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Multi-criteria Design Optimizations (MDOs) are performed for a 2-D mixed compression supersonic inlet intended for an air breathing missile. The multiple criteria are the optimization of specific objective functions based on the inlet performance for three different stages of the missile mission, *i.e.*, the mass capture ratio ε during acceleration, and the total pressure recovery coefficient η during cruise and maneuver. The MDO yields the Pareto Front in the space of the objective functions. Three different MDOs are performed based on two different flow solvers. The first MDO employs the semi-empirical inlet analysis code OCEAS, developed by Aérospatiale Matra Missiles. OCEAS requires typically 2 sec cputime per simulation, but is limited to inlets with entirely supersonic flow upstream of the inlet throat. The second MDO employs 2ES2D, developed by Aérospatiale Matra Missiles and Rutgers University. 2ES2D requires typically 2 minutes cputime per simulation, and can treat inlets with mixed subsonic/supersonic flow upstream of the inlet throat. The third MDO employs both OCEAS and 2ES2D in a self-adaptive methodology whereby OCEAS is employed except for those configurations where subsonic flow occurs upstream of the inlet throat. The self-adaptive methodology yields essentially the same Pareto Front as obtained using 2ES2D alone but with a 40% reduction in cputime. The Pareto Front obtained using the self-adaptive methodology or 2ES2D exhibits significantly better designs than the Pareto Front obtained using OCEAS alone.

Introduction

Rapid advances in computer technology and optimization methodology have dramatically changed the process of aerodynamic design. Automated optimal design of air vehicle components (*e.g.*, wings, inlets, etc) is now common in industry.[7,14]

The objectives of this paper are twofold. First, we present three Multi-criteria Design Optimizations (MDOs) for a 2-D mixed compression supersonic inlet intended for an air breathing missile. The multiple criteria are the optimization of specific performance measures for three different phases of the missile mission, *i.e.*, acceleration, cruise and maneuver (Fig. 1). Each MDO yields a Pareto Front of non-dominated designs. This represents an extension of previous supersonic inlet design optimizations[2,3] for a missile mission wherein a single fitness function was employed. Second, we evaluate the effectiveness of a self-adaptive methodology for reducing the cputime required to achieve the Pareto Front. The methodology is based on two different flow solvers which are characterized by nested domains of validity and substantial differences in cputime (*i.e.*, the domain of validity of the (faster) flow solver is contained within the domain of validity of the (slower) flow solver). We demonstrate that a self-adaptive methodology employing both flow solvers can substantially reduce the cputime required to achieve the same Pareto Front as obtained with the

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slower flow solver alone.

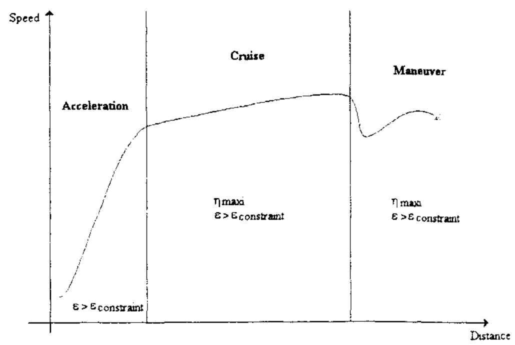

Fig. 1 Mission profile

Inlet Aerodynamics

The function of a conventional (*i.e.*, non-scramjet) supersonic inlet is to provide a specified mass flow rate to the engine (*e.g.*, compressor in the case of a turbojet, or combustor in the case of a ramjet) at a given subsonic speed with minimal loss of total pressure and minimal flow distortion. We consider a mixed compression supersonic inlet wherein the flow is decelerated from supersonic to subsonic speeds by a system of shock waves which are both external and internal to the inlet (Fig. 2).

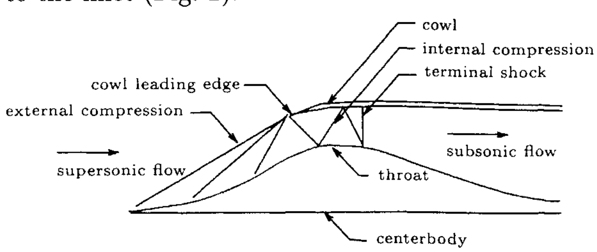

Fig. 2 Mixed compression inlet

The inlet performance is typically defined in terms of two parameters. The first parameter is the total pressure recovery coefficient

$$\eta = \frac{\bar{p}_t}{p_{t_\infty}} \tag{1}$$

where $\bar{p}_t$ is the area-averaged total pressure at the outflow of the subsonic diffuser and p_{t_∞} is the freestream total pressure. A perfectly isentropic compression would yield $\eta = 1$; however, in practical configurations η is less than one due to total pressure losses in the shock waves and boundary layers. The vehicle performance depends directly on η. For example, the specific impulse of a ramjet engine is[9]

$$I = \frac{a_o h}{g c_p T_o} M_o \left[1 + \frac{(\gamma-1)}{2} M_o^2\right]^{-1} \left[\frac{\varsigma\sqrt{\tau_b} - 1}{\tau_b - 1}\right] \tag{2}$$

where $a_o = \sqrt{\gamma R T_o}$ is the freestream speed of sound, g is the gravitational constant, h is the heat added per unit mass of fuel burned, M_o is the freestream Mach number, τ_b is the ratio of total temperatures across the combustor, and

$$\varsigma = \sqrt{1 - \frac{2}{(\gamma-1)} \frac{\sigma}{M_o^2}} \tag{3}$$

where

$$\sigma = \eta^{-(\gamma-1)/\gamma} - 1 \tag{4}$$

Thus, $\partial I / \partial \eta > 0$, and consequently an increase in η results in an increase in I. For flight at a constant velocity u_o and lift to drag ratio L/D, the range is

$$R = u_o I \left(\frac{L}{D}\right) \log \frac{M_g}{M_g - M_f} \tag{5}$$

where M_g is the initial gross weight and M_f is the mass of fuel consumed. Thus, the range depends linearly on the specific impulse, and an increase in η results in an increase in range.

The second parameter is the mass flow rate coefficient

$$\varepsilon = \frac{\dot{m}}{\dot{m}_m} \tag{6}$$

where $\dot{m}$ is the air mass flow rate into the inlet, and $\dot{m}_m$ is the maximum mass flow rate (for a given Mach number, altitude and inlet geometry) at zero angle of attack and sideslip. The maximum flow rate occurs when the external compression system (*i.e.*, shocks and/or isentropic compression) is focused on the cowl leading edge. This is denoted the *design condition*.

Flow Solvers

OCEAS

OCEAS (Outil de Conception d'Entrées d'Air Supersoniques[10]) is a flow solver specifically developed for 2-D/axisymmetric supersonic inlets by Aérospatiale Matra Missiles. The supersonic flowfield is calculated using the Method of Characteristics with the Rankine-Hugoniot shock jump conditions. Expansions are approximated as discontinuities using the Prandtl-Meyer formula and the conservation of mass. The terminal shock system is treated as either a single normal shock (using the average Mach number at the geometric throat) or as a vertical sequence of normal shocks corresponding to the individual uniform regions defined by the compression and expansion waves at the geometric throat. Viscous losses in the subsonic diffuser are modeled using an empirical method.[6,8] OCEAS has been demonstrated to predict the total pressure recovery coefficient within 8% and the mass capture ratio ε within 6% for a range of inlet configurations by comparison with experiment.[2] Typical cputime for OCEAS is 2 sec on a DEC Alpha 2100 (275 MHz).

2ES2D

2ES2D (Euler Semi-Empirical Simulation Code 2-D) is a hybrid simulation methodologies developed by Blaize[4] and Bourdeau *et al*[5] for 2-D inlets. Three steps are employed as illustrated in Fig. 3. First, the entire inlet (including the subsonic diffuser) is computed using an Euler code (GASP[1]) with zero gradient outflow boundary conditions. This provides an accurate representation of the supersonic portion of the inlet. However, there is no terminal shock system in this calculation and therefore the flow in the nominally subsonic portion of the diffuser is supersonic. Second, a Virtual Terminal Shock (VTS) model is applied at (or near) the geometric throat to determine the total pressure losses across the terminal shock system. A normal shock is assumed to exist at the throat for each computational cell of the Euler simulation, and the area-averaged total pressure recovery downstream is computed. Third, the subsonic diffuser losses are computed.[5]

Boundary layer bleed is not employed in 2ES2D due to the assumption of inviscid flow. It is assumed that an acceptable boundary layer bleed schedule can be obtained (using a RANS simulation) *a posteriori*. This assumption must be verified on a case-by-case basis.

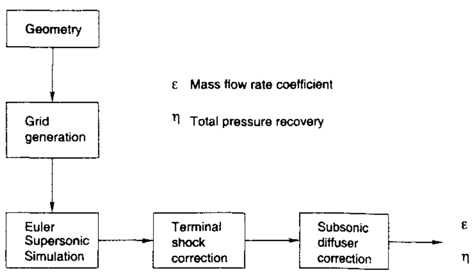

Fig. 3 2ES2D

The advantage of 2ES2D compared to OCEAS is greater generality. 2ES2D can compute inlet flowfields with small subsonic zones upstream of the geometric throat. This capability does not exist for OCEAS since it is based on the Method of Characteristics. A mixed compression inlet optimized for a single flight condition would not likely have a subsonic region upstream of the geometric throat; however, an inlet optimized for an entire mission may experience subsonic flow upstream of the throat under some flight conditions. It is therefore important to be able to compute the inlet performance in such circumstances.

2ES2D has been validated by comparison with experimental data for three inlet configurations.[5] The total pressure recovery coefficient η was predicted within 4% for two configurations. For a third inlet characterized by a large subsonic region beneath the cowl, the total pressure recovery coefficient was predicted within 14%. However, the third inlet is atypical of an optimized inlet which would exhibit a *small* subsonic region (if at all) upstream of the inlet throat. The mass capture ratio ε was predicted within 3% for all configurations. Therefore, the accuracy of 2ES2D is considered to be comparable to OCEAS within the range of applicability of OCEAS[5] (*i.e.*, for mixed compression inlets with supersonic flow upstream of the inlet throat), and the range of applicability of 2ES2D is considered to be greater than OCEAS (since 2ES2D can treat inlets with small subsonic regions upstream of the inlet throat). The typical cputime for 2ES2D is 2 min on a DEC 2100 (275 MHz).

Self-Adaptive

The self-adaptive flow solver employs both OCEAS and 2ES2D in a sequential manner. A given inlet design is first computed using OCEAS. If the flowfield upstream of the inlet throat is entirely supersonic, then the result for η and ε obtained from OCEAS is employed in the optimization since it is expected that 2ES2D would return essentially the same result. If, however, the flowfield exhibits a subsonic region upstream of the inlet throat, then the inlet flowfield is recomputed using 2ES2D. This procedure is *self-adaptive* since the proper flow solver is selected dynamically during the optimization.

Optimization

We consider the general nonlinear Multi-criteria Design Optimization (MDO) problem

$$\text{minimize} \quad F_i(x) \quad i = 1, \ldots, m \tag{7}$$

$$\text{subject to} \quad G_{ij}(x) \leq 0 \quad j = 1, \ldots, c(i) \tag{8}$$

where *minimize* is taken in the sense of Pareto order (see below) and x is the vector of design variables

$$x = (x_1, x_2, \ldots, x_n) \tag{9}$$

where n is the number of design variables. The *fitness functions* $F_i(x)$ are real-valued and incorporate both an *objective function* $O_i(x)$ and a *penalty function* $P_i(x)$ according to

$$F_i(x) = O_i(x) + P_i(x) \tag{10}$$

The objective function $O_i(x)$ is intended to be minimized[i]. The penalty function $P_i(x)$ is positive if any constraints are violated, and zero if all constraints are met.

The optimization employs the concept of Pareto order. Consider two designs x_a and x_b where

$$\begin{aligned} x_a &= (x_{1_a}, x_{2_a}, \ldots, x_{n_a}) \\ x_b &= (x_{1_b}, x_{2_b}, \ldots, x_{n_b}) \end{aligned} \tag{11}$$

where $x_{1_a}, \ldots, x_{n_a}$ are the design variables of design a. Consider the m fitness functions $F_1(x)$, $F_2(x)$, …,

[i]There is no loss of generality in assuming the objective function is minimized, since the maximization of a function is equivalent to the minimization of its negative.

$F_m(x)$ defined according to (10). Design a is *dominated* by design b if

$$\begin{array}{ll} F_i(x_a) \geq F_i(x_b) & \text{for } i = 1, \ldots, m \text{ except } i = k \\ F_k(x_a) > F_k(x_b) & \text{for } i = k \end{array} \tag{12}$$

where k is some integer in the range $1 \leq k \leq m$. Thus, design a is dominated by design b if each of its fitness functions F_i are never better than the corresponding fitness function of design b except for one fitness function $F_k(x_a)$ which exceeds $F_k(x_b)$. The set $x_\alpha, x_\beta \ldots$ of *non-dominated* designs is called the *Pareto Front.* It represents the best set of designs in the following sense: among the designs in the Pareto Front, it is possible to improve a specific fitness function only at the expense of a degradation in another.

Table 1 GADO Operations

Step	*Action*
1	Select two designs
2	Crossover operation
3	Mutation operation
4	Fitness computation
5	Replacement

We employ the genetic algorithm GADO developed by Rasheed.[12,13] GADO (Genetic Algorithm for Design Optimization) searches the design space in a five step procedure (Table 1) to determine the Pareto Front. First, two designs are chosen from the population (Fig. 4). Second, a *crossover operator* is selected and applied to the two designs to generate a new design. Third, a *mutation operator* is applied (if appropriate). The resultant design is denoted the *newborn.* Fourth, the fitness function of the newborn is determined. Fifth, the newborn *replaces* a member of the population. GADO is a *steady state* genetic algorithm wherein the size of the population remains fixed.

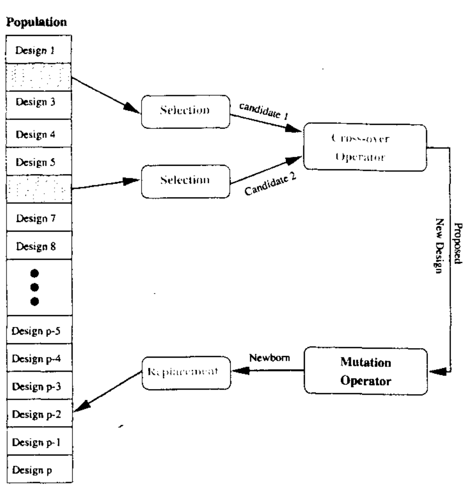

Fig. 4 GADO

There are five different crossover operators in GADO which are organized into two categories. Each operator employs two parent designs x_a and x_b and produces a new design x_c. The first category, denoted *non-guided crossover*, is comprised of four operators. *Point crossover* is a cut-and-paste operation which takes a portion of the design variables from the first parent and the remainder of the design variables from the second. Consider the two designs $x_a = (x_{1_a}, x_{2_a}, \ldots, x_{n_a})$ and $x_b = (x_{1_b}, x_{2_b}, \ldots, x_{n_b})$. The point crossover selects a random position l within the design vector and generates the new design as

$$x_c = (x_{1_a}, x_{2_a}, \ldots, x_{l-1_a}, x_{l_a}, x_{l+1_b}, \ldots, x_{n_b}) \tag{13}$$

Line crossover is a linear combination of the design vectors of the parents defined by

$$x_c = \nu x_a + (1 - \nu) x_b \tag{14}$$

where $-2 \leq \nu \leq 3 + 2\varphi(i)$ where $\varphi(i)$ is defined as

$$\varphi(i) = \tfrac{i}{i_m} \tag{15}$$

where i is the iteration number and i_m is the maximum number of iterations allowed. *Double line crossover* is a hybrid of line and point crossover. *Random crossover* selects elements randomly from the design vector of the two parents. The second category is *guided crossover* which mimics the Method of Steepest Descent and is typically employed towards the end of the optimization.

At each iteration, the crossover operator is selected as follows. First, the category is selected probabilistically. The probability of selecting guided crossover is initially zero and increases linearly with the number of iterations to a user-defined upper bound (typically, 0.25). Second, if non-guided crossover is selected, then one of the four crossover operators is selected probabilistically based upon user-defined probabilities.

There are three mutation operators in GADO. The operator, chosen probabilistically and applied only after a non-guided crossover, generates a new design x'_c from x_c. *Shrinking window* randomly perturbs one of the elements of the design vector with an amplitude which decreases as the optimization progresses. *Non-uniform mutation* is similar to shrinking window except that it is biased against producing designs near the limits of the design space. *Greedy mutation* generates a new design according to

$$x'_c = \begin{cases} x_c + (u - x_c) r_1 r_2 & \text{with probability } 0.5 \\ x_c - (x_c - l) r_1 r_2 & \text{with probability } 0.5 \end{cases} \tag{16}$$

where r_1 and r_2 are two random values chosen uniformly in the interval $0 \leq r_1, r_2 \leq 1$.

The *replacement* algorithm in GADO is a crowding technique.[11] The design in the existing population which is closest to the new design and within a specified group is selected for replacement. The group includes those designs which are worse in fitness than the new design and among the worse in fitness of the designs in the current population.

The design optimization methodology is illustrated in Fig. 5. An initial population is generated randomly. Subsequent designs generated by GADO are first examined to determine if they violate any constraints (see below). If any constraints are violated, then the penalty function is computed and the fitness functions F_i returned to GADO without performing a flow simulation. If no constraints are violated, then the flow simulator is called for each of the three mission stages.

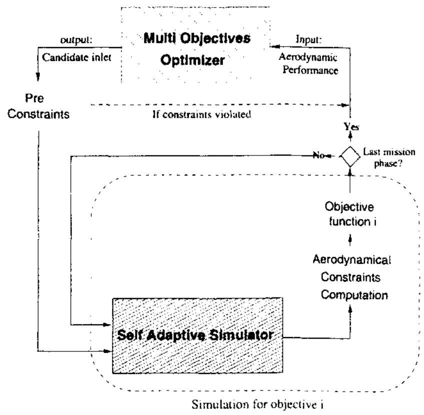

Fig. 5 Optimization methodology

Table 2 Optimizations

No.	*Simulator*	*Iterations*	*Population*
1	OCEAS	15,000	120
2	2ES2D	5,000	120
3	OCEAS+2ES2D	5,000	120

Three different types of simulators are employed as indicated in Table 2. The first simulator is OCEAS. The second simulator is 2ES2D. The third simulator is a self-adaptive algorithm which first employs OCEAS and then 2ES2D if OCEAS indicates that a subsonic region is observed upstream of the inlet geometric throat.

At each stage of the optimization, the population is ordered into *groups* based upon the Pareto ranking as illustrated in Fig. 6. An iterative procedure is employed for the ordering. First, the set of all non-dominated designs in the population is defined as Group 1. This is the current Pareto Front. Second, Group 1 is removed from the population and the set of all non-dominated designs in the remaining population is defined as Group 2. This process is repeated until all members of the population have been ordered into groups.

Each member of the population is assigned a *niching coefficient* in addition to its fitness functions F_i. The niching coefficient is based on on the proximity of the design to other designs in its group. The proximity is computed using both the physical design variables and fitness values. A high value of the niching coefficient implies that the design is close to others.

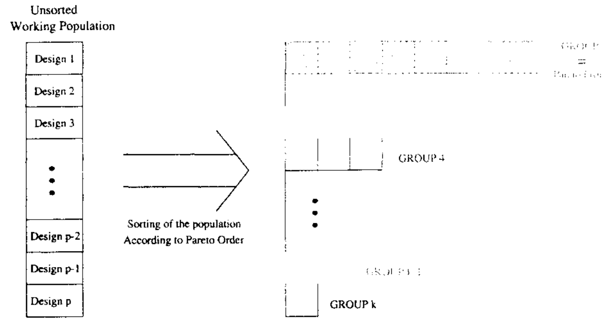

Fig. 6 Decomposition into groups

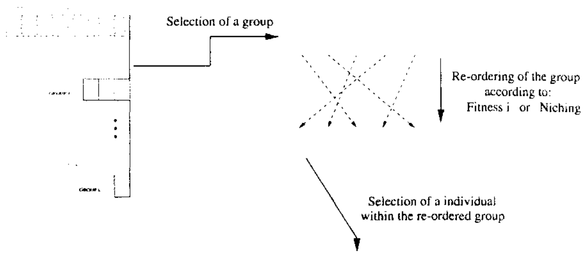

Fig. 7 Selection of design

GADO is implemented for MDO in the following manner. The first step is the selection of two designs from the population (Fig. 4) as follows. A group is selected stochastically with higher probability given to groups of low level (*i.e.*, closer to the Pareto Front). Within the selected group, a design is chosen according to one of its fitness functions (selected at random) or its niching coefficient (Fig. 7). The second step is the crossover operation whereby a newborn design is generated from two parent designs. The third step is the mutation of the newborn design (if appropriate). The fourth step is the computation of the fitness function. The fifth step is the replacement of the design into the population.

Description of Problem

We consider a Multi-criteria Design Optimization (MDO) of a two dimensional mixed compression inlet. The performance of the inlet during three separate stages of a mission constitutes the multiple design criteria. The inlet geometry is shown in Fig. 8 and the eight design parameters in Table 3.

The optimization is performed for a mission comprised of three stages as described in Table 4. The first stage is acceleration at Mach 2 and 18 km altitude with an objective function $O_1(x) = -\varepsilon$. The second stage is cruise at Mach 4 and 20 km altitude, and the third stage is maneuver at Mach 2.5 and sea level. The angle of attack α is 1°, 5° and −4° for the acceleration, cruise and maneuver stages, respectively. The objective functions for the second and third stages

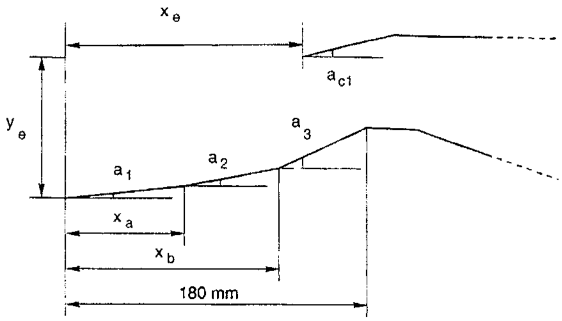

Fig. 8 Inlet geometry

Table 3 Design Parameters

Parameter	*Description*
x_e	abscissa of cowl leading edge
y_e	ordinate of cowl leading edge
ac_1	angle of cowl inner segment
x_a	abscissa of end of first ramp
x_b	abscissa of end of second ramp
a_1	angle of first external ramp
a_2	angle of second external ramp
a_3	angle of third external ramp

are $O_2(x) = -\eta$ and $O_3(x) = -\eta$. Flow distortion is not considered in this study.

Typically, inlet designs are subject to a self-start constraint, *i.e.*, the ability to achieve the internal shock system at a specified Mach number. The self-start criterion is based on the internal contraction ratio of the inlet. The self-start criterion is satisfied at the specified Mach number if the contraction ratio is less than the maximum contraction ratio for which a pitot inlet would self-start based on the flow conditions at the inlet entrance. In this study, we assume that the acceleration phase replaces the self-start constraint.

Table 4 Mission Stages

Quantity	*Accel*	*Cruise*	*Maneuver*
Mach	2.0	4.0	2.5
Altitude (km)	18	20	0
α (deg)	1	5	-4
$O(x)$	$-\varepsilon$	$-\eta$	$-\eta$

Results

The results of the optimization are presented in Fig. 9 which displays the designs on the Pareto Fronts for Optimization Nos. 1 to 3 in the objective space. The three axes are $\varepsilon_{M=2}$ (increasing to right), $\eta_{M=4}$ (increasing vertically) and $\eta_{M=2.5}$ (increasing to the left). The Pareto Front obtained by Optimization No. 1, shown as the blue line of points in the lower right corner, is closer to the origin, thereby indicating lower values of $\eta_{M=4}$ and $\eta_{M=2.5}$. This is attributable to the limitations of OCEAS which is incapable of predicting the total pressure recovery coefficient when a subsonic zone appears upstream of the inlet throat. The Pareto Fronts obtained by Optimization Nos. 2 (red points) and 3 (white points) are essentially the same, indicating that the self-adaptive methodology (using OCEAS first, and then using 2ES2D if OCEAS fails) produces the same result as 2ES2D alone.

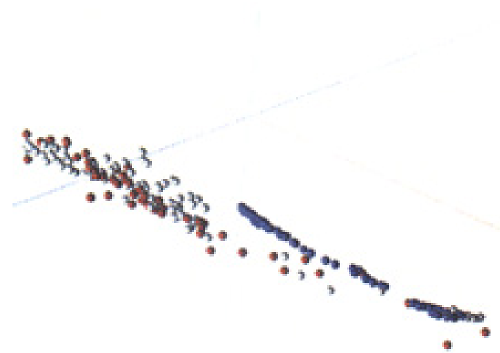

Fig. 9 Pareto Front in perspective

Details of the optimizations are presented in Table 5. *Feasible inlets after constraints* is the number of inlet designs which satisfied the preliminary geometric constraints (*e.g.*, $x_a < x_b$ in Fig. 8). Since GADO is a stochastic optimizer, it can generate designs which violate these obvious geometric constraints (denoted *infeasible* designs). The flow solvers are not called for infeasible designs. *Feasible inlets* is the number of inlet designs which satisfy *both* the preliminary geometric constraints and the aerodynamic constraints (*e.g.*, a requirement on the minimum mass capture ratio ε). *OCEAS Simulations* is the number of calls to OCEAS, and *Successful OCEAS Simulations* is the number of successful OCEAS simulations (*i.e.*, there was no subsonic region detected upstream of the inlet throat). Similarly, *2ES2D Simulations* is the number of calls to 2ES2D, and *Successful 2ES2D Simulations* is the number of successful results. *Successful simulations* is the sum of the successful simulations by OCEAS and/or 2ES2D. *Reduction in 2ES2D simulations* is the number of 2ES2D simulations saved by using OCEAS first. The principal result in Table 5 is the 40% reduction in computer time achieved by the self-adaptive methodology.

Conclusions

Three Multi-criteria Design Optimizations (MDOs) of a 2-D mixed compression supersonic inlet intended for an air breathing missile are presented. The criteria are specific performance measures for the three different phases of the missile mission, *i.e.*, acceleration, cruise and maneuver. Two different flow solvers are employed. The flow solvers are characterized by nested domains of validity and substantial differences

Table 5 Summary of MDOs

Parameter	*Opt No. 1*	*Opt No. 2*	*Opt No. 3*
Flow solver	OCEAS	2ES2D	OCEAS/2ES2D
Feasible inlets after constraints	11661	3404	3628
Feasible inlets	5157	1004	1254
OCEAS simulations	24029		7120
Successful OCEAS simulations	17676		2601
2ES2D simulations		6081	4136
Successful 2ES2D simulations		5063	3198
Successful simulations	17676	5063	5799
Reduction in 2ES2D simulations			2984

in cputime, *i.e.*, the faster flow solver (OCEAS) has a domain of validity which is contained with the domain of validity of the slower flow solver (2ES2D). Three separate optimizations are performed using OCEAS alone, 2ES2D alone and OCEAS with 2ES2D. In the third case, 2ES2D is employed only when the design is outside the range of validity of OCEAS as determined by the appearance of subsonic flow upstream of the inlet throat.

Two important results are obtained. First, the Pareto Front obtained using 2ES2D displays significantly better designs than the Pareto Front achieved using OCEAS alone for the specified mission. Second, the self-adaptive methodology (OCEAS/2ES2D) achieves essentially the same Pareto Front as achieved using 2ES2D but with a 40% reduction in cputime.

Acknowledgments

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