Simulación y Modelado en Ingeniería y Ciencias
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Optimal Design of Aerospace Systems[1]

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Abstract In this paper we describe briefly a set of procedures for the optimal design of full mission aerospace systems. This involves multiphysics simulations at various fidelity levels, surrogates, distributed computing and optimization of the resulting nonlinear programming problem. Low-fidelity analysis is used to populate a database of inputs and outputs of the system simulation and Neural Networks are then designed to generate inexpensive surrogates. Higher fidelity is used only where is warranted and also to do a local exploration after global optimization techniques have been used on the surrogates in order to provide plausible initial values. The ideas are exemplified on a generic supersonic aircraft configuration, where one of the main goals is to reduce the ground sonic boom.

Keywords: Optimal Design, Surrogates, Response Surfaces, Multifidelity Analysis, Aerospace Systems

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. INTRODUCTION

Optimization problems in many industrial applications are extremely hard to solve in a eneral manner. Good examples of such problems can be found in the design of aerospace ystems. Due to the high level integration of today's systems and the increase in complexity of nalysis and design methods for the evaluation of system performance, such problems are haracterized by multi-disciplinary simulations, goal functionals and constraints that are xpensive to evaluate and, in addition, they often have large-dimensional design parameter paces that further complicate the solution of the problem.

Moreover, the resulting optimization problems are frequently non-convex, i.e., multi-odal and ill-conditioned, making complete optimizations of complex aircraft configurations ohibitively expensive. Finally, the simulations may require using legacy or commercial codes at have to be used as black boxes which, in particular, may not produce the derivative formation required by some optimization techniques.

Multi-modal, ill-conditioned problems require global optimization techniques and gularization [12,15] and present some of the most challenging problems for robust itialization and ulterior accurate solution. In high-dimensional spaces the available techniques e problematic at their best and one often must resort to surrogate models, divide and conquer chniques and parallel computing, in order to even have a chance to solve the problem in a asonable time [2,7,14,15].

In addition to all of these complexities, the available optimization strategies are such that, ven initial conditions that are not in the vicinity of the true global optimum, the optimization ocedure may fail to converge or even produce a feasible sub-optimal design. This is rticularly true of system vehicle designs (aircraft and spacecraft), where many disciplines eract in a complex multi-disciplinary analysis, and where the models of each of the disciplines y be noisy and even discontinuous.

However, if a reasonable starting point can be provided for the design, the likelihood of nvergence to the optimum is greatly improved: the design space is much better behaved in the ghborhood of the optimum and since the range of variations of the design parameters is more tricted, multi-modal design spaces are typically avoided.

This view of the initialization problem requires a flexible environment that can be ored to specific applications in order to have the best possibility of success in the design of nplex multi-disciplinary systems. For that reason, **we have chosen to develop an advanced lbox for design that will contain the necessary modules (approximation, optimization, cipline-specific analysis) to tackle a wide variety of aerospace-related problems.** These ls can be combined by advanced users and developers to create new design applications with tively low investment. We present here some preliminary results of what has been achieved far.

2. THE PROBLEM CONSIDERED AND THE VARIOUS MODULES EMPLOYED FOR ITS SOLUTION

We start from a high plateau with an existing prototype of a general Toolbox for Optimization, which has been successfully applied to other multidisciplinary realms [16], and a number of proven tools for aircraft design [1,2,7,8,9]. In this work we sketch some of the principal components necessary to carry on this type of task. We focus on the generation of sample data for the aerodynamic and boom characteristics of a generic supersonic aircraft configuration, the fitting of this data using Neural Networks, and the use of the resulting surrogate models in a representative design optimization problem.

For this test example, a small number of the most relevant design parameters were selected, as decribed below. Although this is a small number of design variables relative to a realistic aerospace vehicle design, it has all of the elements necessary to exercise and evaluate the initialization and optimization techniques. The main goals are to maximize the takeoff weight and to minimize the ground boom, while satisfying a number of mission and buildability constraints.

For aerodynamic modeling we are currently using the A502 solver, also known as PanAir [5,6], a flow solver developed at Boeing to compute the aerodynamic properties of arbitrary aircraft configurations flying at either subsonic or supersonic speeds. This code uses a higher-order (quadratic doublet, linear source) panel method, based on the solution of the linearized potential flow boundary-value problem. Results are generally valid for cases that satisfy the assumptions of linearized potential flow theory – small disturbance, not transonic, irrotational flow and negligible viscous effects. Once the solution is found for the aerodynamic properties on the surface of the aircraft, A502 can then easily calculate the flow properties at any location in the flow field, hence obtaining the near-field pressure signature needed for sonic boom prediction. In keeping with the axisymmetric assumption of sonic boom theory, the near-field pressure can be obtained at arbitrary distances below the aircraft [3].

To provide a suitable description of the geometry to A502 a well-defined surface in three-dimensional space, which constitutes the outer mold line (OML) of the vehicle, needs to be generated as a function of the selected design variables. Because of the importance of the OML, a separate utility, Aerosurf, is used to generate and manage it. Aerosurf was specifically created for the analysis and design of aircraft configurations. The baseline geometry of an aircraft configuration is given to Aerosurf in the form of separate components, each one being described by a series of point-wise cross sections. These components can be fuselages, pylons, nacelles, and wing-like surfaces. After lofting the sections that define each component using a bi-cubic spline method, Aerosurf intersects these components and divides the resulting surface into a series of patches. At this stage, Aerosurf creates a parametric description of each patch and then distributes points on their surface, forming a fine structured watertight mesh. Thus, the set of points formed by the grids of all patches represents a watertight discretization of the OML within Aerosurf. For Euler or Navier-Stokes computations the surface mesh can be used for the generation of the volume meshes as well as the deformation of an existing mesh for design purposes.

The method for computing the ground boom signature is shown in Figure 2. At the near-field plane location, the pressure signature created by the aircraft is extracted and it is propagated down to the ground using extrapolation methods based on geometric acoustics.

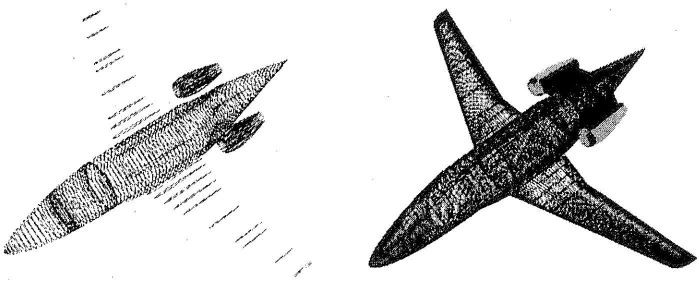

Figure 1: Un-intersected components of a transonic business jet configuration (left) and intersected components forming the OML (right).

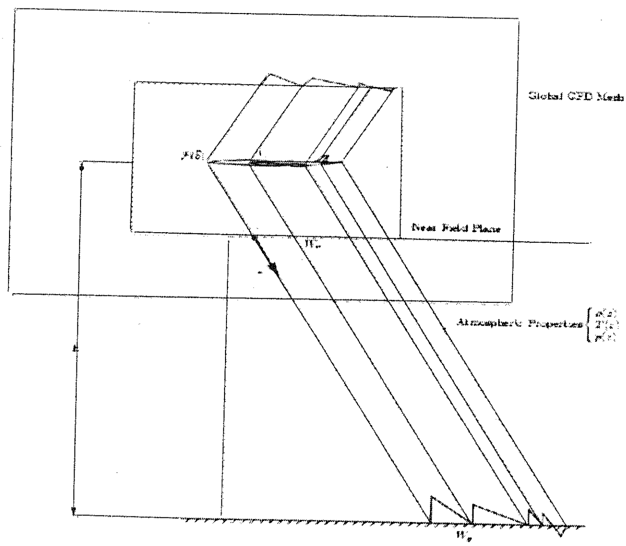

Figure 2: Sonic boom propagation procedure.

The location of the near-field must be far enough from the aircraft so that its flow field is y axisymmetric and there are no remaining diffraction effects, which cannot be handled by xtrapolation scheme. Since A502/Panair only uses a surface mesh for all of its calculations it e to obtain near-field pressures at arbitrary distances without changes in the computational cost.

In this work we are using the Sboom [17] extrapolation method to propagate near-field signatures into ground booms. The sonic boom extrapolation method accounts for vertical gradients of atmospheric properties and for stratified winds (although the winds have been set to zero in this work). The method relies on results from geometric acoustics for the evolution of the wave amplitude, and utilizes isentropic wave theory to account for nonlinear waveform distortion due to atmospheric density gradients and stratified winds.

Our past research on low-boom aircraft design focused on reducing the magnitude of only the initial peak of the ground boom signature [1,8]. This requirement, which had been suggested as the goal of the DARPA-sponsored Quiet Supersonic Platform (QSP) program ($\Delta p_0 < 0.3$ psf), neglects the importance of the full signature, which depends on the more geometrically complex aft portion of the aircraft where empennage, engine nacelles and diverters create more complicated flow patterns. Moreover, such designs often have two shock waves very closely following each other in the front portion of the signature [6,9], a behavior that is not robust and is therefore undesirable.

For these reasons, we are computing the perceived loudness of the complete signature (dbA). Frequency weighting methods are used to account for the fact that humans do not have an equal response to sounds of different frequencies. In these calculations, less weighting is given to the frequencies to which the ear is less sensitive. In addition, all signatures computed are post-processed to add a physical rise-time across the shock waves that yield loudness numbers that are more representative of those perceived in reality.

3. GENERATION OF RESPONSE SURFACES (SURROGATES)

Using the tools described above, 300 configurations obtained via Latin Hypercube Sampling (LHS) were generated. These sample data were fitted using a Neural Network. The NN was a single hidden layer perceptron with sigmoid activation functions that provided a general nonlinear model. We use for its fast training (i.e., determination of the NN parameters) a Variable Projection algorithm (VARPRO [13]) to solve the resulting nonlinear least squares separable problem in order to generate a reduced cost approximation of the design space. This is combined with a global optimization algorithm since the resulting problems are generally multimodal [4].

The training of a single hidden layer Neural Network (NN), using sigmoid activation functions results in a separable nonlinear least-squares problem in which the unknown parameters in the network are determined to best fit in the L_2 sense the training data (i.e., the input/output data contained in the simulation database). This results in a surrogate function that is a linear combination of sigmoids:

$$S(x;\alpha) = \textstyle\sum_j a_j(1/(1+\exp^{-(<\alpha j,x>+\alpha_0^j)})),$$

where $x \in R^k$ corresponds to the input or design parameters, a_j are the linear parameters, and $\alpha^j \in R^k$, α_0^j, are the nonlinear parameters; $<\,,\,>$ stands for vector inner product.

The data used corresponds to a representative supersonic business jet configuration. For each output, the training files contain 300 data points, while a test set of an additional 150 data points are used for evaluation of the fit. There are eight independent or input variables, namely:

- Wing reference area,
- Wing aspect ratio,
- Longitudinal position of the wing,
- Wing sweep angle,
- Lift coefficient at initial cruise,
- Lift coefficient at final cruise,
- Altitude at initial cruise,
- Altitude at final cruise.

here are10 dependent variables that we want to approximate with Neural Networks, namely:

- Drag coefficient at initial cruise,
- Sonic boom initial rise at initial cruise,
- Sonic boom sound level at initial cruise w/out rise time modification,
- Sonic boom sound level at initial cruise w/ first type rise time modification,
- Sonic boom sound level at initial cruise w/ third type rise time modification,
- Drag coefficient at final cruise,
- Sonic boom initial rise at final cruise,
- Sonic boom sound level at final cruise w/out rise time modification,
- Sonic boom sound level at final cruise w/ first type rise time modification,
- Sonic boom sound level at final cruise w/ third type rise time modification.

We scale the input variables so that they have zero mean and variance equal to 1. In ıble 1 we show the results of training and testing for each one of the 10 outputs.

Table 1. Neural Network results for surrogate functionals

Max. Value	#Sigmoids	RMS training	RMS test	Time (sec)	Max. Res.
	8	0.0000865	0.00033	872	0.0009
	8	0.0033	0.206	831	0.15
	10	0.406	1.2	1872	1.5
95	10	0.848	2.0	2332	3.0
95	10	0.541	2.01	2393	1.9
0.017	10	0.0000721	0.000229	2782	0.00023
3	8	0.0364	2.66	1393	0.26
99	10	0.414	1.14	1773	1.9
94	10	0.747	4.46	2090	3.2
94	10	0.545	1.71	1917	2.2

The approximate aerodynamic and boom model generated using VARPRO will be used :onjunction with low-order, first-principles based weight estimation and performance analysis ls. This include component structural weight estimation, takeoff/landing distance, mission ge and/or loiter, climb performance, etc.

For a mission profile to be determined, the approximation model developed using VARPRO and the additional weight and performance tools will be used to run representative optimizations. These will be performed with both gradient-based methods, e.g. SNOPT [11], and non-gradient methods, e.g., NSGA-II [10] and will be reported in a future paper.

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