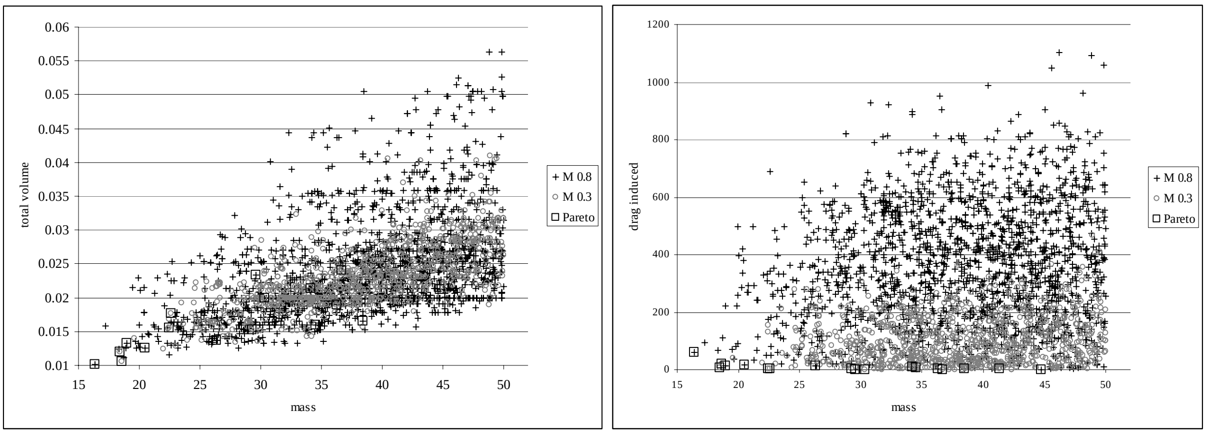

Figure 2. Performance space of solutions obtained for all the mutation probability and both life cycle stages

Some solutions relating to the flight point for a Mach 0.8 speed may correspond to a bigger volume of heat exchangers than for a Mach 0.3 speed. However, the exchanger masses are quite equivalent.

Figure 2 also highlights solutions minimizing the three performance criteria: mass, volume and drag force. This selection was obtained by computing the set of optimal solutions according to a Pareto method (see §4.1). Pareto optimal solutions are highlighted by squares in this figure.The solutions selected for a Mach 0.8 speed are close to the ones selected for a Mach 0.3. speed

The exploration algorithm discards any redundant solution. As a consequence, every point in the figure corresponds to one particular solution of the design problem.

3.2 Random search

In order to achieve a first assessment of the size of the solution space, the exploration process was performed using a pure random search algorithm. This pure random search was obtained by generating random samples of solution principles and by testing their corresponding performances. These results are illustrated in figure 3. In this figure, every solution is displayed in the performance space (mass, volume, drag force). The performance criteria values reached using the random search appear to be quite similar to those obtained using genetic algorithms. However, the solution space corresponding to the random search is a bit wider than the one corresponding to the genetic algorithm whatever the value of the mutation probability. Nevertheless, the density of the solution set found using the random search algorithm is much lower.

On the other hand, despite the low number of solutions obtained with this approach, some solutions appear to fit for the two flight points (diamond shapes in figure 3): they correspond to the same design

variables (fin types and exchanger dimensions). Many of these common solutions range within the same zone (see figure 3): the exchanger masses are close to 30 kilograms and their volumes are close to 20 liters. On the contrary, drag forces appear to be much more distributed, which is appropriate to discriminate the best solutions according to this performance criterion. Figure 4 shows the shared solutions between the two flight points in the masses-drag forces performance space.
Finally, figure 3 shows that most of the shared solutions are distinct from the solutions belonging to the Pareto optimal front. Pareto optimal solutions correspond to the best compromise from the design objective minimization point of view. This minimization may lead to solutions which are not suitable for several different flight phases. Though, one of the common solutions belongs to the Pareto optimal front for the Mach 0.3 speed.

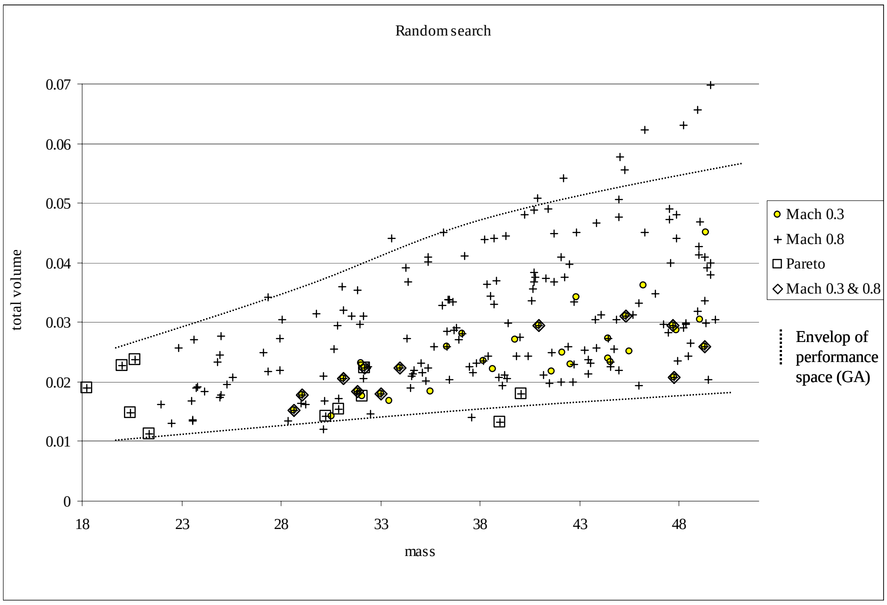

Figure 3. Performance space of solutions obtained with random search, for both life cycle stages

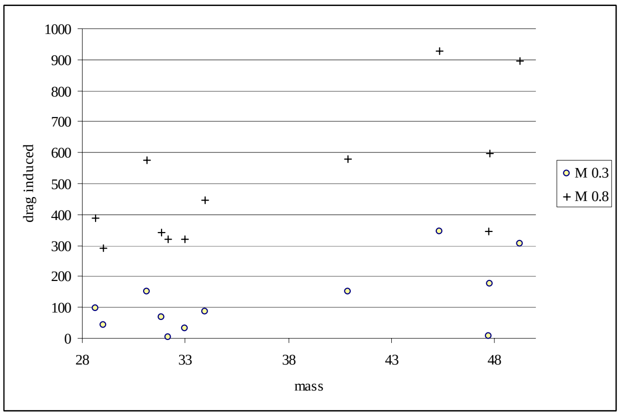

Figure 4. Performance space of the common solutions to the life cycle stages

3.3 Comparison of solving methods

To observe the influence of the solving method on the nature of the results, figures 5 and 6 present the solutions obtained using a genetic algorithm with 3 different mutation probability values or the pure random search algorithm. It is important remember that these result sets have been obtained for a computation time of one hour.

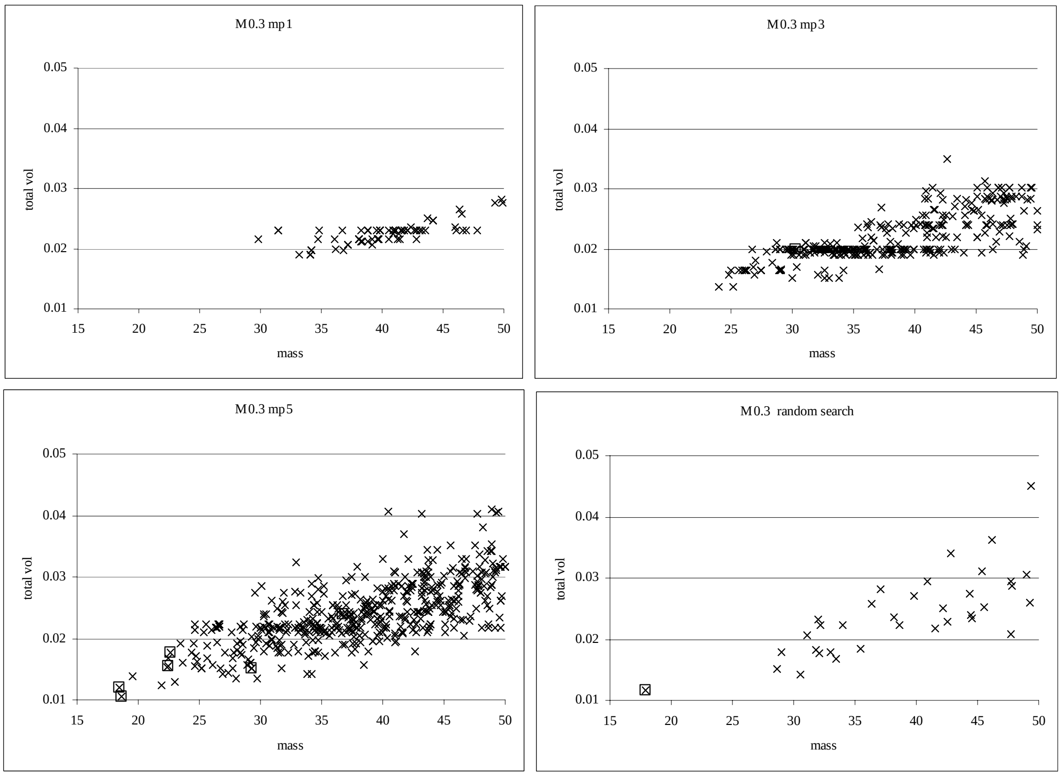

Figure 5. Solutions obtained for Mach 0.3 displayed in the performance space, according the mutation probability (pm) or random search

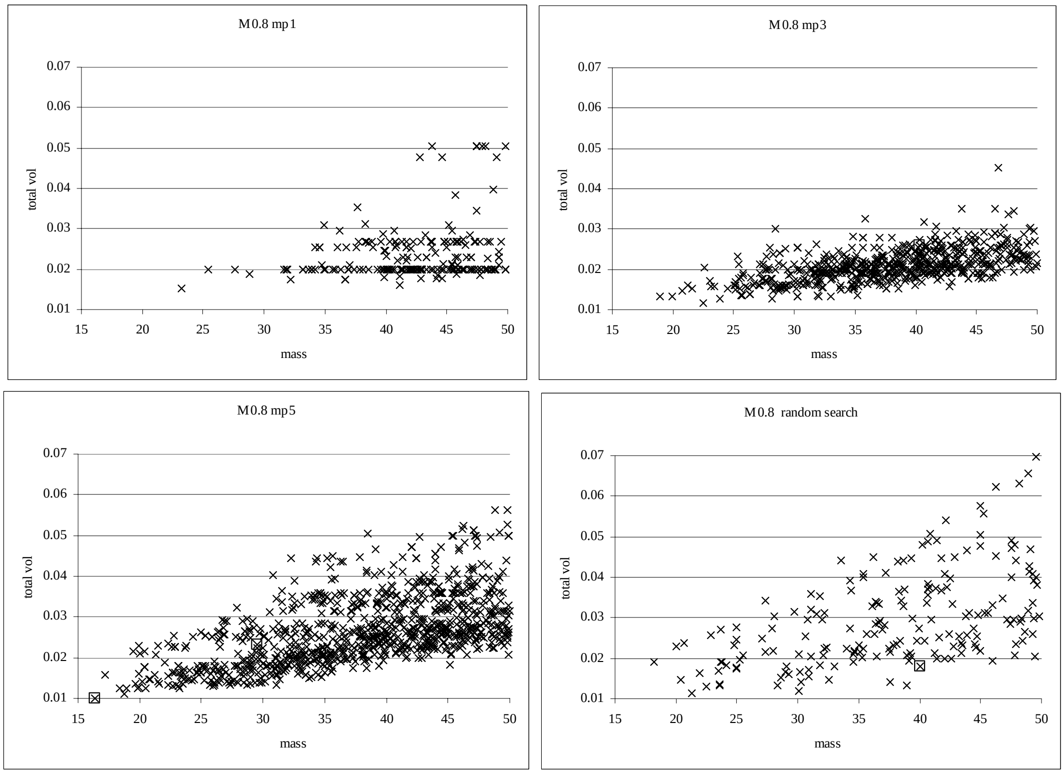

Figure 6. Solutions obtained for Mach 0.8 displayed in the performance space, according the mutation probability (pm) or random search

Genetic algorithm based solving processes lead to increasing numbers of solutions according to the mutation probability. However, the pure random search algorithm converges to a much lower number of solutions whatever the flight phases being considered. According to the phase considered, the number of solutions differs; however, this number is higher for the Mach 0.8 case whatever the value of the mutation probability. More to the point, the number of optimal solutions according to the Pareto method (displayed as squares in figures 5 and 6) increases with the mutation probability. Thus, it seems profitable to investigate the Pareto front using the high values of this probability. Pure random search leads to a wide investigation of the design space but supplies a lower number of design solutions.

4 DESIGN SPACE EXPLORATION

Once the investigation of the design configurations is performed, we aim to support the decision of the designers by guiding the exploiting of the results. This means:

- supporting decisions among the solutions by reducing the solution space and find suitable solutions for the two flight phases (Mach 0.3 and 0.8),
- guiding the choice of design variables among the variables of the problem by finding the relevant design variables or the relevant combinations of variables.

4.1 Solution space reduction

The types of fins and the arrangement of the stacked plates in the heat exchangers have a decisive influence on the mass and the volume of the system. They also affect the efficiencies of the exchangers (to be maximized), and therefore the air-conditioning efficiency of the system. Moreover, some air feeding the conditioning systems is scooped off the surface of the aircraft using a scoop. This air bleeding induces a drag force at the surface of the aircraft, which is detrimental to the global performance of the aircraft. This drag force has to be minimized. Therefore, a compromise has to be found between these antagonistic requirements.

The solution classification has been investigated with an objective function [14], but a weight-factor method raises the problem of factor value assignment.

The Pareto-optimal solutions correspond to a trade off between disparate and conflicting design performances [15]. Every Pareto solution is non-dominated [16], and the optimal front definition aims at minimizing the performance criteria values. In the present case, less than 1% of the solutions belong to the Pareto front of the complete solution space. A solution is non-dominated if no other solution is relating to best values for all criteria. This selection process makes the number of solution drop from 957 solutions (AG and random) to 9 solutions for an aircraft speed of Mach 0.3. For an aircraft speed of 0.8, the set of 2022 solutions narrows down to 10 solutions. Figure 7 displays the performance space and locates the Pareto optimal solutions matching the performance criteria pair by pair. A solution minimizing two performance criteria may be detrimental to the third performance criterion. For instance, for a Mach 0.8 speed, the solution corresponding to a mass of 16.362 kilograms is the Pareto optimal solution according to the masses and volumes of the heat exchanger but is detrimental to the drag force.

Furthermore, whatever the speed of the aircraft, the Pareto optimal solutions are located in the same space. Some solutions corresponding to equivalent masses, volumes and drag forces exist for every value of the aircraft speed.

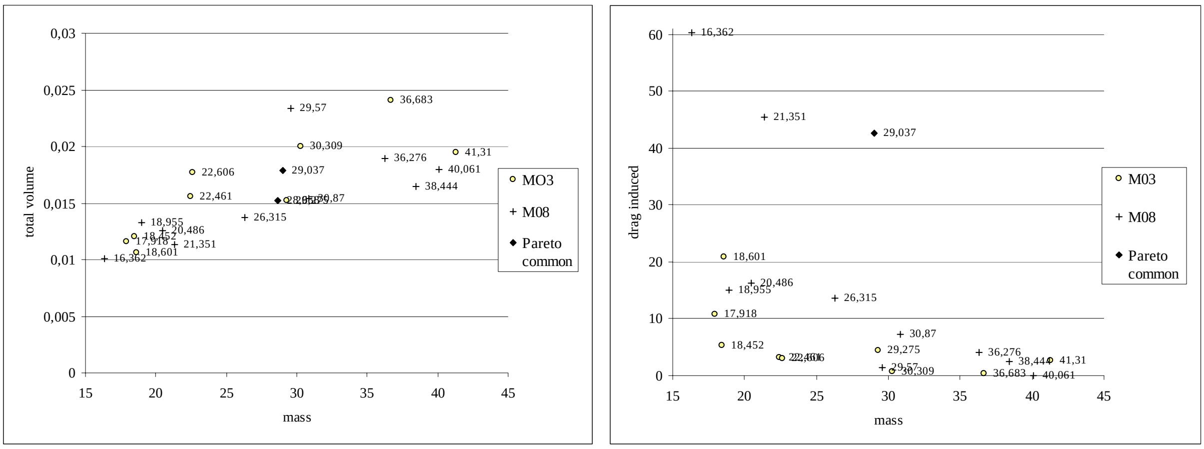

Figure 7. Performance space of Pareto optimal solutions (with mass value)

The solution space was also reduced by looking for solutions suitable for the two flight phases. Twelve solutions have been identified among the solutions resulting from pure random search processing. Then, the solution space was reduced by looking for Pareto optimal solutions among these solutions. Two solutions appear to belong to the Pareto front for Mach 0.3 and 0.8 aircraft speeds. These solutions are presented as diamonds in the figure 7. These performances appear to be close to the mean value of the performances of the Pareto optimal solutions (GA and random).

4.2 Design space and decision support

Despite the reduction of the solution space, design decisions remain difficult. To overcome this difficulty, we propose to supply designers with an overview of the design space: the solutions are displayed according to combined design variables, to assist designers in making choices among them.
Figures 8 and 9 show the design variable space corresponding to the two fin types of the two heat exchangers (main exchanger and pre-cooling exchanger). The design variable values have been sorted according to the circuit of the air flowing through the exchangers (main air and ram air). In spite of the high number of solutions, which correspond to different performance criteria values, many design variable values overlap. More to the point, some fin types don't match any solution.
Following each air circuit (ram air and main air), there is no visible link between the choices of exchanger surface types resulting from the computation. The entire design variable space appears to be filled by solution points and any surface type may be related to other surface types. However, some fin types seems to be well adapted to one particular air circuit and one particular exchanger. These particular fins are related to design solutions while solutions are functioning in association with different types of fins. Furthermore, some fin types are applied in the definition of design solutions for the two flight phases (aircraft speed of Mach 0.3 or 0.8). Fin types 7 or 34 may be used in the ram air circuit in both cases. Finally, some fin types don't match any design solution and, therefore, seem to be irrelevant for the Bootstrap application. For instance, whatever the flight phase and the air circuit being considered, types 17 and 19 are never involved in the functioning of the main heat exchanger.

The preceding analysis cannot guide designers to the optimal solution of the Bootstrap design problem. However, this investigation supports designer decisions by suggesting relevant guidelines and avoiding some irrelevant choices.

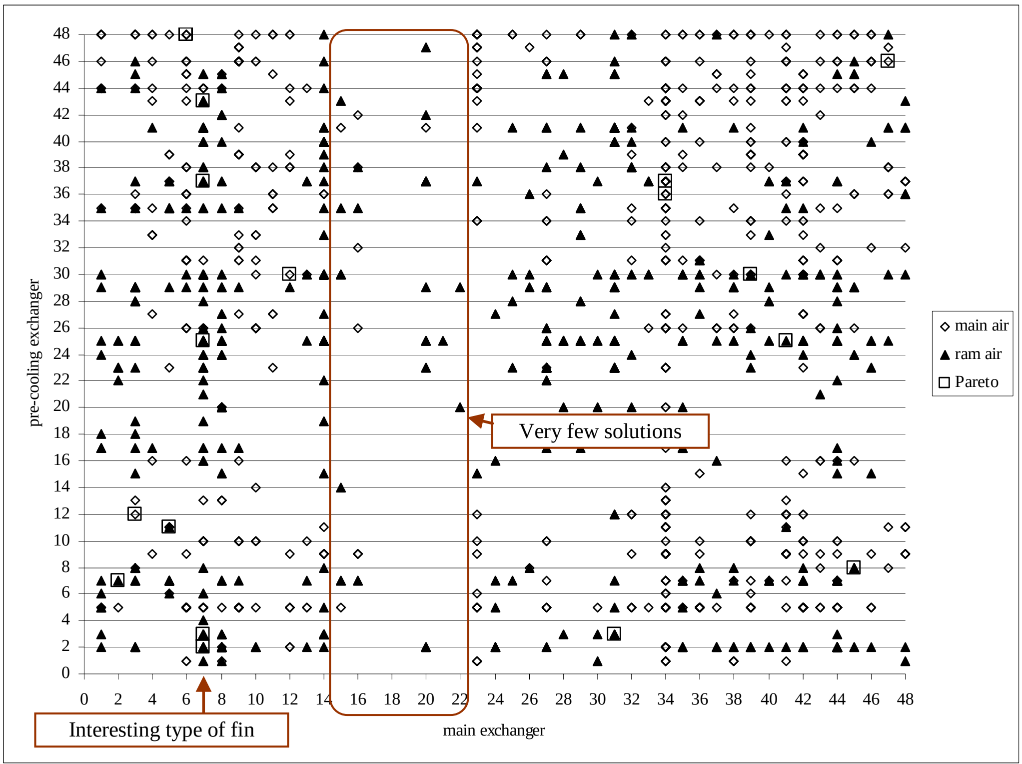

Figure 8. Design space: fin types for each circuit (Mach 0.3)

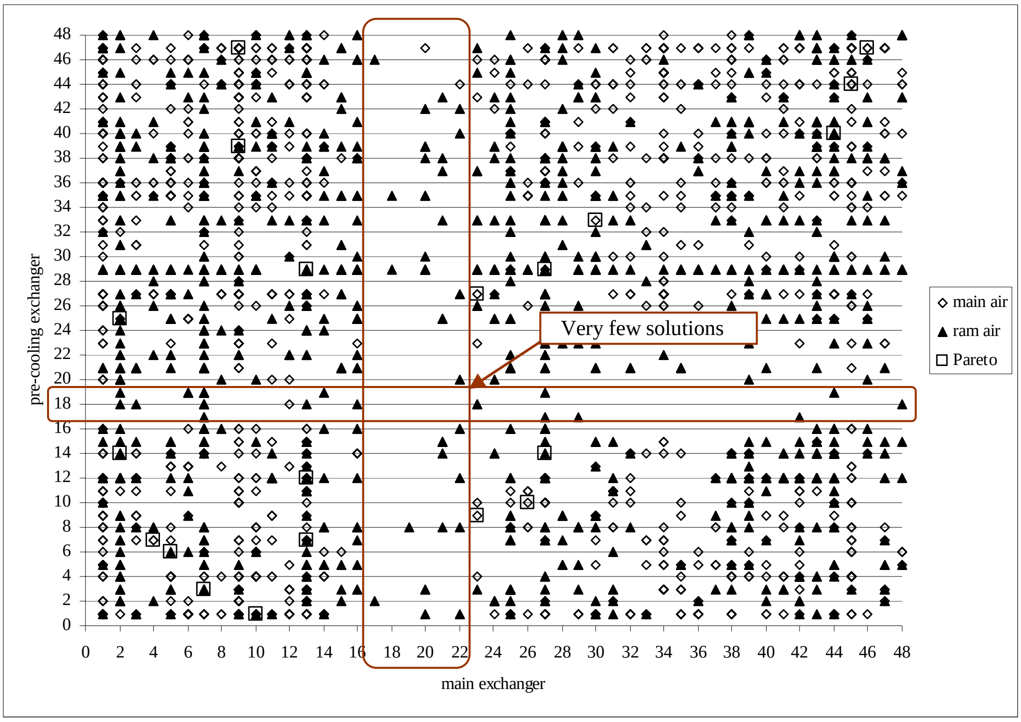

Figure 9. Design space: fin types for each circuit (Mach 0.8)

Figures 8 and 9 illustrate the fin types corresponding to computed design solutions. The Pareto front solutions are highlighted by means of squares. The Pareto-optimal solutions are the design solutions managing compromise between requirements. These solutions are shown on figure 10 to put emphasis on the optimal associations of fin types according to Pareto analysis. For example, type 7 is relevant for the main exchanger on the ram air circuit because many solutions are existing, and some of them are Pareto-optimal (figure 8).

A small number of optimal solutions meets the totality of the design constraints for the two flight phases. This consideration corroborates the difficulty of finding design solutions suitable for the complete Bootstrap life cycle; this difficulty appears to be the bottleneck of the Bootstrap design process. Design solutions presented in figure 10 show evidence of the dissociation between the optimal solutions according to one particular flight phase and optimal solutions according to the two flight phases.

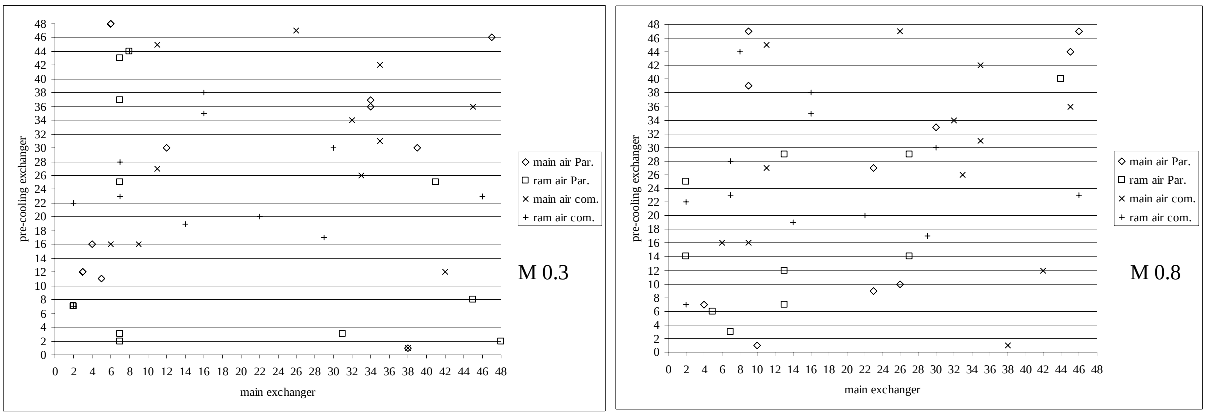

Figure 10. Design space (fin types for each circuit): Pareto optimal solutions and solutions common to both life cycle stages

5 CONCLUSION

In this paper, we discussed the design of an aircraft air conditioning system (Bootstrap). Two flight phases were taken into account in the Bootstrap life cycle. Classical design processes are based on the investigation of a little number of design configurations. In this paper, a wide design space has been explored without considering a priori choices. This digital approach is based on Genetic Algorithms and has proved to be influenced by some genetic parameters; mainly the mutation probability. This probability influences the size of the solution space. On the contrary, a pure random search algorithm leads to a wider exploration of the design space, but the exploration appears to be slower and retrieves less solutions. Despite the fact that the computing process found 2979 design solutions, a few design solutions proved to be adapted to the two aircraft flight phases. Among these joint solutions, barely 2 solutions belong to the set of the optimal Pareto solutions.

This approach supports designers in the process of determining feasible embodiments. Such an approach may be relevant to design complex industrial systems or when the life cycle of the system is faced with varying situations. Not only designers can identify pertinent values or irrelevant values to the design variables, but also find relevant design solutions managing compromise between requirements. However, it has been observed that optimal solutions according to one particular life cycle situations may be unrelated to optimal solutions according to several life cycle situations.

Our perspectives concern the analysis of the multiple situations in the Bootstrap life cycle and the coupling between the preceding method and robustness analysis based approaches.

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