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MANAGING UNCERTAINTY IN PRELIMINARY AEROSHELL DESIGN ANALYSIS

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ABSTRACT

An analysis tool to aid in preliminary design of re-entry aeroshells for interplanetary exploration is presented. The computational tool addresses a common feature of design analysis, the need to make use of results from several analysis regimes and from several sources. This paper formalizes for computation what has historically been a matter of informal engineering judgment. The automation of design analysis allows for more extensive search of the design space, and thus supports a design process that is at once more thorough and more efficient.

The human designer uses experience and intuition to combine results from different analyses. Here, this combination is formalized by recognizing that each analysis tool is valid in particular regimes of the design problem; where regimes overlap, a combination based on participation factors (and utilizing the mathematics of fuzzy sets) is employed. An aggregated level of confidence for each solution point is also calculated.

Keywords:

Design Methods and Models; Design Representations; Computational Methods of Design

INTRODUCTION

The late 1980's and early 1990's have seen a change in the direction of space research conducted by NASA, with an emphasis on smaller, lighter spacecraft and missions with budgets and time frames an order of magnitude (or two) less than the missions of the 1960's and 1970's, allowing for less expensive, more frequent launches (see Figure 1). This shift in emphasis highlights the need for design tools to support preliminary design, since mission designers no longer have the luxury of long times for prototyping, testing, and redesign.

The need for simulation-based analysis tools is particularly clear in the design of spacecraft, as operating environments (*e.g.*, microgravity) are often difficult or impossible to reproduce to test prototypes. This paper examines some of the issues of the management of information in preliminary design using simulation-based analysis and including uncertainty and data of varying reliability.

A formal system, known as the *Method of Imprecision* or M_oI, for the representation of imprecise information in preliminary engineering design, as expressed through designer preferences, has been previously developed at Caltech by the authors (Wood and Antonsson, 1989) and others. Early work on the method assumed the availability of reliable analysis tools for the determination of design performance from design variables. Recent work (Law and Antonsson, 1996) has used the statistical methods of Design of Experiments (DOE) (Barker, 1985) to address issues of design imprecision using approximations to analysis tools, the full use of which would be prohibitively expensive. At the same time, one of the unifying themes of research on the M_oI has been the aggregation of preferences. The research presented here continues this earlier work by considering preliminary design when the design space is not well modeled by a
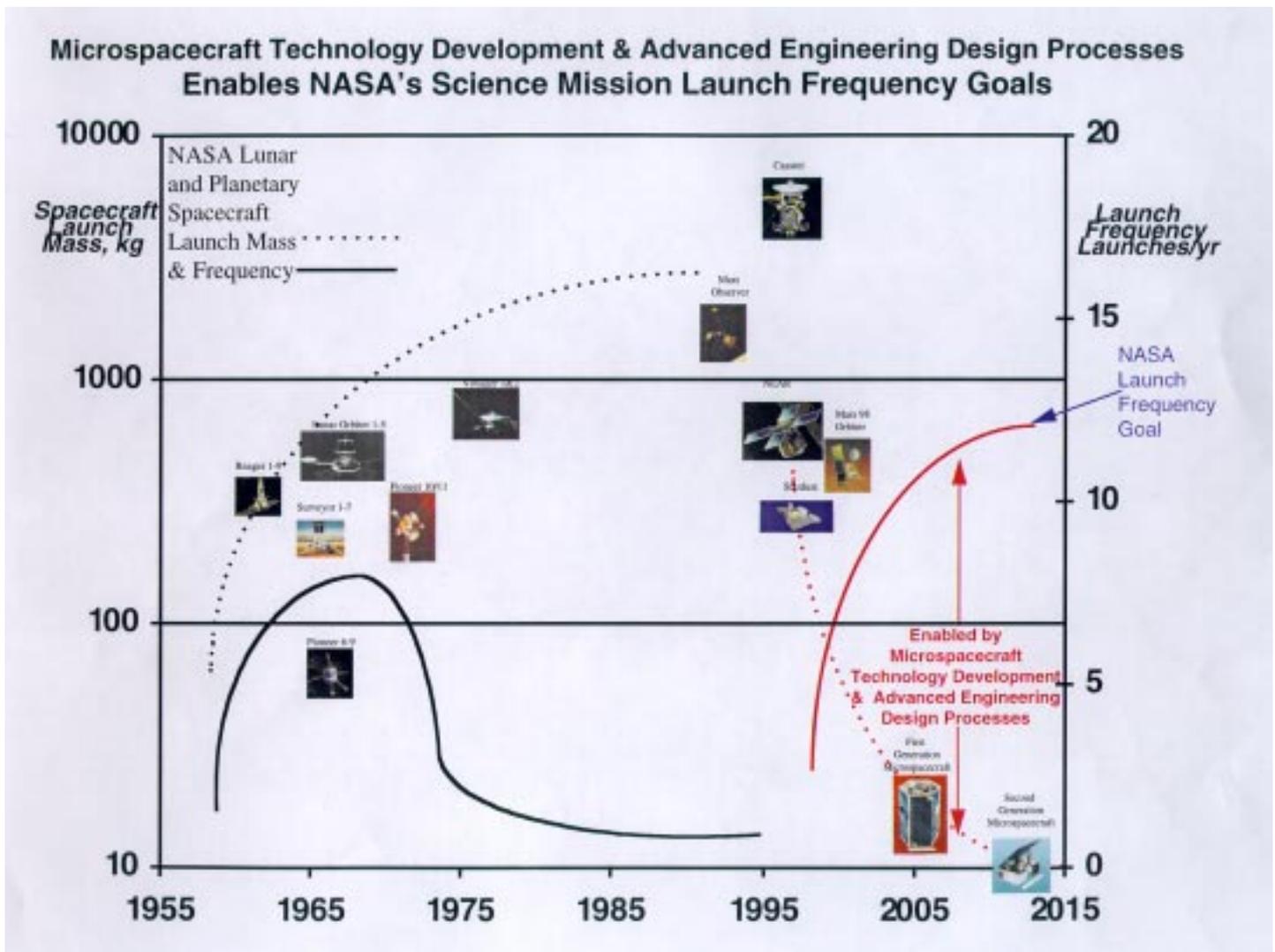

Figure 1. LAUNCH FREQUENCY AND PAYLOAD SIZE OF NASA SPACE MISSIONS, 1955–2015 (USED BY PERMISSION, JOHN PETERSON, JPL, MAY 15, 1997)

single (even a single expensive) design tool, but when significant irregularities or discontinuities in the mapping between points in the design space and their corresponding performances call for the application of different analysis tools in different regimes. The formal mathematics developed for preference and for aggregation are extended to the problem of combining output from several analyses for different (often overlapping) regimes, and the resolution of conflicts where data from multiple sources disagree.

AEROSHELL DESIGN

The example presented here is the design of a re-entry aeroshell that is to be released from a spacecraft as it enters the Martian atmosphere. Two devices of this type are expected to be launched with the DS-2 Mars probe in January of 1999. After descent to the Martian surface, the aeroshell's payload, a penetrator with some instrumentation, will puncture the Martian surface so that soil experiments can be conducted and the results transmitted by radio. We shall not treat the soil penetration problem other than considering the orientation of the aeroshell at impact; the general problem here is the design of an aeroshell that will reach the surface near a desired velocity and angle of attack.

There are several sources of significant uncertainty in the operating conditions of the aeroshell during its descent:

- The shell is released from a tumbling spacecraft, so the angle of attack upon entering the atmosphere is unknown.
- The shell flies through the Martian atmosphere, the properties of which are not well characterized.
- The shell encounters unknown winds.
- The shell hits the ground, which is at an uncertain orientation and has uncertain soil properties.

These uncertainties are interesting, difficult and worthy of study, yet there are other issues of uncertainty in the analysis of the problem that take precedence. An automated or semi-automated analysis would allow for a computer search of the design space to (at least) guide preliminary design. Several levels of simulation are available, and their reliability increases with the computation time involved. If, for example, an assumption of terminal velocity could be made, computation time would be milliseconds, but the assumption is not correct in general. A single run of a full CFD model takes on the order of a day to set up and run on a supercomputer, which is far too computationally intensive for the project time-frames and costs envisioned. A compromise analysis program is a numerical integration of forces over the flight path, with aerodynamic coefficients determined at each time step as functions of atmospheric conditions and the attitude, velocity, and geometry of the aeroshell. The computation time required makes classical optimization, genetic algorithms, and simulated annealing procedures realistic. However, the integration routine is not simply an accurate black box: to successfully integrate over the flight path through the Martian atmosphere requires considerable engineering judgment in the calculation of the aerodynamic coefficients used at each time step of the integration. Furthermore, the output from the integration program gives no indication of how accurately the coefficients were determined.

The problem encountered here by the aeroshell designer is a common one in design analysis, that of how to guarantee good results when the problem may cover one or more of several "analysis regimes". These regimes may be inherent in the physics of the problem, as in the transition between transsonic and supersonic flow, or they may be determined by the availability of information, as in the case when experimental results are available for some (but not all) points in a design space.

PROBLEM SCOPE

The problem of aeroshell design involves a number of fields (*e.g.*, aerodynamics, thermodynamics, material science, structural mechanics). The aerodynamic analysis, even if considered apart from all other fields, is greatly complicated by the need to treat multiple flow regimes (hypersonic, supersonic, transsonic, subsonic, Newtonian, detached shock, free-molecular), and even if the analysis can be made tractable, the aerodynamic design
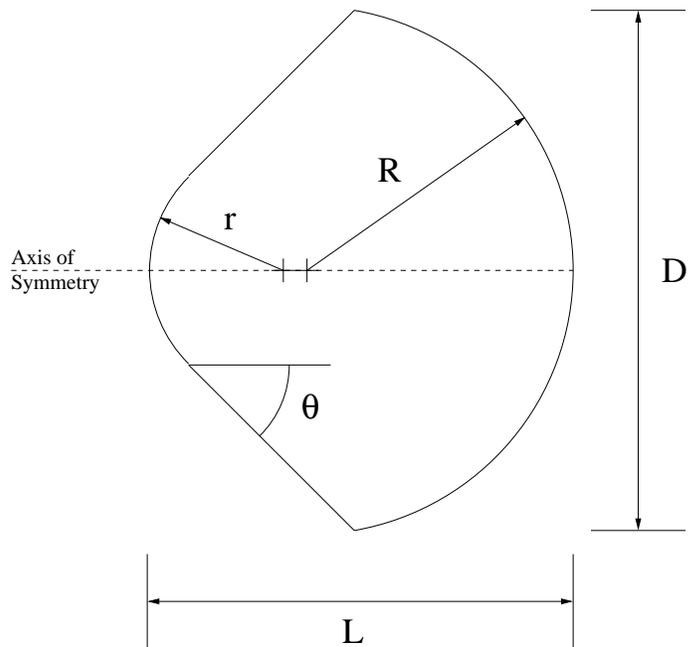

Figure 2.   SCHEMATIC OF AEROSHELL

problem has such a huge set of potential solutions so as to make a search for a globally "optimal" solution to the problem impractical. The present approach to aeroshell analysis is to construct an aerodynamic database for a single candidate design; the analysis is thus useful to validate a design that has already been selected, but is not seen as a tool to explore the design space (see, for example, Mitcheltree et al. (1997)).

A long-term goal in the field of aeroshell design would be an analysis program that addressed all possible candidate configurations in all flow regimes. In order to make the problem more tractable and to address the issues of analysis in the presence of uncertainty, we shall restrict ourselves to the aerodynamic analysis of one configuration of the aeroshell. This configuration is a spherical-nosed cone with a spherical aft section, as shown schematically in Figure 2. The distance between the centers of the two spheres is expected to be quite small. Three nondimensional parameters completely describe the idealized aeroshell: the Bluntness Ratio B (the ratio of the nose radius to the aft section radius), the Fineness Ratio F (the ratio of overall length L to maximum diameter D), and θ, the cone semiangle. The extra information gained by allowing B, F, and θ to vary is useful not only for exploration of alternative designs, but also for analysis of a single fixed design, as the geometry of the aeroshell may change: the heat shield burns during reentry, for example.

The general design problem is to determine values of B, F, and θ that will (robustly) deliver the aeroshell to the surface at a given velocity and angle of attack, in the presence of the op-

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erating uncertainty. The more immediate problem is to deliver a reliable integration routine for computer implementation in the presence of uncertainty in the determination of aerodynamic coefficients. The designer, also referred to here as the analyst or engineer, who is interested in using an integration routine to test the performance of a design can draw upon several sources to determine the aerodynamic constants required at each time step of the integration:

- Experimental results from the literature. These might be of varying reliability. Also, the experimental results do not cover the entire design space, so interpolation between experimental points and extrapolation to unexplored areas of the design space is necessary. The reliability of an interpolated or extrapolated answer will decrease with distance from experimental points.
- Simulation data from computational fluid dynamics (CFD) computations (executed point by point — one computation for a particular configuration, angle of attack, and Mach number). These are also of imperfect reliability.
- Analytical computational models, of which there are at least three in this particular problem:
  - Newtonian flow
  - free-molecular flow
  - detached shock flow

  The aeroshell travels through several flow regimes (and is often in an indeterminate state between regimes) during the integration. In addition, most analytic models have been developed for a particular aeroshell geometry, and must be modified to provide useful information for other geometries.
- Rules of thumb: experience- and intuition-based knowledge.

The distillation of information from these sources (each of which is imperfect) is a matter of engineering judgment. As designers determine the aerodynamic constants, at the same time they refine their understanding of each of the sources (a technical reference giving experimental data that deviates significantly from a number of other experiments may be depreciated or discarded, the analytical models may be updated to better fit experimental data, *etc.*).

Fuzzy aggregation has been applied here to interpolate, extrapolate, and combine data from different analysis programs that hold in different regimes. Simultaneously, the level of confidence in the analysis has been explicitly represented and propagated using a mathematics of fuzzy sets (Zadeh, 1965) similar to that used to combine preferences in the M_OI.

FORMAL TREATMENT OF THE PROBLEM

The statement of the general problem is as follows: Find f such that

$$f(\vec{d}, \vec{x}) = (\vec{p}, \vec{\mu})$$

where $\vec{d}$ is a vector of design variables describing a point in design space, $\vec{x}$ is a vector of operating conditions, $\vec{p}$ is a vector of performances, and $\vec{\mu}$ is some measure of the reliability of the answer $\vec{p}$ ($\vec{\mu}$ is a vector since the reliability of the components p_i of $\vec{p}$ need not be the same for all i, though in the example presented here the μ_i will always agree). We shall also use the more compact notation $\vec{y}$ to represent $(\vec{d}, \vec{x})$. In the example under consideration, $\vec{d} = (B, F, \theta)$ describes the geometry of the aeroshell. The operating conditions can be described by the attitude of the aeroshell and the atmospheric conditions, which for the example here can be described by the angle of attack α, the Mach number M, and the atmospheric density ρ. The performances desired are aerodynamic constants: the normal coefficient C_n, the axial coefficient C_a, the moment coefficient C_m, and the center of pressure C_p. Thus the example problem is to find f such that:

$$f(B, F, \theta, \alpha, M, \rho) = (C_n, C_a, C_m, C_p, \vec{\mu})$$

The function f is a combination of various subfunctions f_i, so that

$$f(\vec{d}, \vec{x}) = \mathcal{P}(f_1(\vec{d}, \vec{x}), \ldots, f_n(\vec{d}, \vec{x}))$$

where $\mathcal{P}$ represents the combination. The subfunctions $f_1, \ldots, f_n$ are the sources of information available, and the set of f_i is subject to change. Adding a new source f_{n+1} to the list may make other sources unnecessary. Since a level of confidence is one of the outputs of the function f, evaluation is possible with any set of f_i; indeed, it is because the analysis is uncertain and imprecise that the combination is necessary. The human designer making such a judgment in analysis will arrive at an answer and will also have an idea of how valid that answer is. This paper presents a formal representation for both.

For the aeroshell re-entry problem, data for f is available from experimental sources, CFD computations, and analysis models. At the highest level,

$$f(\vec{d}, \vec{x}) = \mathcal{P}(f_{\text{exp}}(\vec{d}, \vec{x}), f_{\text{CFD}}(\vec{d}, \vec{x}), f_{\text{analytic}}(\vec{d}, \vec{x}))$$

and subfunctions can be further refined, as for example,

$$f_{\text{analytic}}(\vec{d}, \vec{x}) =$$
$$\mathcal{P}(f_{\text{Newtonian}}(\vec{d}, \vec{x}), f_{\text{free}-\text{molecular}}(\vec{d}, \vec{x}), f_{\text{detached\_shock}}(\vec{d}, \vec{x}))$$

The calculations for Newtonian, free-molecular, and detached shock flow regimes are rapidly computable, and the interpolation of experimental data is a well-understood problem. Each subfunction lends itself to simple automation.

A formal solution to the problem of combining the subfunctions f_i must fulfill several purposes. Some important features of a formal solution are as follows:

- Calculation of each subfunction comes from expertise from the particular discipline. The formal solution must allow for calculation modules to be added, removed, updated, exchanged.

- Propagation of confidence is separate from combination of results, but confidence information is necessary for combination of results. The formal solution should propagate and combine confidences in a justifiable manner.
- Combination of results is easy to do, but easy to get wrong. An arithmetic mean, while computationally tractable, is often *not* the right choice (Biegel and Pecht, 1991; Vincent, 1983). The formal solution should use combination methods that are based in domain expertise; the methods of combination, like the calculation modules, should permit easy modification. Combination functions such as other weighted means (those between *min* and *max*) have been used previously in preference aggregation (Otto and Antonsson, 1991; Scott and Antonsson, 1995), and the fuzzy sets literature (Zimmermann, 1985) has an extensive treatment of t-norms (less than *min*) and t-conorms (greater than *max*).
- One feature of this sort of analysis, when it is handled informally by a human designer, is that the subfunctions (or calculation modules) are updated when analysis by other means indicates shortcomings. The formal solution should allow for such back-propagation of information; while the ultimate goal is to provide a proposed change in a particular submodule, an acceptable intermediate step is to provide feedback to the designer, who can modify subfunctions as necessary.

The need to incorporate and modify rules points to fuzzy set theory as a candidate for the combination model. In addition, the combination of designer preference has been represented as the aggregation of fuzzy sets (Antonsson and Otto, 1995), and this problem exhibits many similarities to the designer preference problem. The aggregation will be best illustrated through the presentation of the example.

APPLICATION TO THE EXAMPLE

The aeroshell analysis problem presented in this paper has been restricted so that the analysis space is spanned by six variables: three design variables and three variables to describe the operating conditions. While experimental data are available for some regions of the analysis space, there are no experimental data points for many regions of interest. In addition, analytic (and thus easily computed) analyses have been previously constructed to cover some of the regions in which the aeroshell will operate, usually with reference to a particular fixed geometry; in this example, the authors had access to a Newtonian analysis code and a free-molecular analysis code. These analytic codes can be applied to other aeroshell geometries if they are suitably modified. The analyst who combines these sources of information has tasks of two varieties: to interpolate and extrapolate experimental and analytic results to "new" areas of the design space, and to determine a level of confidence in the interpolated results. The interpolation and extrapolation of data is well under-

stood, and the analysis tool presented here uses polynomial and spline fitting in its implementation. The extension of analytic results to new aeroshell geometries is treated as an interpolation problem in the error.

If we consider the experimental data alone, then the analysis space can be separated into two regimes: one where the experimental data holds, and one where it is not adequate. This distinction is fuzzy; only at the actual experimental points, and only then if the experiment was reliable, can one be certain that the experimental data holds. Anywhere else in the analysis space, the confidence that the designer holds in the data will depend (at least) on how close it is to actual data points.

The designer's confidence is uncertain but not probabilistic; it is not the case that the analysis has a 70% chance of being right and a 30% chance of being wrong. The designer's uncertainty about the reliability of the data is naturally modeled as the degree of membership in a fuzzy set (Zimmermann, 1985). The confidence (or preference, in M$_O$I terminology) $\mu_{\mathrm{exp}}(\vec{y})$ for the applicability of interpolated experimental results to a particular point $\vec{y}$ is a function of the point's distance from existing experimental points, taking a value of 1 (perfect confidence) at experimental points, and tailing off to 0 at some distance. The confidence in interpolation will also depend in general on the particular point; the transsonic flow regime, for example, is notoriously ill-suited to interpolation.

The calculation of μ_{exp} (or any other μ) is a matter of engineering judgment. Sometimes it may be possible to express μ_{exp} simply and analytically. For example, one might define the confidence $\mu_{\mathrm{exp}}(\vec{y})$ in the interpolated answer as a function of the (Euclidean) distance of the point $\vec{y}$ from the nearest experimental point $\vec{y}_{\mathrm{nearest}}$, and let the confidence tail off as some unacceptable distance d_{max} is approached, for example with:

$$\mu_{\mathrm{exp}}(\vec{y}) = \frac{1}{d_{\mathrm{max}}^4}(|\vec{y}-\vec{y}_{\mathrm{nearest}}|-d_{\mathrm{max}})^2(|\vec{y}-\vec{y}_{\mathrm{nearest}}|+d_{\mathrm{max}})^2,$$

a plot of which is shown in Figure 3. This quartic confidence curve has zero slope at μ-values of 0 and 1, and falls off fastest at the midway point. However, there is no proof that the nuances of the curve are an accurate model of the engineer's thinking. The only truly "fixed" points on the curve are those that reflect the engineer's highest confidence ($\mu=1$, if the experiment is completely trusted) in those points where experiments were performed, and those that show that confidence degrades to zero at some distance d_{max} which is specified by the engineer. Other researchers have argued that the human capacity to distinguish many points on a preference curve is limited (Miller, 1965), and so the detailed shape of the curve is unimportant. A linear interpolation is then *a priori* no worse, and has the advantage of simpler calculation:

$$\mu_{\mathrm{exp}}(\vec{y}) = \frac{d_{\mathrm{max}} - |\vec{y} - \vec{y}_{\mathrm{nearest}}|}{d_{\mathrm{max}}}$$

Other subtleties in the determination of a level of confidence in
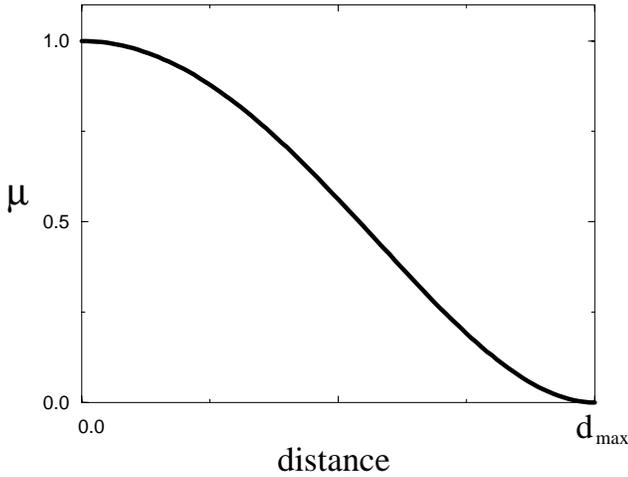
Figure 3. EXAMPLE CONFIDENCE CURVE

the interpolated data, some of which have been alluded to before, contribute to the difficulty of representing confidence with a single curve:

1. Only a few points on a confidence curve such as the one shown in Figure 3 will be meaningful to the engineer.

2. The specification of d_{max} as a single number assumes that Euclidean distance in different dimensions of the design space are equivalent, or at least comparable. This is plainly not true in general, for even if all dimensions can be scaled so that units are comparable, it cannot be assumed that the analyst is equally concerned with "distance" in all directions.

3. The confidence in interpolated data will depend on the operating point; in other words, d_{max}, even if well-defined, is a function of $\vec{y}$. For example, the designer is likely to have much more confidence in interpolated data for Mach numbers M between 3 and 8 than in the transsonic range where $M \approx 1$.

4. The confidence in interpolated data will depend on several nearest points, not just on the single nearest experimental point $\vec{y}_{\mathrm{nearest}}$.

5. Confidence may be quite different for extrapolated data than for interpolated data.

6. When sufficient experimental data is available, the fidelity of interpolation can be checked against other experimental points; the analyst fitting a curve by hand typically uses such a check in the informal calculus of confidence. The d_{max} approach obscures this.

7. Finally, the engineer may recognize the potential importance of all of these subtleties, and yet arrive at a level of con-

fidence without taking all possibilities into account. Especially in preliminary design, the engineer may proceed, considering only the most important confidence criteria, and refine the calculation for more detailed analysis.

A more flexible approach to confidence specification is required to capture these nuances. The natural model of membership in a fuzzy set for the confidence level of a point $\vec{y}$ in design space indicates the use of a rule set to define designer confidence. The transformation of a set of IF-THEN rules into a fuzzy inference matrix is a well-known problem in fuzzy set theory, and commercial packages such as Matlab's Fuzzy Logic Toolbox (Jand and Gulley, 1995) are available to perform this. A rule set is flexible with respect to the difficulties enumerated above, and is easily updated. In some cases the engineer may feel more comfortable circumventing the rule set and specifying confidence functions directly. For instance, for Mach numbers M between 3 and 8, and ρ close to that of air (the value of ρ at which experiments were made), the engineer may wish to define a simple rule for each dimension of the design space describing the loss in confidence as a function of the distance from the nearest experimental points in that dimension. The confidence contribution with respect to Mach number M is $\mu_{\mathrm{exp}:M}$, say:

$$\mu_{\mathrm{exp}:M}(M) = \frac{d_{\mathrm{max}:M} - |M - M_{\mathrm{nearest}}|}{d_{\mathrm{max}:M}}$$

Similar functions for B, F, θ, and α are combined, in this case with a multiplication:

$$\mu_{\mathrm{exp}}(B, F, \theta, M, \alpha, \rho) = \\ \mu_{\mathrm{exp}:B}(B)\mu_{\mathrm{exp}:F}(F)\mu_{\mathrm{exp}:\theta}(\theta)\mu_{\mathrm{exp}:M}(M)\mu_{\mathrm{exp}:\alpha}(\alpha)$$

Note that since ρ has been assumed to be close to that of air, it has no contribution. However, when ρ is different another rule comes into play and the free-molecular analysis must also be considered.

Some data, taken from wind tunnel tests for cone angles of 10, 15, and 20 degrees (Peterson, 1962), is shown in Figure 4. The data is shown here as isolated experimental points. A standard interpolation scheme will generate a surface over the same range, but not all points on the surface will have the same level of confidence. The rule set implemented here maintains high confidence in interpolated data along the dimensions α and M (except across the transsonic region $M \approx 1$, where deviations in M are penalized strictly), but enforces relatively high penalties on deviations from experimental points in θ, B, and F. In particular, with the present data there is sufficient granularity in M and α to check curve fits; as more data becomes available in the other dimensions, the confidence calculations can be updated.

Of the many physical models for fluid flow to handle different regimes, two have been implemented to date: a model for Newtonian flow, and a model for free-molecular flow. Each

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Empirical data: B=0.00, F=0.75, theta=10 fixed

Empirical data: B=0.00, F=0.75, theta=15 fixed

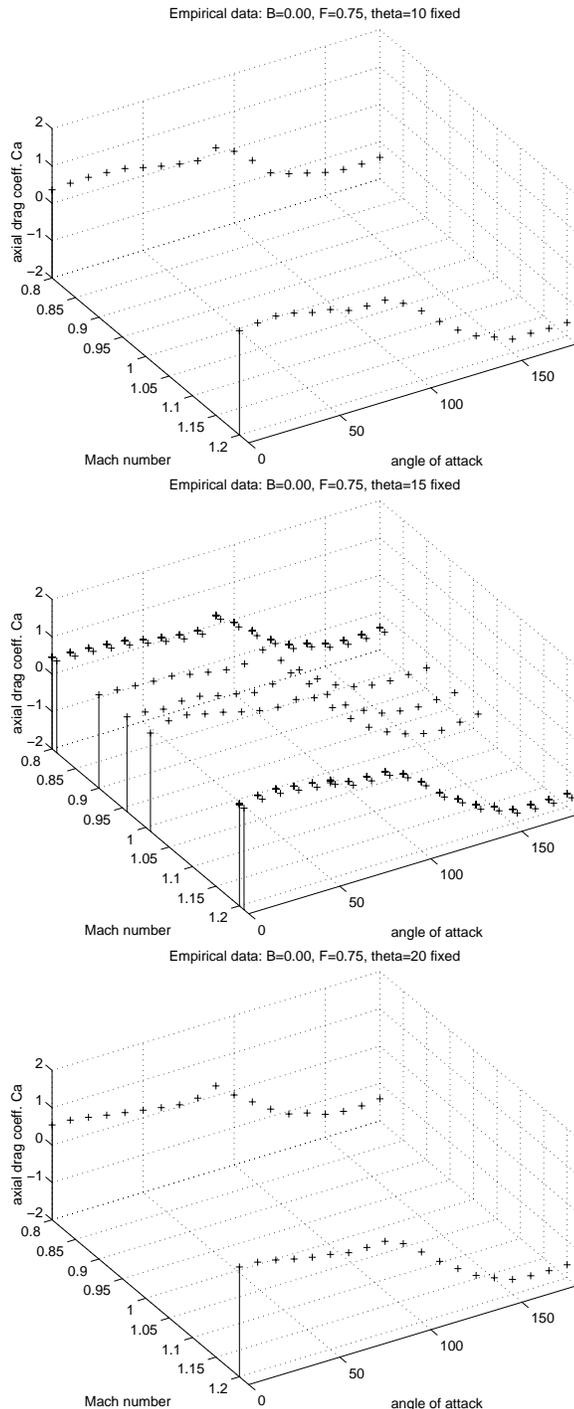Empirical data: B=0.00, F=0.75, theta=20 fixed

Figure 4.   EMPIRICAL DATA: C_a FOR THREE CONE ANGLES θ

of these models covers an analysis regime likely to be encountered by the aeroshell in its descent to the surface, and as was mentioned above, each model was developed for a particular aeroshell geometry. The analyst has some confidence in the output of these models as long as two conditions are satisfied:

1. The operating point $\vec{x}$ is in the appropriate flow regime. For free-molecular flow, a high Knudsen number is required, which translates roughly to a low ρ, and an assumption of Newtonian flow is used for some supersonic flows when the entrained boundary layer can be assumed to stay within the shock cone.

2. The aeroshell geometry $\vec{d}$ must be close to one for which there are experimental data. The analysis is achieved by calculating the analytic model at a set of experimental points, and then curve fitting the error between the analytic model (which was originally developed for a different geometry) and experiment, and interpolating or extrapolating to the operational point of interest. Thus the machinery of the interpolation scheme and its attendant confidence calculation are both relevant here.

Surface plots of each of the two models are shown in Figures 5 and 6, with continuous variation in θ, since Mach number is irrelevant for these two particular flow models. For comparison with Figure 4, a slice of each surface at $\theta = 15°$ is also shown. These analyses are also not accurate over the entire domain; as with the experimental data, there will be varying degrees of confidence.

Aggregation of Data from Disparate Sources

To determine the output parameters and their confidences for a point in analysis space, data from three calculation modules (experimental, Newtonian, and free-molecular) are considered. The varying confidence in each calculation module over the space is represented by membership in a fuzzy set. This membership is determined by the application of a number of fuzzy rules. Confidence in interpolated experimental data is higher near explicitly calculated data points, with greater penalties for deviations in geometry and lesser penalties for deviations in the operating parameters M and α. If the density is low then free-molecular analysis is useful: Figure 7 embodies this fuzzy rule in a fuzzy set on density ρ expressing the applicability of the free-molecular flow analysis. The applicability of Newtonian analysis depends on the entrained boundary layer staying within the calculated shock cone. The rules determining the applicability of each regime are specified by the designer and encoded with fuzzy sets, either directly or through the construction of a fuzzy inference matrix; these sets can be updated as the designer refines the rules. Such modification is inexpensive, as it entails only a change in the aggregation problem, and does not require any expensive analysis calculations to be repeated.
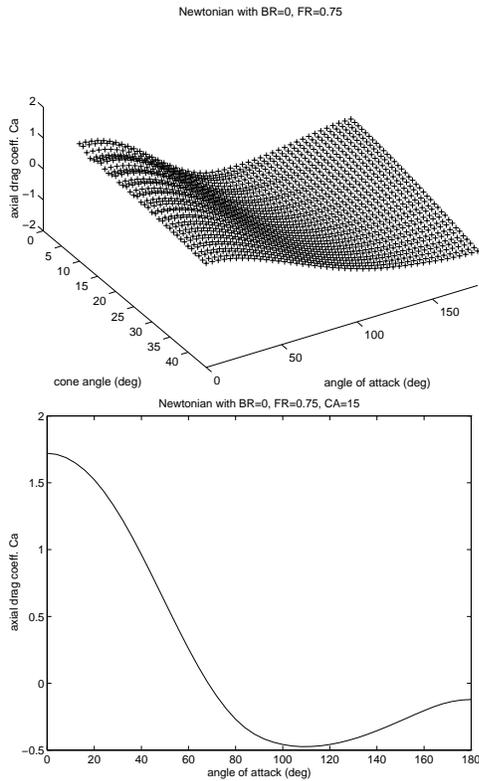
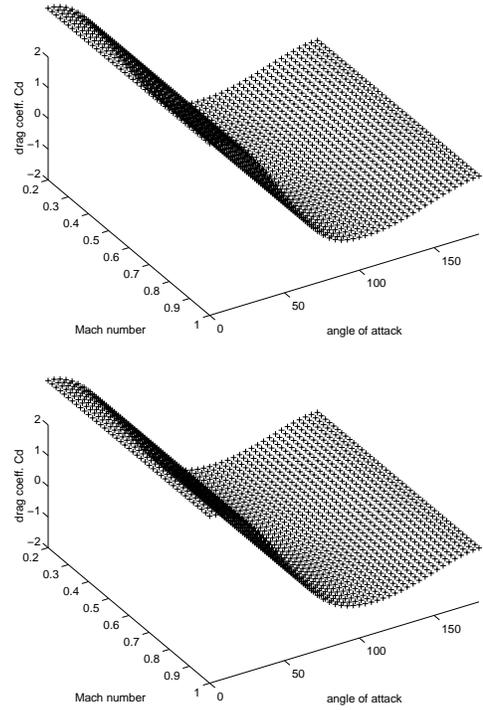Figure 5. NEWTONIAN FLOW MODEL: C_a FOR VARIOUS θ

Figure 6. FREE-MOLECULAR FLOW MODEL: C_a FOR TWO θ

Figure 7. FUZZY SET EXPRESSING APPLICABILITY OF REGIME

The results from all analysis modules are combined, with their participation determined by the confidence in the answer. This analysis will divide the space into regions in which the different analysis modules predominate. Some regions will have high levels of confidence for more than one module, as is the case when experimental data is taken in a regime for which there is an analytical model. In this case, the overall analysis includes feedback as to the legitimacy of the modules. Disagreement between modules may lead to changes in designer confidence or updated models.

Where a single analysis module has a much higher confidence than the other two, the result from that module is used, and the confidence is returned with the result. (The analyst using the tool in an integration scheme can log the confidences, or flag points where confidence falls below a given level.) If the confidence for the other modules is low but zero, the answers from those modules can be compared with the result, and the comparison can be logged for the analyst's later use.

When two or more analysis modules return high confidences, the results must be combined. The most straightforward way to do this is with a weighted sum (the confidence levels can provide the weights). A more useful scheme is to compare the results before combining; when they agree closely, a weighted
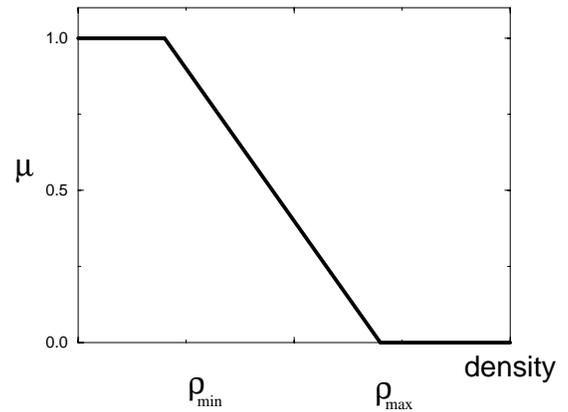
sum is acceptable, and the overall confidence will be greater than either of the single confidences (so that the computation of confidence can be effected with a t-conorm (Zimmermann, 1985)). If the results are not in close agreement, it is perhaps better to use the result with the higher confidence, but return a lower confidence level.
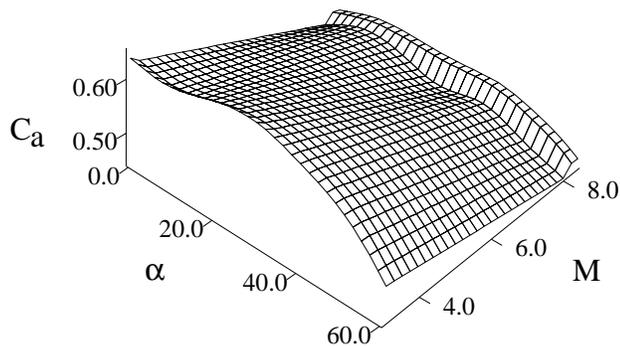
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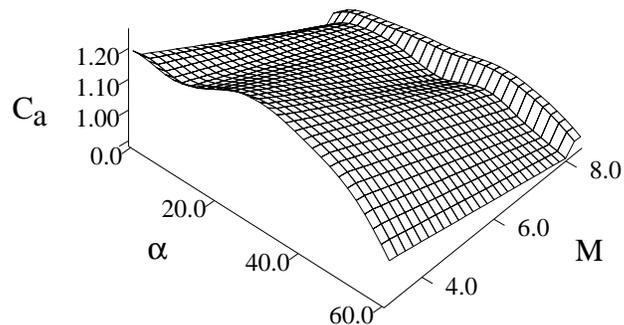Figure 8. INTERPOLATED EXPERIMENTAL RESULTS WITH $B = 0$, $F = 0$, $\theta = 15°$

Figure 9. RESULTS FROM FREE MOLECULAR CODE WITH $B = 0$, $F = 0$, $\theta = 15°$

Especially since only three flow regimes have been implemented, there are regions of the analysis space in which all results have low confidence. This shortcoming may be corrected by incorporating other analysis models (such as the detached shock analysis or a CFD module). Nevertheless, just as the designer working informally must work with the tools available, the formal combination of results here recognizes the shortcomings in the available analysis tools and signals that with low confidences. The analysis program presented here is designed for inclusion in an integration routine; the routine can track confidences to determine the overall reliability of the integration and to determine which regions of the analysis space need further refinement. It would be a poor use of engineering resources to develop a detailed model of the analysis space in a region that the aeroshell never encounters.

Some aggregated results from the analysis program are shown in Figures 8 and 9. Each plot shows a response surface for the axial drag coefficient C_a over a region of the analysis space; Figure 8 contains results where $\mu_{\text{free}-\text{molecular}} = 0$ (density is high, and the free molecular model does not hold) and Figure 9 results where $\mu_{\text{free}-\text{molecular}} = 0.7$ (density is low enough that the free-molecular model has a relatively high confidence level). In both cases, the empirical data dominates where experiments were performed at points that closely approximate operating conditions, and the physical flow approximation models are more important where there is less experimental data. The experimental data are less significant when $\mu_{\text{free}-\text{molecular}} = 0.7$, since these experiments were made with a density that of air. The discontinuities in the plots indicate incomplete knowledge, and may indicate that a model needs to be refined.

CONCLUSION

A method to resolve disagreeing data from multiple sources has been applied to the analysis of design information. The method uses the mathematics of fuzzy sets to represent levels of designer confidence in the data. Resolution, interpolation, and extrapolation are accomplished by the use of fuzzy set aggregation functions. This approach does not add significantly to the computation cost, and thus can be refined without repeating analyses, and is therefore particularly useful when computations are expensive and must be minimized.

The application of this method to the design analysis of an aeroshell re-entry design problem, furnished by the Jet Propulsion Laboratories, has been presented.

ACKNOWLEDGMENTS

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