JOURNAL OF PROPULSION AND POWER
Vol. 19, No. 3, May–June 2003

Multicriteria Design Optimization of Integrated Three-Dimensional Supersonic Inlets

Arnaud Gaiddon*
MBDA France, F-92320 Châtillon Cedex, France
and
Doyle D. Knight†
Rutgers University, Piscataway, New Jersey 08854-8058

Automated optimization by means of numerical simulation is a very promising technique now mainly used for research studies. However, its application in an industrial context is not very common. Optimization of a supersonic inlet is presented in the context of the development of an actual airbreathing missile. The automated optimization loop is described in detail. The aerodynamic evaluation tool (the computational fluid dynamics software 2ES3D) is described, and its validation on realistic cases is presented. The use of the optimization loop on a realistic and complex problem is compared with classical methodology for inlet design. The results are very promising in terms of design cycle time and cost reduction.

Nomenclature

F_i = fitness function
G_j = constraint function
M = Mach number
O_i = objective function
P_i = total pressure
q = mass flow rate
$\boldsymbol{x}$ = vector of parameters
α = angle of attack
ε = mass flow rate coefficient
η = total pressure recovery coefficient

I. Introduction

SUPERSONIC inlets are major components of airbreathing propulsion systems. Their main function is to provide the engine with the specified stable mass flow rate and minimal total pressure recovery loss. They also play an important role in the overall missile drag, mass, and stealth.

Until now, inlet design and development cycles mainly relied on multiple wind-tunnel test campaigns. Although they give very accurate results over the flight domain, they present two major drawbacks: they are very costly, and they do not permit a complete exploration over the design space, that is, the number of tested configurations is very limited.

To reduce the design cycle time and cost, and also to improve the quality of the final shape, an innovative technology can now be used in a real world context: *automated optimization using numerical simulation.* Instead of limiting the application of computational fluid dynamics (CFD) to the performance evaluation of existing designs, CFD software is coupled with an optimization algorithm to determine the set of shapes that give the best performance under several constraints.

In recent years, significant progress has been achieved in the development of robust optimization algorithms. An example is the class of evolutionary strategies that are used in various fields such as biotechnology, mechanics, chemical engineering, telecommunications, microelectronics, physics, production planning, etc. In a recent survey paper, Bäck[1] notes that "the [CFD] field provides a wide range of hard optimization tasks where several optimization techniques have been tried to achieve reasonable results. The application of evolutionary algorithms promises improved results in comparison to the ones from standard techniques, e.g., hill climbers and gradient based methods."

Several applications of automated optimization in the field of missile aerodynamics have been conducted. Dealing with external aerodynamics, Anderson et al.[2] "examine[d] the use of Pareto genetic algorithms to determine high efficiency missile geometries, and demonstrated the capability of these algorithms to determine highly efficient and robust missile aerodynamics design, given a variety of design goals and constraints."

A collaborative research program on supersonic inlet optimization was initiated in 1996 between the former Aerospatiale Missiles (now MBDA France) and Rutgers University.[3] The first studies compared gradient-based algorithms with mono-objective genetic algorithms and demonstrated the superiority of genetic algorithms for a class of inlet design problems. Then Pareto multi-objective genetic algorithms were used to take into account not only one flight point but a complete mission. The modelization level began with semi-empirical software based on a two-dimensional characteristics method. Then two-dimensional CFD tools were introduced. Recent progress in computer power has made it possible to use three-dimensional CFD tools to model fully realistic geometries.

The steps of this collaborative research program have been summarized in several papers. In 1998, Blaize et al.[4] performed the optimization of two-dimensional inlets with a mono-objective algorithm for a single flight point and a mission. This was simulated through one objective function by weighing the contributions of each flight condition, thereby biasing the importance of individual flight conditions. The aerodynamic solver was semi-empirical. This study showed the superiority of genetic algorithms over gradient-based ones for such problems:

> ...when launched from an experimental design point..., CFSQP achieves an improvement of 20%, which can be compared to the 62% improvement achieved by GADO. Moreover, when launched from the optimum found by the genetic algorithm, no further improvement was achieved.... This comparison shows the reliability and the merit of the genetic algorithm used.

(CFSQP is a gradient-based algorithm, and GADO is a genetic algorithm.) Another result of this study was that multi-objective

Received 21 May 2002; revision received 27 December 2002; accepted for publication 27 December 2002.

*Engineer, Computational Fluid Dynamics Team, 2, rue Béranger BP 84; arnaud.gaiddon@mbda.fr. Member AIAA.
†Professor, Department of Mechanical and Aerospace Engineering, 98 Brett Road; knight@soemail.rutgers.edu. Associate Fellow AIAA.

problems (such as a mission) could not be adequately treated with a mono-objective algorithm.

Bourdeau et al.[5] performed the optimization of a three-dimensional supersonic inlet for a single flight point, thus, demonstrating the use of the 2ES3D solver (a semi-empirical method based on a three-dimensional Euler code) for the optimization process. Carrier et al.[6] performed a similar study for a mission. This last study concluded that "the optimization process presented in this paper has reached the point where industrial application can now be envisaged."

The purpose of the present paper is to describe the first industrial application of the automated inlet optimization methodology developed by MBDA France and Rutgers University. We have applied the automated inlet design methodology to the postdesign of the inlet for the French VESTA missile that was originally designed using classical techniques involving a significant amount of wind-tunnel testing. We will demonstrate that the automated inlet design methodology achieves an optimal design comparable to the original VESTA design but at a small fraction of the cost and time.

After a brief description of the present study context, the automated optimization loop is presented through its two main components, the CFD prediction tool and the optimization algorithm. The results obtained are then shown and compared with those obtained with a classical design methodology.

II. Purpose of the Study

The French VESTA missile has been developed to constitute a common vector for two supersonic missiles, the first being ship launched and the second being air launched (Fig. 1). It is equipped with two lateral supersonic inlets that must have a very high level of performances over a wide flight domain. The development of the inlet followed a methodology where the synergy between CFD computations and wind-tunnel tests was fully employed,[7] leading to great improvements of productivity. Wind-tunnel tests make it possible to measure the performance of a limited number of configurations over the entire flight domain. Navier–Stokes computations make it possible to explore a large number of shapes for a limited number of flight points with good accuracy. Therefore, the methodology consisted in using CFD tools to optimize the shape manually on a small number of flight conditions and then to characterize fully the performance of the shape on the flight envelope with wind-tunnel measurements.

However, during the VESTA inlet development, automated optimization tools had not reached a sufficient level of maturity to be industrially employed. The present study is indeed a postdesign of the VESTA inlet with the automated optimization loop and a comparison with the original design in terms of performance. The impact of the automated optimization loop on the development process will be measured, to answer two questions that are fundamental from an industrial point of view.

1) Does the automated optimization loop achieve designs with comparable (or better) performance than the original VESTA design?

2) Does the automated optimization loop permit a reduction in terms of design cycle time and cost?

III. Automated Optimization Loop

A. Overall View of Optimization

Classical design methods consist in creating a basic shape, evaluating its performance (by means of experiment or computation), and then modifying it. This process is iterated using engineering intuition and experience, coupled with CFD simulation of specific configurations, until a sufficient level of performance is obtained.

Automated optimization relies on the coupling of one or several evaluation tools with an optimization algorithm (see Fig. 2). This optimizer has the purpose to obtain the best design (or set of best designs) with a minimum number of evaluations.

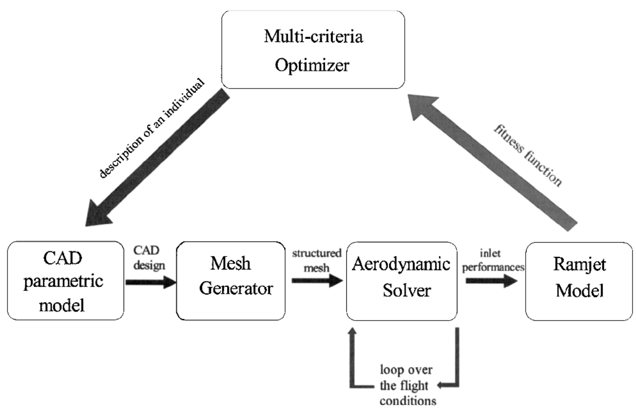


Fig. 2 Automated optimization loop.

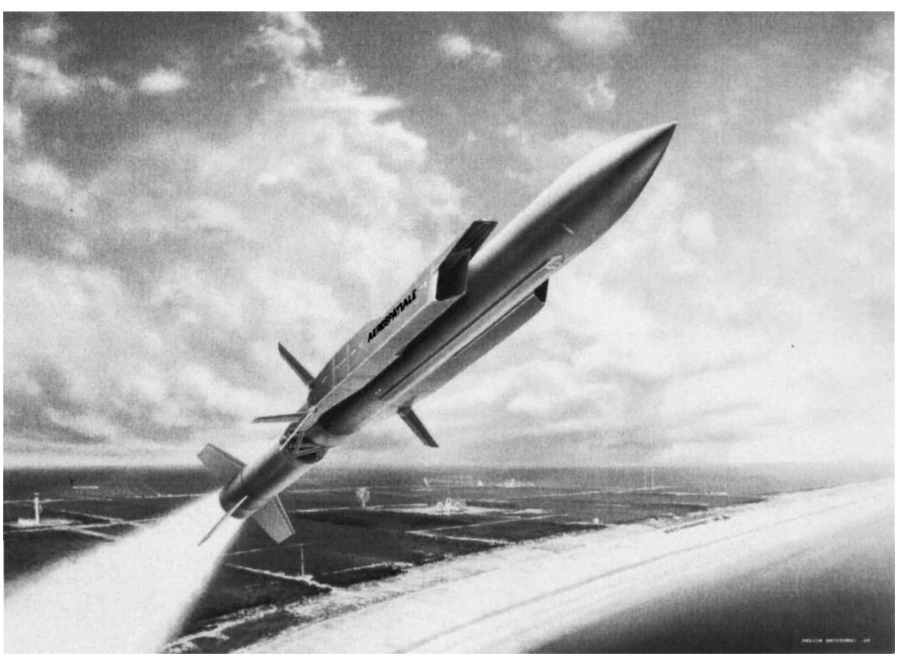


Fig. 1 VESTA missile (©AMM/1996/Bechennec).

B. Definition of Optimization Problem

We consider a multicriteria optimization problem:

$$\text{minimize } F_i(\boldsymbol{x}) \qquad \text{for} \quad i = 1, l$$
$$\text{subject to } G_j(\boldsymbol{x}) \leq 0 \quad \text{for} \quad j = 1, m$$

where l is the number of fitness functions, m is the number of constraints, and $\boldsymbol{x} = (x_1, \ldots, x_n)$ is a vector completely describing the inlet shape. The range of values of the $\boldsymbol{x}_i$ is the design space. Each fitness function $F_i(\boldsymbol{x})$ is decomposed into two terms,

$$F_i(\boldsymbol{x}) = O_i(\boldsymbol{x}) + P_i(\boldsymbol{x})$$

where $O_i(\boldsymbol{x})$ is the objective function, also called the measure of merit. It describes the physical quantities to be optimized. For example, to maximize the mass flow rate of an inlet, the function $O_1(\boldsymbol{x}) = -\varepsilon$, that is, the negative of the mass flow rate coefficient $\varepsilon = q/q_{\text{ref}}$, can be used. $P_i(\boldsymbol{x})$ is a function prescribing the physical penalties to achieve satisfaction of the constraints. For example, to obtain a total pressure recovery better than 0.7, the function

$$P = \begin{cases} 0, & \eta \geq 0.7 \\ e^{\alpha(0.7-\eta)^2} - 1, & \eta < 0.7 \end{cases}$$

can be used, where η is the total pressure recovery coefficient $\langle P_i \rangle / P_i^{\text{ref}}$ and α is a parameter chosen by the user.

The solution to the multicriteria design optimization problem is the Pareto set, that is, the set of nondominated solutions.[8] A design $\boldsymbol{x}$ dominates another design $\boldsymbol{y}$ if

$$\forall i \in [1, l] \qquad F_i(\boldsymbol{x}) \leq F_i(\boldsymbol{y})$$
$$\exists j \in [1, l] \qquad F_j(\boldsymbol{x}) < F_j(\boldsymbol{y})$$

Thus, design $\boldsymbol{x}$ dominates design $\boldsymbol{y}$ if $\boldsymbol{x}$ is as good as $\boldsymbol{y}$ for all of the objectives and if one objective exists for which $\boldsymbol{x}$ is strictly better than $\boldsymbol{y}$. Thus, no member of the Pareto set is dominated by any other individual in the Pareto set, and, therefore, the Pareto set constitutes the best designs.

A Pareto set is a very rich source of information for an engineer facing an optimization problem. It gathers the best individuals and clearly represents the compromise between the different fitness functions because, in the Pareto set, a performance can be improved only at the expense of a loss in another performance. For example, plotting the Pareto set for a supersonic inlet optimization problem can show that, for the best set of designs, an improvement of one point of total pressure recovery at a high Mach number typically costs three points of mass flow rate at a low Mach number. A compromise between both objectives can be accomplished in function of the global need, that is, on the entire mission of the missile. Eventually, a final choice between several individuals of the Pareto set can be based on complementary constraints or performances, such as mechanics, drag, stealth, or guidance.

C. CFD Evaluation Tool

When used in an industrial context where a very high accuracy is needed for aerodynamic design, theoretical or semi-empirical evaluation tools are oftentimes insufficient, and thus, CFD software has to be used. This leads to an additional complexity for the general structure of the loop because the use of a CFD code implies that a mesh is provided, which implies also that a CAD model of the inlet is generated.

From an industrial point of view, the logical choice at MBDA France for the CAD package is Pro/ENGINEER. It is commonly used by the design teams at MBDA France, and it is, moreover, a parametric CAD tool. Each shape is represented with a set of basic geometries (protrusion, extrusion, cut, etc.) associated with a set of variables. A parametric CAD model of an inlet is, indeed, a family of shapes, that is, a potential design space. The CAD can be modified directly by changing the values of the parameters. Of course, these values can be sent to Pro/ENGINEER by an optimization algorithm, which makes the geometric model management very natural.

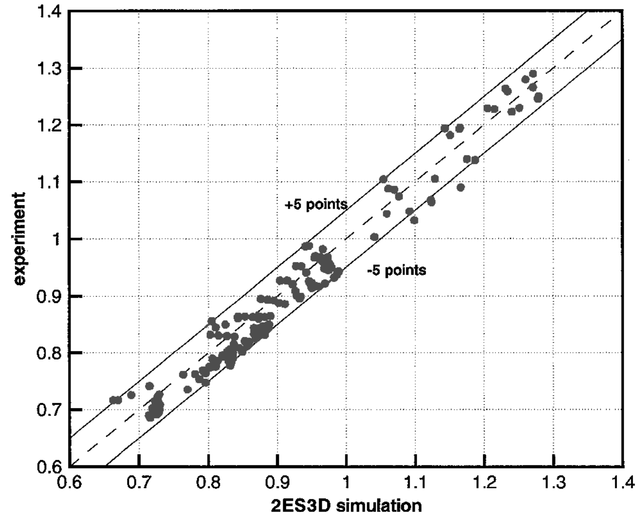


Fig. 3 Validation of the 2ES3D mass flow rate computations.

The creation of the CFD mesh is a very important step because it must not introduce any limitation in the exploration of the design space. An individual design that could not be meshed would be artificially unevaluable and infeasible. Some designs would then be ignored by the optimizer because they can not be meshed, whereas they might otherwise present very good aerodynamic performance. To limit this drawback, the structured mesh topology was chosen to be as general as possible to apply to the maximum number of configurations in the design space. The mesher chosen by MBDA France is ICEMCFD HEXA, which is directly interfaced with Pro/ENGINEER.

The aerodynamic software 2ES3D[9] uses a CFD code solving the three-dimensional Euler equations with a finite volume approach coupled with semi-empirical methods for losses in the terminal shock wave and the subsonic diffuser.[10] This tool enables the prediction of the supercritical mass flow rate and the maximum total pressure recovery of three-dimensional inlets within a 5% accuracy. The software 2ES3D has been intensively validated on realistic inlet configurations. Figure 3 is a demonstration of the accuracy and the reliability of the 2ES3D software for more than 200 mass flow rate computation cases, with several geometries, Mach numbers and angles of attack. Each point is defined by two coordinates: The first one corresponds to the computed result and the second one to the wind-tunnel test measure. If the accuracy is perfect, the point lies on the curve $y = x$. The two curves $y = x \pm 0.05$ defines the 5% accuracy domain. One can see in Fig. 3 that virtually all of the points (indeed 96% of them) are in this domain. The 2ES3D software comprises the following elements.

1) The supersonic part of the inlet (including external ramps, cowl, etc.) is computed with a three-dimensional Euler CFD code.

2) A virtual terminal shock wave model (VTS) is applied at the aerodynamic throat by solving the shock equations;

3) The subsonic diffuser is modeled with a one-dimensional integral method using the average flow conditions found after the VTS.

The use of 2ES3D has the consequence that only the supercritical mass flow rate and the maximum total pressure recovery can be computed. Ideally, the complete performance curve describing the evolution of total pressure recovery vs mass flow rate would have to be computed to determine precisely the engine thrust. Such a complete performance curve can be obtained only with Navier–Stokes computations. However, several thousands of individuals must be evaluated during an optimization process, which makes the use of Navier–Stokes computations impossible for CPU time reasons. Table 1 is a comparison of the CPU time needed on one SGI R12000 350-MHz processor for each method. Moreover, the 40-h time corresponds to a single Navier–Stokes computation, that is,

Table 1 Different levels of modelization available at MBDA France

Software	Method	T CPU
2ES3D	Three-dimensional Euler semi-empirical	10 min
NS3D	Three-dimensional Navier–Stokes	40 h

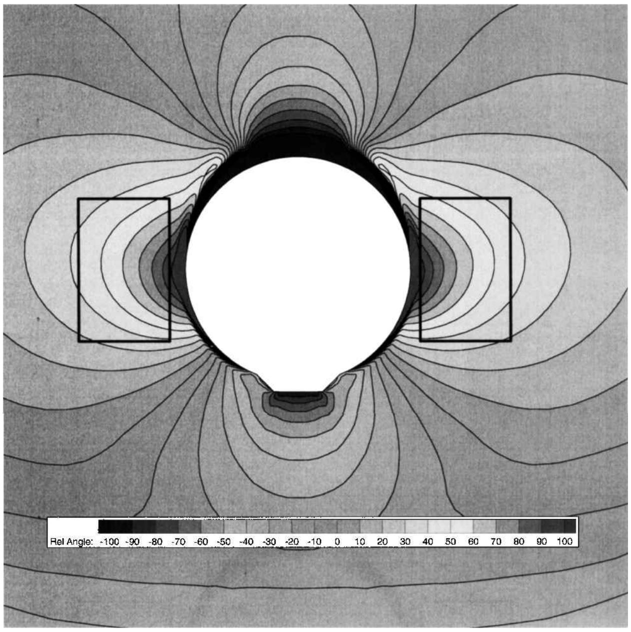


Fig. 4 Relative angle of attack.

for one operating point. Usually, 5–10 of these computations are needed to describe the complete performance curve. Therefore, the strategy is to use 2ES3D in the automatic optimization loop to obtain the optimum or the Pareto set, even though the aerodynamic performance is only partially described. The resulting optimal design (mono-objective optimization) or optimal family of designs (Pareto set of multi-objective optimization) is then fully computed with the Navier–Stokes code to predict the complete performance curves. With the continuing increase in computer power, there is no doubt that Navier–Stokes computations will eventually be used directly in the optimization loop.

The inflow conditions for a realistic inlet attached to a missile are nonuniform. The forebody flowfield is computed using a parabolized Navier–Stokes code. The predicted inflow conditions are used in the 2ES3D and Navier–Stokes (see Ref. 11) calculations of the inlet. Figure 4 shows the field of relative incidence at the capture level, that is, the flow of

$$(\alpha_l - \alpha_\infty)/\alpha_\infty$$

where α_l is the local angle of attack and α_∞ is the freestream angle of attack. One can see in Fig. 4 that the local angle of attack is 50% higher than the freestream one. The flow is, moreover, heterogeneous, which makes an industrial computation of installed inlets more challenging.

A typical three-dimensional Navier–Stokes calculation of an inlet uses 500,000 nodes and requires about 40 CPU h for each assumed downstream pressure. The complete performance curve, that is, the graph of total pressure recovery vs mass flow rate, is obtained by applying several backpressures simulating the engine to obtain all of the operating modes of the supersonic inlet (supercritical, critical, subcritical, and buzz). The accuracy of these computations is of the same order as the wind-tunnel tests (Fig. 5). The three-dimensional Navier–Stokes computations also provide information on the detailed structure of the flow including major physical phenomena (boundary layer/shock wave interaction, separation) so that the causes of loss in performance can be understood and corrected.

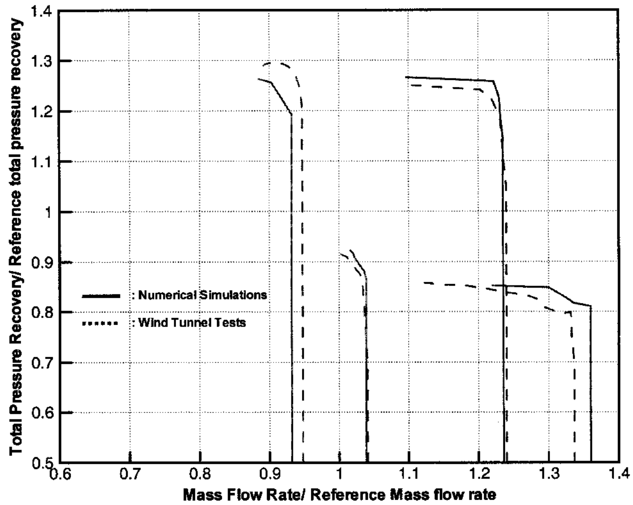


Fig. 5 Navier–Stokes computation accuracy.

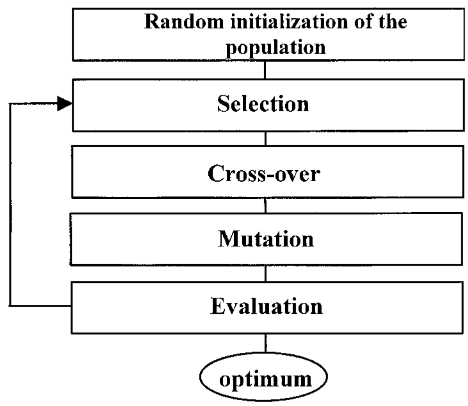


Fig. 6 Operation of the GA.

A last element to be implemented in the optimization loop is a simplified ramjet model so that the optimization can be conducted on the performance not only of the inlet but of the entire propulsion system. It is then possible to maximize directly the thrust of the engine. This part of the loop is not yet operational.

D. Details of the Genetic Algorithm

Genetic algorithms[12,13] mimic the mechanism of natural selection described by Darwin in his evolution theory. In this study, we used the steady-state genetic algorithm GADO developed by Rasheed[14] and Rasheed et al.[15] GADO is initialized with a population of designs selected at random from the design space. GADO then proceeds iteratively as follows (Fig. 6). GADO generates a new design by a series of operators (described later), and the new design is added to the population as appropriate. At the same time, one design is removed from the population, thereby maintaining a constant population size. The iteration procedure is continued until a good approximation to the Pareto set is achieved.

GADO generates a new design in the following manner. First, two parent designs are selected. The selection process is performed by rank because it is the best method when a penalty function is used because the range of fitness function is then wide. Each design is assigned a weight depending on its fitness rank in the population. The weights constitute a decreasing arithmetic series and are used to compute the probability each individual has to be selected.

Second, a crossover operator is applied to the parents to generate a new design. GADO contains five different crossover operators: point crossover, line crossover, double-line crossover, guided crossover, and random crossover.

The point crossover, sometimes called real crossover, mixes genes of both parents in the following way: A crossover position is randomly chosen with uniform probability. The offspring genotype is constituted from the first parent's genotype until this position is reached, and the remaining part comes from the other parent's genotype. For example, let us say that each individual is described by N real-coded genes. If the two parents are $X = (X_1, \ldots, X_N)$ and $Y = (Y_1, \ldots, Y_N)$ and the crossover position is P, then the offspring is $Z = (X_1, \ldots, X_{P-1}, Y_P, \ldots, Y_N)$.

Line crossover works by creating a line between the two real-coded parents, extending it from both sides to a certain distance and choosing randomly a point on this segment as the offspring. The total length of the line increases during the optimization process. Line crossover is useful because many design spaces have good regions that look like thin hyperellipsoids that can not be efficiently explored by classical point crossover operators.

Double-line crossover is a new operator introduced by GADO. It combines the advantages of both point and line crossover. The first step consists in randomly choosing a crossover position in the genotype, like in point crossover. Then two line crossover operations are performed, the first one on the prefix (genes forward of the crossover position) of the parents and the second one on the suffixes (genes aft of the crossover position).

Guided crossover was introduced in GADO to improve its ability to find a solution as close as possible to the actual optimum. A first parent point X is chosen using the classical rank-based selection process. The other parent Y is selected using a different rule: For each individual Z among the population the mutual fitness with X is computed with the following equation:

$$\text{mutual fitness} = \frac{[F(X) - F(Z)]^2}{[D(X; Z)]^2}$$

where $D(X; Z)$ denotes the Euclidian distance between X and Z. The second parent Y is then the individual among the population that maximizes the mutual fitness. Then the offspring is chosen on the line joining both parents with a probability depending on the stage of the optimization process.

Random crossover is a classical operator commonly used in most of genetic algorithms (GAs): Each gene of the offspring is randomly selected, with a uniform probability, from either parent.

GADO chooses at each iteration which crossover operator will be used among the five available ones using the following rule: Guided crossover is chosen with a probability depending on the stage of the optimization process (low probability at the beginning and high at the end). Then if guided crossover is not selected, GADO will choose randomly with equal probability one of the other four operators. The main idea is that guided crossover has the ability to speed up the GA when it has reached a region near the optimum by introducing a simplified gradient (the mutual fitness), but it has not to be used too much because it may endanger diversity.

Third, a mutation operator is applied to the new design to maintain diversity and explore new design space regions. GADO uses three mutation operators: nonuniform mutation, shrinking-window mutation, and greedy mutation. Let us say that a real-coded gene has a value x with a lower boundary l and an upper boundary u and that the optimization process is at iteration t on a possible total number of T. The nonuniform mutation operator produces a mutant value x_{mut} given by the following equation:

$$x_{\text{mut}} = \begin{cases} x + (u - x) \cdot r \cdot [1 - (t/T)] \cdot s & \text{with probability } 0.5 \\ x - (x - l) \cdot r \cdot [1 - (t/T)] \cdot s & \text{with probability } 0.5 \end{cases}$$

where r is a random value uniformly selected in the interval $[0; 1]$ and s a scale number between 0 and 1 chosen by the user to decide how conservative the mutation process is.

Shrinking-window mutation consists in randomly choosing the mutant gene value in a window around the original value that has a size of $(u - l) \cdot s \cdot [(T - t)/T]$, where s is a scale number depending on the crossover operator previously used. Thus, the window progressively shrinks during the optimization process to limit the effect of perturbation when the optimum is almost found.

Greedy mutation is the only mutation operator whose behavior does not evolve during the optimization process. The mutated value of the gene is given through

$$x_{\text{mut}} = \begin{cases} x + (u - x) \cdot r_1 \cdot r_2 & \text{with probability } 0.5 \\ x - (x - l) \cdot r_1 \cdot r_2 & \text{with probability } 0.5 \end{cases}$$

where r_1 and r_2 are two random values uniformly selected in the interval $[0; 1]$. The main purpose of this operator is to maintain reachability of the whole design space any time during the optimization process.

The three mutation operators are chosen with the given probabilities: 0.1 for greedy mutation, 0.4 for shrinking-window mutation, and 0.5 for nonuniform mutation.

At each iteration, GADO created a new design with a crossover and a mutation operator so that one design has simultaneously to be removed from the population thereby maintaining a fixed population size. The replacement strategy is based on a crowding technique taking into account both the fitness and the proximity of individuals in the design space. Candidate designs for elimination from the population are individuals that are neighbors of the offspring and that are also both worse in fitness than the offspring and among the worst in fitness among the whole population.

GADO also includes tools to minimize the number of evaluations needed to perform the optimization: a screening module and a diversity maintenance module. The screening module predicts if an offspring is promising, extrapolating its fitness from the previously computed ones with a K-nearest neighbor approach. That means that a large sample of previously evaluated points (about 30 times the population size) is kept in memory. If the offspring predicted fitness excesses a given threshold, the new design is actually computed by the evaluation tool.

The purpose of the diversity maintenance module is to prevent the optimization process from premature convergence to a nonglobal optimum. It rejects points that are extremely close to previously evaluated designs. The reject radius is based on a given reject tolerance and decreases during the optimization process so that the global optimum can be actually reached. Also, if a critical lack of diversity is detected, a reseeding operation is performed: All points in the population are discarded except the best one, and the population is rebuilt using points from the screening module that have the best fitness and that are far from the previously retained designs.

The GADO parameter settings used in this research reflect our experience with complex inlet optimizations and lead to a good compromise between robustness and efficacy of the results. The size of the population is 10 times the number of variables, that is, 180, based on previous experience.[14] The reseed fraction parameter is 0.5, and the mutation factor is 3. The guided crossover proportion is set to 0.5. Typically, 10,000 iterations of GADO were used. Our prior experience indicates that the number of iterations required for convergence of the multicriteria optimization is about 50 times the population size. Because a lot of designs are not feasible, only 1000–1500 designs are actually computed by 2ES3D.

IV. Results for the VESTA Missile

Our work on postdesign of the VESTA missile inlet began with the original development of the VESTA inlet. Constraints of general dimensions and mechanics were taken into account to create a realistic and complex geometric model that is far more difficult than in the generic cases used in our previous research.

A. Mission Profile

The mission profile of the VESTA missile is shown in Fig. 7. After an initial boost phase using a jettisonable rocket engine and then the integrated booster, the supersonic inlets are opened, and the ramjet is started. The acceleration phase consists in both climbing at high altitude and increasing the flight Mach number. The cruise phase is performed to obtain the best range at high Mach number and high altitude. The mission ends with the maneuver phase, where the missile dives to its target and accomplishes high load factor

Table 2 Variable lower and upper boundaries

Variable	Symbol	Lower boundary	Upper boundary
Ramp 1 length, mm	L_1	5	200
Ramp 1 angle, deg	α_1	0	25
Ramp 2 length, mm	L_2	5	200
Ramp 2 angle, deg	α_2	5	25
Ramp 3 length, mm	L_3	5	150
Ramp 3 angle, deg	α_3	5	25
Ramp 4 length, mm	L_4	5	150
Ramp 4 angle, deg	α_4	5	25
Cowl 1 length, mm	L_{c1}	5	100
Cowl 1 angle, deg	α_{c1}	0	25
Cowl 2 length, mm	L_{c2}	5	100
Cowl 2 angle, deg	α_{c2}	5	25
Cowl 3 length, mm	L_{c3}	5	100
Cowl 3 angle, deg	α_{c3}	5	25
Cowl 4 length, mm	L_{c4}	5	150
Cowl 4 angle, deg	α_{c4}	5	25
Cowl position, mm	X_{cowl}	0	800
Width, mm	W	50	250

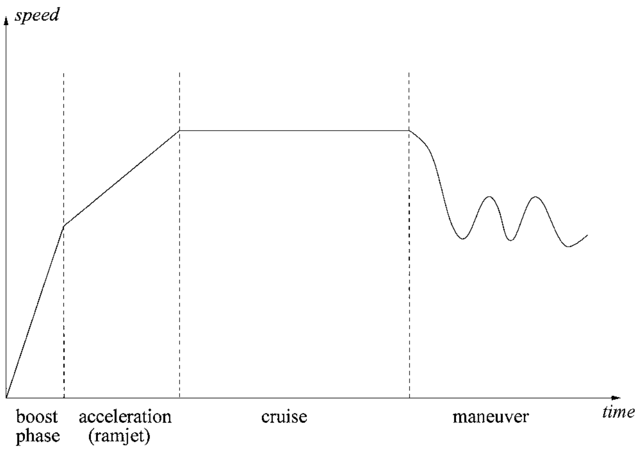


Fig. 7 Mission profile.

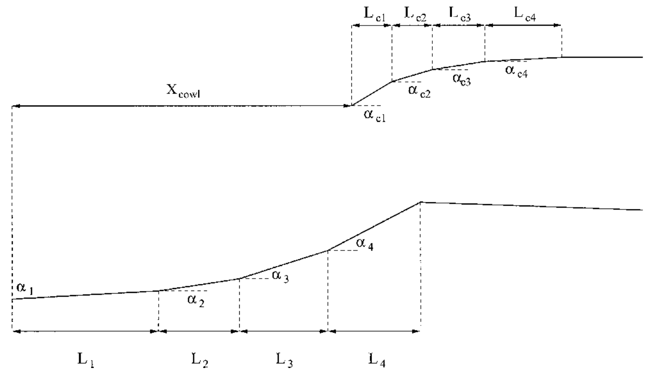


Fig. 8 Geometrical model of the inlet.

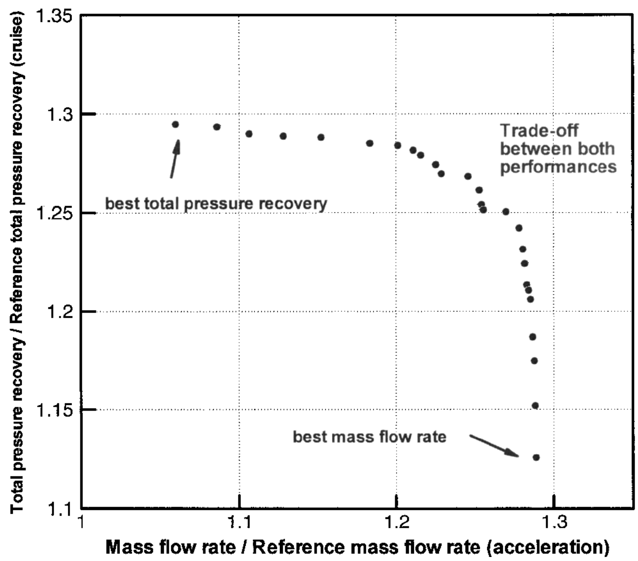


Fig. 9 Pareto set.

direction changes. From the aerodynamics point of view, two flight points have to be considered for the inlet design.

The first point is acceleration: The Mach number and the angle of attack are low. The inlet must provide the engine with a very high mass flow rate;

The second flight point is maneuver: The Mach number and the angle of attack are high. The inlet must provide the engine with the highest total pressure recovery.

These two flight conditions are sufficient to design the shape of the supersonic inlet because they demand opposite criteria: A high mass flow rate at low Mach number requires low compression, whereas a high total pressure recovery at high Mach number requires high compression. Thus, a compromise has to be reached, and the use of automated optimization and of Pareto sets are a great achievement.

B. Geometrical Model

The variable geometrical model consists of a four ramp mixed-compression inlet, as shown in Fig. 8. The cowl comprises four segments. The final cowl used for Navier–Stokes computations and mechanical design is determined by smoothing the segments. The number of design variables is 18. The other geometrical parameters are fixed and determined by the geometrical constraints of integration of the inlet on the missile. The position of the inlet apex is given by results of external aerodynamics with the constraints of stability of the complete missile. The positions of the ramjet entrance and its section are also given. The variables consist of the ramp lengths and angles. The variable names and lower/upper boundaries are given in Table 2.

A few preconstraints are used to limit the number of computed individuals. They apply mostly to the angles of the ramps. Because it is clear that an actual compression ramp is needed, the angles of the ramps are necessarily increasing,

$$\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$$

The cowl has also to create a compression, thus, leading to the sets of constraints

$$\alpha_{c1} > \alpha_{c2} > \alpha_{c3} > \alpha_{c4}$$

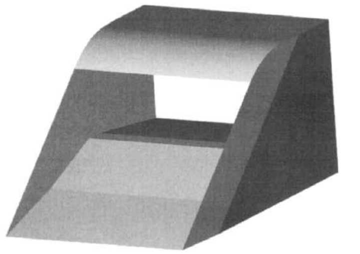
Another well-known result of supersonic inlet design is that the cowl apex must be between the beginning and the end of the last compression. This gives the final constraint,

$$L_1 + L_2 + L_3 < X_{\text{cowl}} < L_1 + L_2 + L_3 + L_4$$

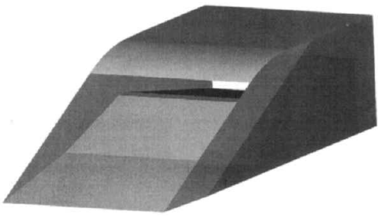
The geometric constraints are used to limit the maximum height and width of the inlet to respect the constraints of integration. Notice that, because the capture area is fixed during the optimization, the width of the inlet (one variable parameter) also gives its height. The value of the capture area was chosen on the basis of studies made during the ramjet engine predesign.

C. Results

The optimization problem is a multi-objective one. The purpose is to maximize both mass flow rate at low Mach number and total pressure recovery at high Mach number. The resulting Pareto set is given in Fig. 9. The vertical axis is the normalized total pressure recovery at the cruise condition, and the horizontal axis is the normalized mass flow rate at the acceleration condition. Each point represents a particular three-dimensional inlet shape. Both ends of the Pareto



a) Shape for best mass flow rate at acceleration



b) Shape for best total pressure recovery at cruise

Fig. 10 Examples of inlets in Pareto set.

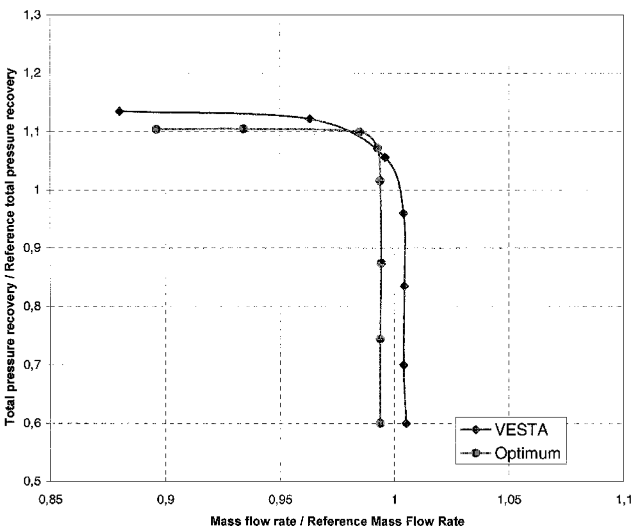


Fig. 11 Performance curves of the VESTA and the optimal inlet.

set are the optima corresponding to each objective. Of course, the performance for the other objective is very bad, and these shapes are not good compromises for the global performances of the missile. The Pareto set was achieved in about 10,000 iterations, where one iteration is the creation of a single new design and its replacement (as appropriate) into the population.

The Pareto set presents three major areas.

The first is an almost horizontal line: When started from the shape having the best total pressure recovery for the maneuver, the mass flow rate at the acceleration point can be improved with very few losses in the total pressure recovery. An example of one design from this portion of the Pareto set is shown in Fig. 10.

The second area is an almost vertical line: When started from the shape giving the best mass flow rate at the acceleration point, the total pressure recovery for the maneuver can be improved with very few losses in mass flow rate. An example of one design from this portion of the Pareto set is shown in Fig. 10.

The third is a tradeoff area: It gathers the best compromises between both performances. The optimal shape was selected from the inlet configurations in the tradeoff area of Fig. 9 by taking into account the missile flight trajectories. A few configurations, very close in terms of aerodynamic performance, were separated using other criteria such as mechanics or stealth. The performance curves of the optimal inlet configuration and of the VESTA inlet are compared on one flight point in Fig. 11. The vertical axis is the normalized total pressure recovery, and the horizontal axis is the normalized mass flow rate. The performance of both designs is very close. This means that the classical methodology used during the development actually realized an optimum inlet shape, but also that automated optimization permits us to reach the same level of performance much faster, thus achieving real improvements in terms of design cycle time and costs.

V. Conclusions

The automated optimization loop has demonstrated the capability of achieving a design comparable to the actual VESTA design in terms of performance, but in a significantly shorter time frame. The VESTA inlet was obtained in about two years with classical methods, whereas the automated optimization cycle required only three months: one month for the setting of the geometrical model and of the loop, one month for optimization computations, and one month for Navier–Stokes computations. Therefore, in our view, the automated optimization loop allows a significant reduction in the number of wind-tunnel test campaigns necessary to characterize the inlet performance over the entire flight domain and, thus, significantly reduces design costs.

Even though our automated optimization loop for multicriteria optimization of three-dimensional inlets is reliable in an industrial context, several improvements can be considered.

1) The 2ES3D aerodynamic software should be modified to give more information on the performances of the inlet. A prediction of the subcritical mass flow rate would be essential to have precise data for the ramjet model.

2) The ramjet model should also be used more to permit optimization of the ramjet engine thrust.

3) A trajectory module should be added to have a better description of the mission and to be able to optimize global performances of the missile (maneuverability, range, ceiling, etc.).

4) Finally, multi-objective algorithms make it possible to accomplish multidisciplinary optimizations. The same optimization loop could be used to obtain best configuration taking into account aerodynamics, stealth and mechanics.

Such optimization tools would allow consideration of the design process from a global point of view. They would be very powerful and useful to find the best compromise by automatically performing a concurrent engineering optimization between several performances and disciplines.

Although optimization tools were not available early enough to play an important role during the development of the VESTA inlet, they will undoubtedly be used in an intensive manner for future airbreathing supersonic missile developments.

References

[1]Bäck, T., "Applications of Evolution Strategies," *von Kármán Institute Lecture Series 2000-07*, von Karman Inst., Rhode-Saint-Genèse, Belgium, 2000.

[2]Anderson, M. B., Burkhalter, J. E., and Jenkins, R. M., "Missile Aerodynamic Shape Optimization Using Genetic Algorithms," AIAA Paper 99-0261, Jan. 1999.

[3]Knight, D. D., "Application of Genetic Algorithms to High Speed Air Intake Design," *von Kármán Institute Lecture Series 2000-07*, von Karman Inst., Rhode-Saint-Genèse, Belgium, 2000.

[4]Blaize, M., Knight, D. D., and Rasheed, K., "Automated Optimal Design of Two Dimensional Supersonic Missile Inlets," *Journal of Propulsion and Power*, Vol. 14, No. 6, 1998, pp. 890–898.

[5]Bourdeau, C., Carrier, G., Knight, D. D., and Rasheed, K., "Three-Dimensional Optimization of Supersonic Inlets," AIAA Paper 99-2108, June 1999.

[6]Carrier, G., Bourdeau, C., Knight, D., Kergaravat, Y., and Montazel, X., "Multi-Flight Condition Optimization of Three-Dimensional Supersonic Inlets," *RTO AVT Symposium on Aerodynamic Optimization*, Research and Technology Organization, Neuilly-sur-Seine, France, 1999.

[7]Pagan, D., and Gaiddon, A., "Design Methodology for Supersonic Air Intakes," AIAA Paper 2001-3881, July 2001.

[8]Goldberg, D. E., *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley Longmar, Reading, MA, 1989.

[9]Bourdeau, C., Blaize, M., and Knight, D. D., "Performance Analysis for an Automated Optimal Design of High Speed Missile Inlets," AIAA Paper 99-0611, Jan. 1999.

[10]Johnston, J. P., "Diffuser Design and Performance Analysis by Unified Integral Methods," AIAA Paper 97-2733, July 1997.

[11]Montazel, X., Kergaravat, Y., and Blaize, M., "Navier–Stokes Simulation Methodology for Supersonic Missile Inlets," International Symposium on Air Breathing Engines, ISABE Paper 97-7029, Sept. 1997.

[12]Holland, J. H., *Adaptation in Natural and Artificial Systems*, Univ. of Michigan Press, Ann Arbor, MI, 1975.

[13]Bäck, T., Some Theory of Evolution Strategies, *von Kármán Institute Lecture Series 2000-07*, 2000.

[14]Rasheed, K., "GADO: a Genetic Algorithm for Continuous Design Optimization," Ph.D. Dissertation, Dept. of Computer Science, Rutgers Univ., Piscataway, NJ, Jan. 1998.

[15]Rasheed, K., Hirsh, H., and Gelsey, A., "A Genetic Algorithm for Continuous Design Space Search," *Artificial Intelligence in Engineering*, Vol. 11, No. 3, 1997, pp. 295–305.