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Needs and Opportunities for Uncertainty-Based Multidisciplinary Design Methods for Aerospace Vehicles

Thomas A. Zang, Michael J. Hemsch, Mark W. Hilburger, Sean P. Kenny, James M. Luckring, Peiman Maghami, Sharon L. Padula, and W. Jefferson Stroud
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July 2002

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Summary

This report consists of a survey of the state of the art in uncertainty-based design together with recommendations for a Base research activity in this area for the NASA Langley Research Center. In particular, it focuses on the needs and opportunities for computational and experimental methods that provide accurate, efficient solutions to nondeterministic multidisciplinary aerospace vehicle design problems. We use the term *uncertainty-based design* to describe this type of design method. The two major classes of uncertainty-based design problems are robust design problems and reliability-based design problems. A *robust design* problem seeks a design that is relatively insensitive to small changes in the uncertain quantities. A *reliability-based design* seeks a design that has a probability of failure that is less than some acceptable (invariably small) value.

Traditional design procedures for aerospace vehicle structures are based on combinations of factors of safety and knockdown factors. The aerodynamic design procedures used by the industry are exclusively deterministic. There has been considerable work on "robust controls," but this work has been limited to using norm bounds on the uncertain variables. Reliability-based design methods have been used within civil engineering for several decades and in aircraft engine design for about a decade. Applications to the structural design of airframes are only now starting to emerge. Only academic studies of reliability-based design methods within the aerodynamics and controls disciplines are known to the authors.

To use uncertainty-based design methods, the various uncertainties associated with the design problem must be characterized and managed, and these characterizations must be exploited. In the context of computational modeling and simulation, two complementary categorizations of uncertainties are useful. One categorization distinguishes between parameter uncertainties and model form uncertainties. *Parameter uncertainties* are those uncertainties associated either with the input data (boundary conditions or initial conditions) to a computational process or with basic parameters that define a given computational process, such as the coefficients of phenomenological models. *Model form uncertainties* are uncertainties associated with model validity, i.e., whether the nominal mathematical model adequately captures the physics of the problem. Systematic procedures for characterizing and managing uncertainties in experimental activities include design of experiment methods and statistical process control techniques. The former focuses more on characterizing the uncertainties and the latter more on managing them.

Parameter uncertainties are typically specified in terms of probability density functions, membership functions, or interval bounds. Model form uncertainties are very difficult to characterize. Generic techniques are available for assessing the effects of uncertainties on discipline and system performance predictions, and some optimization methods can account for uncertainties. However, better and less resource-intensive methods are needed for both uncertainty propagation and optimization under uncertainty. Certainly, the deployment of existing and new techniques within the aerodynamic, controls, structures, and systems analysis disciplines for applications to aerospace vehicles is critically needed.

The principal barriers to the adoption of uncertainty-based design methods for aerospace vehicles are as follows:

B1. Industry feels comfortable with traditional design methods.

B2. Few demonstrations of the benefits of uncertainty-based design methods are available.

B3. Current uncertainty-based design methods are more complex and much more computationally expensive than deterministic methods.

B4. Characterization of structural imperfections and uncertainties necessary to facilitate accurate analysis and design of the structure is time-consuming and is highly dependent on structural configuration, material system, and manufacturing processes.

B5. There is a dearth of statistical process control activity in aerodynamics.

B6. Effective approaches for characterizing model form error are lacking.

B7. There are no dependable approaches to uncertainty quantification for nonlinear problems.

B8. Characterization of uncertainties for use in control is inadequate.

B9. Methods for mapping probabilistic parameter uncertainties into norm-bounded uncertainties do not exist.

B10. Existing probabilistic analysis tools are not well suited to handle the time and frequency domain response quantities that are typically used in the analysis of closed-loop dynamical systems.

B11. No methods are available for optimization under nonprobabilistic uncertainties.

B12. Current methods for optimization under uncertainty are too expensive for use with high-fidelity analysis tools in many disciplines.

B13. Extending uncertainty analysis and optimization to applications involving multiple disciplines compounds the complexity and cost.

B14. Researchers and analysts lack training in statistical methods and probabilistic assessment.

The principal benefits of uncertainty-based design are

P1. Confidence in analysis tools will increase.

P2. Design cycle time, cost, and risk will be reduced.

P3. System performance will increase while ensuring that reliability requirements are met.

P4. Designs will be more robust.

P5. The methodology can assess systems at off-nominal conditions.

P6. Use of composite structures will increase.

The proposed role for NASA Langley Research Center in uncertainty-based design is:

> Evaluate and improve methods for management of uncertainty with applications to multidisciplinary aerospace vehicle design by developing and validating strategies, algorithms, tools and data to
>
> > characterize and manage the uncertainties from the individual aerospace vehicle design disciplines, especially aerodynamics, structures, and controls, based on the best available experimental and computational results;
> >
> > characterize the norm and distribution of the resulting uncertainties in system metrics; and
> >
> > account for uncertainties in the design of aerospace vehicles at the conceptual through the detailed design stages.

Detailed lists of uncertainty-based design technology needs for the structures, aerodynamics, controls, and systems analysis disciplines are found in section 4.

1. Introduction

This white paper focuses on the needs and opportunities for computational and experimental methods that provide accurate, efficient solutions to problems of multidisciplinary aerospace vehicle design in the presence of uncertainties. These methods are a subset of what are sometimes referred to as nondeterministic approaches. The essential distinction is between the *formulations* of the design problem and the *methods* used for its solution. A nondeterministic problem formulation is one in which some essential components—the problem statement (e.g., uncertainty of the outer mold line due to manufacturing variability), experimental data (e.g., measurement uncertainty), or computational solutions (e.g., discretization error)—are treated as nondeterministic. The uncertain aspects may be expressed in a number of ways, for example by interval bounds or by probability density functions. Analysis methods that employ stochastic approximations, such as Monte Carlo approximation of integrals, are only of interest here to the extent that they are brought to bear on a genuinely nondeterministic problem formulation. Likewise, random search techniques, such as genetic algorithms and simulated annealing, are not intrinsically of interest in the present context. We use the term *uncertainty-based design* to describe those design problems that have a nondeterministic formulation.

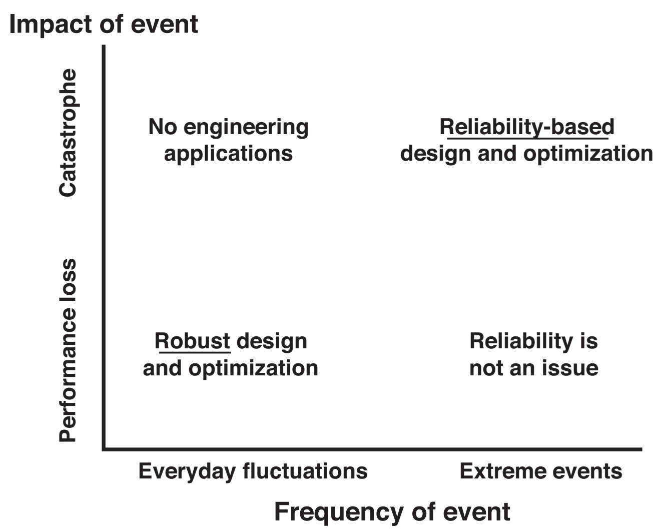

Figure 1. Uncertainty-based design domains (from Huyse 2001).

The two major classes of uncertainty-based design problems are robust design problems and reliability-based design problems. A *robust design* problem is one in which a design is sought that is relatively insensitive to small changes in the uncertain quantities. A *reliability-based design* problem is one in which a design is sought that has a probability of failure that is less than some acceptable (invariably small) value. The same abstract mathematical formulation can be used to describe both robust design and reliability-based design. However, their domains of applicability are rather different.

Figure 1 illustrates these domains. The two major factors are the frequency of the event and the impact of the event. No system is viable if everyday fluctuations can lead to catastrophe. Instead, one would like the system to be designed such that the performance is insensitive, i.e., robust, to everyday fluctuations. On the other hand, one would like to ensure that the events that lead to catastrophe are extremely unlikely. This is the domain of reliability-based design. In both cases, the design risk is a combination of the likelihood of an undesired event and the consequences of that event. An example of risk in the robust design context is the likelihood that the aircraft design will fail to meet the aerodynamic performance targets and will consequently lose sales and perhaps even go bankrupt. An example of risk in the reliability-based design context is the probability that a critical structural component will fail, which could lead to the loss of the vehicle or spacecraft, payload, and passengers, and to potential lawsuits.

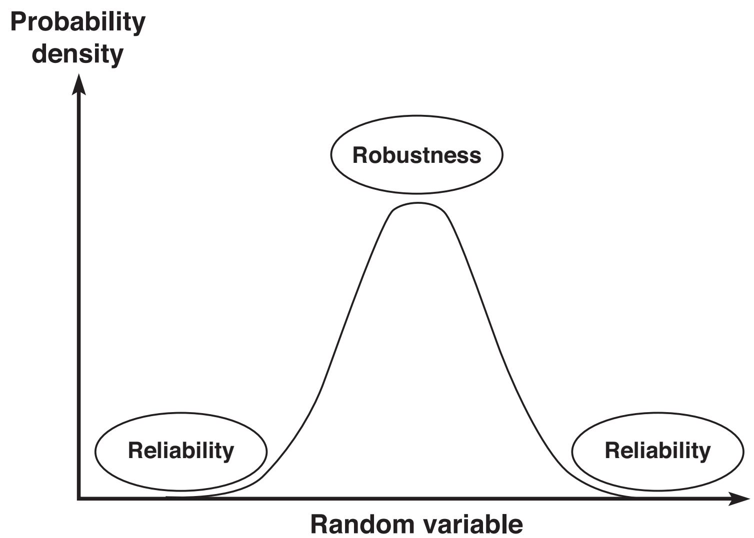

Figure 2. Reliability versus robustness in terms of the probability density function.

As figure 2 illustrates, robust design is concerned with the event distribution near the mean of the probability density function, whereas reliability-based design is concerned with the event distribution in the tails of the probability density function. Obviously, it is much more difficult to accurately characterize the tail of a distribution than the center of the distribution. An additional consideration in distinguishing between robustness and reliability is that the mathematical techniques used for solving robust design problems are considerably different from those used for solving reliability-based design problems. The mathematical methods for robust design procedures are less well developed than those for reliability-based design procedures, and this work is still largely confined to academic studies. Certainly, the aerodynamic design procedures in use in industry are exclusively deterministic. (Recall that we are excluding the use of random search methods to solve a deterministic problem.) There has been considerable work on "robust controls," but this work has been limited to using norm-bounded descriptions of uncertain variables. Although the robust design principles of Taguchi (1987) are used in aerospace engineering, these are not necessarily the best or even appropriate methods for many robust design problems.

Traditional design procedures for aerospace vehicle structures are based on combinations of factors of safety and knockdown factors, as illustrated in figure 3. Factors of safety are numbers greater than 1.0 that are applied to the loads. Knockdown factors are numbers less than 1.0 that are applied to the strengths. Both factors are intended to account for uncertainties. They have proven useful during nearly six decades of design for conventional metal airframes.

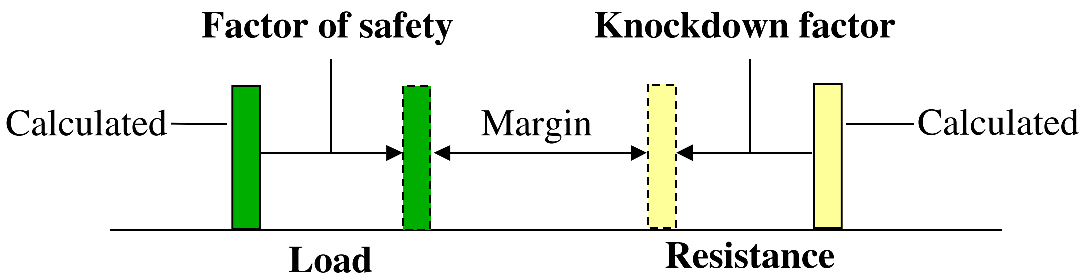

Figure 3. Factor of safety approach.

Traditional design procedures have several shortcomings. First, these procedures may be difficult to apply to aerospace vehicles that have unconventional configurations and that use new material systems. Second, measures of reliability and robustness are not provided in the design process. Consequently, it is not possible to determine (with any precision) the relative importance of various design options on the reliability and robustness of the aerospace vehicle. In addition, with no measure of reliability it is unlikely that the level of reliability and performance will be consistent throughout the vehicle. That situation can lead to excess weight with no corresponding improvement in overall reliability. Moreover, the factor of safety approach is logically inconsistent. It attempts to scale conditions using a mean or "worst-case" condition. In reality, a worst-case condition is rarely identifiable.

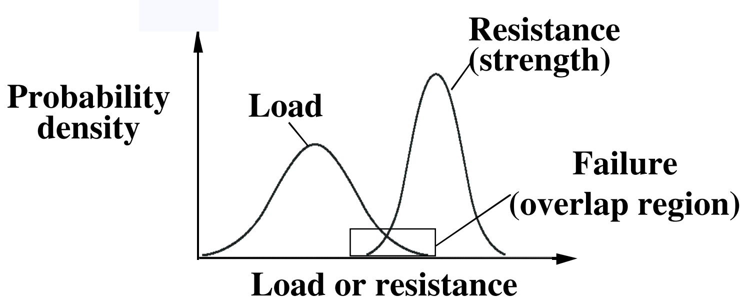

Figure 4. Reliability-based design approach.

In contrast to the traditional design procedure shown in figure 3, figure 4 illustrates how uncertainties are handled in the reliability-based design approach. Here both the load and the strength are characterized by probability density functions. These distributions are due to uncertainties in the loads applied to the system (or subsystem) and to the strengths of different realizations of the system. The overlap region (where the load exceeds the strength) indicates the probability of failure. Note that for design of systems with small probabilities of failure, the tails of both the load and the strength distributions are the most relevant. Reliability-based design methods have been used within civil engineering (Sundararajan 1995) for decades[1] and in aircraft engine design (Cruse 2001) for about a decade. Applications to the structural design of airframes are only now starting to emerge. Only academic studies of reliability-based design methods within the aerodynamics and controls disciplines are known to the authors.

[1] Civil engineering projects are generally designed using standard design codes. Many of these codes contain factors that can be adjusted based on the likelihood of occurrence of high loads or critical events, such as an earthquake of a specified magnitude. These factors provide the target reliability. The probabilistic aspects of these design codes may be hidden from the designer.

Newly emerging uncertainty-based design procedures will help to overcome the shortcomings of the traditional design procedures. In particular, measures of reliability and robustness will be available during the design process and for the final design. This information will allow the designer to produce a consistent level of reliability and performance throughout the vehicles—with no unnecessary over-designs in some areas. As a result, designers will be able to save weight while maintaining reliability. In addition, with an uncertainty-based design procedure it will be possible to determine the sensitivity of the reliability to design changes that can be linked to changes in cost. As a result, it will be possible to make trade-offs between reliability and cost. For the same cost, airframes can be made safer than with traditional design approaches—or, for the same reliability, the airframe can be made at a lower cost.

This white paper consists of a survey of the state of the art in uncertainty-based design together with recommendations for a Base research activity in this area for the NASA Langley Research Center. In particular, section 2 provides a generic overview of current uncertainty-based design methods. Section 3 focuses on uncertainty-based methods for aerospace vehicle design, describing the status of these methods and the barriers to their adoption. Section 4 proposes some specific research objectives with both short-term and long-term impact on industry and NASA design processes. Section 5 discusses the expected results from uncertainty-based design research. Our discussion is limited to the disciplines of aerodynamics, controls, structures, and systems analysis. Although other disciplines are excluded from the discussion, the reader will note that the authors have a diverse background, not just in terms of their disciplinary heritage but also in terms of their particular penchants towards experimentation, methods development, or applied computation. This diversity, combined with the relatively recent interest of most of the authors to this particular field of uncertainty-based design, has inevitably led to different emphases in the different disciplinary sections of this report and perhaps to occasional inconsistencies in terminology. The authors' views on this challenging subject are a work in progress. They have chosen to put their current thinking out for comment now rather than wait the several years necessary for a full meeting of their minds.

2. Overview of Available Uncertainty-Based Design Methods

The use of uncertainty-based design methods requires that the various uncertainties associated with the design problem be characterized and managed, and that the analysis and optimization methods incorporate this characterization of the uncertain quantities. In section 2.1 we focus on the characterization and management of uncertainties, and in section 2.2 we focus on the use of uncertainties in design.

2.1. Characterizing and Managing Uncertainties

Characterization and management of uncertainties is required at the individual discipline level as well as at the integrated, system level. These involve the computational and experimental uncertainties produced by the discipline analysis methods themselves, and the relationship of the uncertainties affecting the input with the uncertainties affecting the output of the methods.

2.1.1. Computational Uncertainties

In the context of computational modeling and simulation, two complementary categorizations of uncertainties are useful. One categorization distinguishes between parameter uncertainties and model form uncertainties.[2] *Parameter uncertainties*, sometimes referred to as parametric uncertainties or parameter variability, are those uncertainties associated either with the input data (boundary conditions or initial conditions) to a computational process or with basic parameters that define a given computational process, such as the coefficients of phenomenological models. *Model form uncertainties*, sometimes referred to as structural uncertainties, nonparametric uncertainties, or unmodeled dynamics, are associated with model validity, i.e., whether the nominal mathematical model adequately captures the physics of the problem.

Oberkampf et al. (1998) categorized uncertainties into three distinct classes. *Variability* refers to "the inherent variation associated with the physical system or the environment under consideration." *Uncertainty* is "a potential deficiency in any phase or activity of the modeling process that is due to lack of knowledge." *Error* is "a recognizable deficiency in any phase or activity of modeling and simulation that is not due to lack of knowledge;" an error may be either an *acknowledged error* or an *unacknowledged error*. The value of this categorization is that the approaches to characterizing and managing uncertainties are considerably different for the three classes. We are not going to emphasize this distinction in this white paper, and the interested reader should consult Oberkampf et al. (1998) for more information. In the material that follows, we shall typically use uncertainty in the more general sense. Whenever we mean the more specialized definitions of this paragraph, we shall use italics for the terms.

In the context of a computer code used for computational modeling and simulation, the parameter uncertainties can be specified by means of interval bounds, membership functions, or probability density functions, as illustrated in figure 5. Interval bounds should be used when only the crudest information is known. They use only an upper and a lower bound for the parameter value; norm-bounded uncertainties are a special case. Probability density functions are the most detailed description. Membership functions, which are used in fuzzy logic approaches, provide an intermediate level of detail. The parameter uncertainty characterization can be based on expert opinion, experimental data, analytical estimates, or results from upstream computational processes. A more detailed discussion of the general mathematical framework for characterization of uncertainties from an engineering perspective can be found in Oberkampf, Helton, and Sentz (2001).

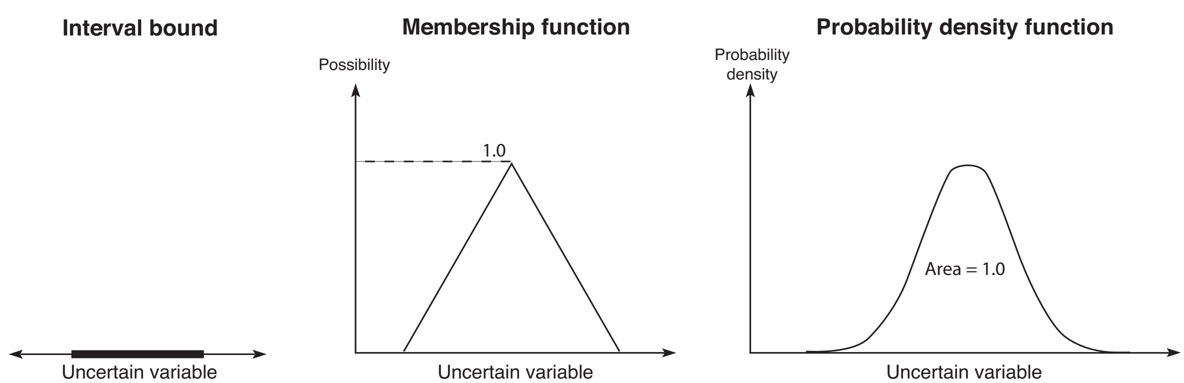

Figure 5. Uncertainty descriptions.

Strategies for characterization of model form uncertainty are far less well developed than those for

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[2] The terms *model uncertainty* and *modeling uncertainty* are occasionally used in the literature to mean the uncertainty in the model arising both from the model form and the model parameters. These terms should not be confused with the term *model form uncertainty* as we are using it here.

parameter uncertainties. Two general references of note are Beck (1987) and Draper (1995). A short summary of the Bayesian approach to model form uncertainty, together with some additional references, is given by Alvin et al. (2000). There do not appear to be any systematic applications of model form uncertainty characterization strategies to airframe design applications.

Few systematic approaches are available for managing uncertainties in computational simulations. Adaptive mesh refinement is the most well developed, but most techniques are based on heuristic rather than rigorous approaches. Moreover, adaptive mesh refinement is limited to just one aspect of the uncertainty in the output of a code (discretization error) and it does not address the uncertainty in the model output due to uncertainty in the model input.

2.1.2. Experimental Uncertainties

The traditional approach to account for uncertainties in structural design is to introduce so-called design or safety factors on the loads and statistically based material properties. Thus, in a classical deterministic analysis, all the uncertainties are accounted for in a "lump-sum" fashion by multiplying the maximum expected applied stress by a single safety factor, e.g., 1.5. The specification of safety factors is generally based on empirical design guidelines established from years of structural testing and experience. Statistically based material properties are determined from a series of coupon tests. Design verification is achieved through testing by applying the worst-case loading condition to the structure and testing to failure.

Uncertainties can be accounted for using probabilistic methods. Techniques for deriving probabilistic information and for estimating parameter values from observed data are found in the methods of statistical inference in which information obtained from sample data is used to make generalizations about populations from which the samples were obtained. Traditional methods of estimation include point and interval estimates. The common methods of point estimation are the method of maximum likelihood and the method of moments. Interval estimation includes determining the interval that contains the parameter value and a prescribed confidence level. However, when population parameters are estimated based on finite samples, errors of estimation occur. Explicit consideration of these errors is accounted for in the Bayesian approach to estimation. With this approach, subjective judgments based on intuition, experience, or indirect information are incorporated with observed data to obtain a balanced estimation. Validity of assumed uncertainty distributions is verified or disproved statistically by goodness-of-fit tests, such as chi-squares or Kolmogorov-Smirnov methods.

For situations in which sample data necessary to quantify parameter uncertainties is limited or nonexistent, fuzzy set (possibilistic) analysis can be used to account for uncertainties. Uncertainties are introduced by specifying membership functions.

Systematic procedures for characterizing and managing[3] uncertainties in experimental activities include design of experiment methods (Taguchi 1987) and statistical process control techniques (Wheeler and Chambers 1992). The former focuses more on characterizing the uncertainties and the latter more on managing them.

2.1.3. Uncertainty Analysis

The objective of uncertainty analysis (or uncertainty propagation) is to characterize the uncertainties in

[3] Although in this context the word "control" is more conventional, we prefer the term "manage" to prevent confusion with the "controls" discipline.

the system output given some knowledge of the uncertainties associated with the system parameters together with one or more computational models and, ideally, some experimental data. This subsection will provide an overview various approaches to estimating the effects of parameter uncertainties; approaches to model form uncertainties are far less developed. Several methods are available for estimating the uncertainties in the performance predictions due to parameter uncertainties. They depend, of course, on whether the parameter uncertainties are specified in terms of probability density functions, membership functions, or interval bounds.

***2.1.3.1. Probabilistic Analysis*.** The most well developed approaches to uncertainty analysis are based on parameter uncertainties specified in terms of probability density functions (PDFs). Uncertainty-based design methods using detailed PDFs are generally referred to as probabilistic methods. In this case, the uncertainty computing engine produces the nominal value of the performance functions as well as their PDFs. This process is typically completed by using some type of Monte Carlo or statistical sampling method. The concept is straightforward; the process model is invoked repeatedly for deterministic analyses performed for a set of input parameters generated according to their PDFs to produce a set of output samples. The statistical properties of the output performance functions are then deduced from the output samples. This approach is usually referred to as a simulation method or a sampling method. See Melchers (1999) for a general overview. The simplest approach is the basic Monte Carlo method, in which the sampling points are drawn strictly according to the PDFs of the input parameters. Construction of accurate output PDFs can easily take thousands or even millions of simulations. Two of the more popular alternatives to the basic Monte Carlo method are Importance Sampling and Latin Hypercube Sampling (McKay, Beckman, and Conover 1979). The former enables accurate estimates of the tails of the PDFs; it is most useful in reliability-based design problems. The latter provides samples that ensure coverage of the full range of the input parameters with far fewer simulations than the basic Monte Carlo method. However, the tails of the output PDFs are generally quite inaccurate; it is most useful in robust design problems. Yet another refinement is Directional Sampling, which is useful for concentrating the sampling on a subset of the parameters of particular interest. At least a half-dozen general-purpose commercial software packages are available to serve as probabilistic uncertainty computing engines.

A different approach to probabilistic uncertainty analysis is by the solution of stochastic differential equations. With this approach, the uncertainties may be associated with initial conditions, boundary conditions, transport properties, and source terms. Wiener (1938) developed a method of representing the associated randomness in the solution with an expansion in orthogonal polynomials in which the burden of representing the random component is carried by the polynomials; the coefficients of the expansion are smooth functions. Ghanem and Spanos (1991) and Ghanem (1999) refined Wiener's method and applied it to structural analysis problems. Xiu and Karniadakis (2001) have generalized the class of expansion functions and applied it to fluid mechanics and fluid-structures problems; they have shown that the set of Wiener-Askey polynomials contains an appropriate (and rapidly convergent) polynomial family for many of the PDFs of physical interest. This approach is referred to as *Polynomial Chaos*. One obtains the PDFs of every component of the solution at every space-time point. The cost is typically one to two orders of magnitude greater than that of a deterministic solution for the differential equation, yet is still orders of magnitude cheaper than required for an ensemble of solutions generated by a Monte Carlo method.

2.1.3.2. Fuzzy Logic. When the parameter uncertainties are characterized by membership functions, fuzzy logic is the basis for assessing the uncertainties in system output. Fuzzy logic allows one to create models based on inexact, incomplete, or unreliable knowledge or data, and, moreover, to infer approximate behavior of the system from such models. Fuzzy logic provides a computational engine to process these models (Harris, Moore, and Brown 1993). To date, fuzzy logic has found many applications in controls, manufacturing, pattern recognition, and even finance (Holmes and Ray 2001; Ham, Qu, and Johnson 2000; Inoue and Nakaoka 1998; Isermann 1998; Dexter 1995; Hung 1995; Lim and Hiyama 1991; Lee

1990; Box and Draper 1987). Fuzzy logic is an extension of multivalued logic. Its predicates can be both crisp (not fuzzy), such as numbers, or true and false, and non-crisp (fuzzy), such as greater than, small, etc. Uncertainty characterizations using membership functions are sometimes referred to as possibilistic, which is often used to contrast this approach with the probabilistic approach.

The central concept of fuzzy logic is the membership function, which represents the degree of membership of the fuzzy variable within the fuzzy set (Harris, Moore, and Brown 1993). The membership function may be thought of as a possibility function in contrast to the probability density function in probability theory. In fuzzy logic, input and output mappings are established through fuzzy algorithms based on a collection of rules, in the form of conditional statements. The composition of an input variable(s) with the fuzzy rules (relations) produces a fuzzy set for the output. To obtain a crisp output, the fuzzy set has to be de-fuzzified to a single value; different techniques can be used to accomplish this task.

Fuzzy logic is appealing for its simplicity of application and implementation. It may be useful in applications wherein accurate physical models are not available, for preliminary design and analysis, or in cases wherein crude or fuzzy inferences and actions are acceptable. However, in uncertainty-based design and analysis, the use of fuzzy logic may be confined to the conceptual design and early preliminary design stages; the level of accuracy required in most aerospace applications in late preliminary and detailed design is far too stringent to allow for fuzzy logic.

***2.1.3.3. Interval Analysis*.** Interval analysis was initially developed to account for errors in floating point arithmetic. The chief distinguishing element of its framework is that variables are represented by two scalars: a lower bound value and an upper bound value. These numbers reflect a measure of uncertainty in the knowledge of the actual value of the variable. Interval arithmetic involves the rules developed to perform mathematical operations with interval numbers. Interval analysis is ideally suited to deal with parametric uncertainties in systems. In its simplest form, a combinatorial analysis is used to construct interval distributions of the performance quantities. It has been applied in a variety of fields, including structural analysis and dynamic analysis, to accommodate uncertainties in parameters (Piazzi and Visioli 2000; Jaulin and Walter 1997; Oppenheimer and Michel 1988; Ugur Koyluoglu and Elishakoff 1998; Qiu, Chen, and Elishakoff 1995; Rao and Berke 1997). However, these applications involve mainly simple problems of small order. Applications to medium-large size problems are lacking because by nature, interval arithmetic produces potentially conservative results, i.e., the results are not practical. The level of conservatism may be reduced if interval variables and arithmetic are used in closed-form solutions of the problem output, as opposed to throughout the numerical solution. Unfortunately, closed-form solutions are rarely available, except for the simplest of problems. Another minor problem with interval analysis is that it is computationally more expensive than traditional mathematics since it deals with intervals and not just scalars. However, with recent advancements in computing technology, this higher computational expense is not an issue anymore. In fact, interval arithmetic is accommodated in the latest SUN Microsystems Forte Fortran 95 Compiler. One other potential problem is that interval analysis may not be amenable to accommodating correlated uncertainty distributions. This issue may lead to additional conservatism in the predictions of bounds for the system output.

2.1.4. Sensitivity Analysis

Sensitivity analysis is related to, but different from, uncertainty analysis. The recent book edited by Saltelli, Chan, and Scott (2000) provides thorough coverage of this vast subject. The overview chapter by Campolongo et al. (2000) defines sensitivity analysis as “the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation, and of how the given model depends upon the information fed into it.” As used here, sensitivity analysis ascertains which parameters have the greatest influence on the system output. It is a deterministic question. Its primary relation to uncertainty analysis is to enable the identification of which parameters really matter—conducting an analysis of the impact of the uncertainty of a parameter that has an insignificant effect upon the performance measures is futile. Given the high cost of most uncertainty analysis methods, it usually pays to first conduct a sensitivity analysis to weed out consideration of unimportant parameters. This process is often "step 0" in the construction of a response surface.

Campolongo et al. (2000) list three general approaches to sensitivity analysis with numerical models. *Factor screening* determines which parameters (or groups of parameters) have the greatest impact on the model output variability. Various design of experiment techniques are typically employed. These consist of evaluating model output at the extreme values of the ranges of the parameters. *Local sensitivity analysis* utilizes first-order derivatives of model output quantities with respect to the parameters. Like factor screening, local sensitivity analysis is a deterministic calculation, but it is usually performed for a nominal set of parameter values. Some computational tools provide accurate and efficient sensitivity derivatives, but in most cases costly (and sometimes inaccurate) finite-difference approximations are used to compute the derivatives. *Global sensitivity analysis* typically uses statistical sampling methods, such as Latin Hypercube Sampling, to determine the total uncertainty in the model output and to apportion that uncertainty among the various parameters.

If efficient sensitivity derivatives for the model are available, then local sensitivity analysis is by far the least costly in terms of computational time. At worst, its cost increases linearly with the number of parameters. However, it is limited to the vicinity of the nominal parameter values. The cost of factor screening methods that look at one factor at a time increases linearly with the number of parameter values, whereas methods that look at the full set of mutual interactions have an exponentially increasing cost. Statistical sampling approaches typically require thousands of evaluations of the computational model, although their cost is in principle independent of the number of parameters. This approach is prohibitively expensive for models with nontrivial computational times. The only feasible approach for this important class of models is to generate an approximation to the model, and then to perform the statistical sampling on the approximation. Constructing such an approximation, however, is only feasible for a small number of parameters.

2.1.5. Approximations

Clearly, the methods described previously for uncertainty propagation and for sensitivity analysis are impractical when the computational time required to evaluate the process model is large. This problem is usually dealt with by using approximations. Several alternatives to sampling methods have been developed for estimating the PDF of the performance function. The Advanced Mean Value method (Wu and Wirsching 1989) exploits a first-order approximation to the performance function together with a Fast Probability Integration technique. The first-order approximation requires the computation of the gradients of the performance function with respect to all the random variables. The Fast Probability Integration then performs an integration over this linear approximation. Field, Paez, and Red-Horse (1999) have improved this method to yield more accurate moments of the PDF. Du and Chen (2000a) have developed a method based on Most Probable Point techniques for efficiently constructing the PDF. It, too, utilizes the first-order derivatives of the performance function. Both of these methods are usually implemented with finite-difference approximations to the gradients of the performance functions. Their cost can be dramatically lower if efficient methods for computing these derivatives are exploited.

More generally, one can build an approximation, typically a response surface model, for the exact process model. The response surface is then used in lieu of the exact process model by the uncertainty computing engine. Response surface approximations are constructed by the following three steps:

- Experiment points are selected.
- Response surface model order is selected.
- Experiment points are fitted to the chosen model.

The selected experiment points determine where in the design space the exact process model will be evaluated. Design of experiment techniques are typically employed; for an excellent treatment on the selection of the experiment points see Box and Draper (1987). When selecting the response surface model order, quite often either linear or quadratic surfaces are assumed. Once the model order has been determined, the response surface is fit using least squares. In some cases the model order is not selected beforehand; instead the response surface model is chosen such that the first two statistical moments of the response surface match that of the exact process model, resulting in first-, second-, or even higher-order surfaces.

2.2. Analysis and Optimization Incorporating Uncertainties

The previous subsection focused on methods for describing the uncertainties in the performance measures of a discipline or system. This description may be in the form of probability density functions, membership functions, or interval bounds. In this subsection, we discuss methods that use this information in design, e.g., by computing failure probabilities, by design of control systems, or by optimizing a system in the presence of uncertainties.

2.2.1. Impact of Uncertainty on Performance Measures

A type of performance measure that is pervasive in reliability-based design is a limit state function. Limit state functions are generally nonlinear relationships (constraints in the optimization context) used to define system failure conditions. Examples of the engineering quantities that may be embedded in limit state functions are stress, dynamic stability, temperature, fracture, or buckling. Conventionally, the failure domain is described by $g(x) \leq 0$, where g is the limit state function. Figure 6 is an example of a limit state function for a problem with two design parameters.

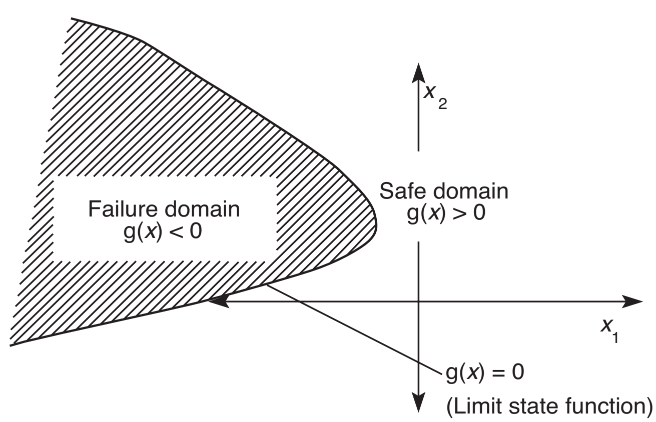

Figure 6. Limit state function.

To date, limit state functions have been used exclusively with probabilistic uncertainty analysis. Mathematically, the failure probability P_F is defined as

$$P_F = P\left[g(X) \leq 0\right] = \int\limits_{g(x)\leq 0} f_X(x)dx \tag{1}$$

where $f_X(x)$ is the joint probability density function of X and the integration is carried out over the entire failure domain. For many engineering applications, solving equation (1) may entail a substantial computational effort. Some of the difficulties in evaluating the right-hand side of equation (1) include:

- High dimensionality of the design space makes the integration very costly
- Mathematical and computational complexity of the domain boundaries given by $g(x) = 0$
- Lack of information regarding the joint probability density, $f_X(x)$

Because of these complexities, exact solutions of failure probabilities for general systems with arbitrary parameter uncertainty PDFs are not feasible; therefore, efficient numerical methods for computing approximate failure probabilities are required. In fact, the development of efficient approximate numerical techniques has been the subject of much research.

The goal of First-Order Reliability Methods (FORM) and Second-Order Reliability Methods (SORM) is to compute failure probabilities efficiently by exploiting approximate forms of the limit state function. FORM and SORM replace the limit state function in equation (1) with first-order and second-order approximations, respectively. FORM and SORM reliability methods consist of four basic computational steps:

1. Transform from physical space to standard normal space.
2. Determine the most probable point (MPP).
3. Approximate the limit state function at MPP.
4. Compute the failure probability using the approximated limit state function from step 3.

Step 1 is particularly important because of the properties of standard normal space. The most important property of standard normal space in regards to computing failure probabilities is that probability densities decay exponentially with the square of the distance from the origin. Therefore if one approximates the limit state function in the vicinity of the MPP (the closest point to the origin), the majority of the failure probability will be captured by an approximate limit state function because it is most accurate in the region that contributes the most to the integration. The specifics for computing failure probabilities for FORM and SORM differ slightly, but the primary difference between them is the order of the approximated hypersurface. In FORM, the limit state function is approximated by a tangent hyperplane at the MPP; in SORM, a quadratic hypersurface is used. This difference generally results in SORM producing more accurate estimates of failure probabilities, but at the cost of greater computer time due to the second-order gradient computations.

Rackwitz (2000) has written a detailed review of FORM and SORM methods. Thacker et al. (2001) have provided a useful description of the weaknesses of current FORM and SORM algorithms. Thacker et al. (2001) note that Importance Sampling Methods are often used to increase the accuracy of the limit state function probabilities near the MPP. Choi and Youn (2001) have recently developed an alternative approach to reliability analysis that inverts the objective and constraint functions in the optimization used to identify the MPP.

2.2.2. Bounded Uncertainty Design and Analysis

The controls community has developed a special approach that they refer to as bounded uncertainty design and analysis. In this approach, system uncertainties can be either parametric or nonparametric. Furthermore, the uncertainties can be real or complex time-independent functions, or linear/nonlinear time-varying functions (Balas and Packard 1996; Doyle, Wall, and Stein 1982). No matter what form of uncertainty one is dealing with, the uncertainty is assumed to be norm bounded, i.e., the maximum excursions of uncertainties are assumed to be known a priori. Figure 7 is an example of how the bounded uncertainty is added to a system. In this figure, **P** is the plant, **d** represents the exogenous inputs (typically unknown disturbances or reference signals), $\mathbf{y_p}$ are the sensor measurements, $\boldsymbol{\Delta}$ is the uncertainty block, and **W** and **Z** are used to define the interconnection between the plant and the uncertainty block.

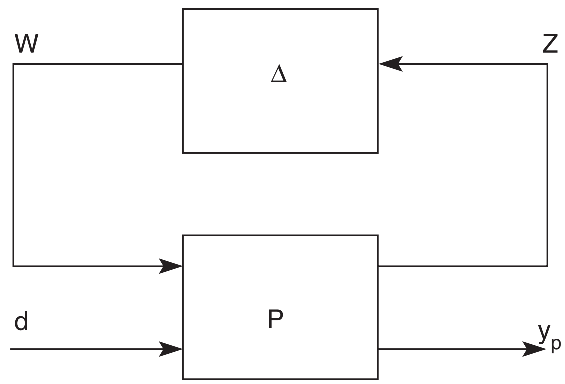

Figure 7. Bounded uncertainty structure.

The main objective in the Bounded Uncertainty Design and Analysis approach is to obtain bounds on the potential variations in system performance based on the bounds on the parametric and nonparametric uncertainties. The type of analysis required in this approach can vary significantly from one application to another. It can be simply a norm-based analysis in which the norm bounds at the uncertainty levels are propagated through to the system performance, e.g., bounds on stress levels due to bounded uncertainty in the material properties. Substantial work has been done for linear time-invariant dynamical systems in this area (Balas and Packard 1996; Doyle, Wall, and Stein 1982; Moser 1993; Balas and Doyle 1994; Gagnon, Pomerleau, and Desbiens 1999; Bendotti and Beck 1999; Nishimura and Kojima 1999; Pannu et al. 1996; Cheng and De Moor 1994; Balas et al. 1998). Various techniques are available to incorporate parametric and nonparametric uncertainties within the linear system. Both structured and unstructured uncertainty models can be considered in this framework (Balas and Packard 1996). A structured uncertainty model denotes a model in which uncertainty is directly associated with specific parameters in the system, while in the unstructured uncertainty model, uncertainties are general, and hence are not associated with any specific parameter in the model. Several methods are available for analysis of dynamic stability and performance of these systems. An example is the Linear Matrix Inequality framework, which uses convex programming (Scherer, Gahinet, and Chilali 1997; Apkarian and Adams 1998). The treatment of linear time-invariant systems with uncertainty can be extended to linear time-varying systems as well as a certain class of nonlinear systems (e.g., linear parameter varying systems) with the aid of the Linear Matrix Inequality framework (Scherer, Gahinet, and Chilali 1997; Apkarian and Adams 1998). For general nonlinear systems, the treatment of bounded uncertainties is somewhat *ad hoc*, as there are no formal methods for dealing with such systems. However, in some cases, Lyapunov stability theory and norm-based propagation can be used to establish bounds on the performance of the nonlinear system.

2.2.3. Optimization Under Uncertainty

Several design optimization methods include uncertainty. For the purpose of this paper, the methods can be divided into three groups: sampling methods, robust optimization, and optimization for reliability. Sampling methods can be used to solve either robust optimization or reliability-based optimization problems, but we find it useful to discuss these methods separately. The sampling methods perform all experiments (whether mathematical simulations or physical tests) simultaneously and then optimize the design based on the results of those experiments. Robust optimization methods use the numerical optimization procedure to specify which simulations are needed and evaluate those simulations one at a time. The optimization for reliability methods also use numerical optimization procedures but with the goal of reliability rather than robustness.

2.2.3.1. Sampling Methods. Sampling methods are based on the assumption that the designer will choose an optimum design by evaluating a performance or cost measure at a large number of points in design space. Ideally, these points define a smooth hypersurface with a well-defined feasible region and a single optimum point. If the cost measure (also called objective function) includes parametric uncertainty, then many evaluations are required at each point in design space to accurately characterize the hypersurface.

Trouble arises when the value of the objective function is evaluated with a variety of different computer simulations and experimental data. Each source of measured and computed data includes errors (e.g., due to simplification in the mathematical models) and uncertainty (e.g., due to the difference between the ensemble averages and the individual test results). For a good overview of available sampling and response surface approximation techniques see Robinson (1998). For a discussion of the types of *variabilities*, *uncertainties*, and *errors* found in simulation codes and for uncertainty estimation methods see Alvin et al. (2000).

Conceptually, optimization that includes uncertainty can be achieved by fitting all available data with some smooth surface and then using a mathematical optimization procedure to determine the best design. All sampling approaches considered here use the following three steps: (1) sample the design space, (2) approximate the objective function, and (3) estimate the optimum of the approximate surface. These steps can be repeated one or more times on smaller and smaller neighborhoods surrounding the current optimum point.

Several popular techniques differ in steps (1) and (2). For example, the design space can be sampled using Taguchi arrays, Latin hypercubes, random points, or some subset of available data. Similarly, the approximate surface can be constructed using neural nets, polynomials, or splines under tension. The choice of method depends on knowledge of the design space (e.g., the objective function may vary linearly with respect to some design variables) and on the amount of available data.

Response surface methods (RSM) and Taguchi parameter design methods are the most commonly used procedures. Venter and Haftka (1999) explain that RSM reduces the computational burden and simplifies the integration of optimization and analysis codes. Roy (1990) and Nair (1992) discuss the Taguchi method and some of its known strengths and drawbacks. Unal, Stanley, and Joyner (1993) provide a good tutorial on Taguchi methods written from an engineering perspective. The principal limitations of both RSM and Taguchi parameter design methods are: neither constraints nor multiple objective functions are accommodated; dimensionality restricts the application of these methods to problems with a small number of parameters and design variables; and they are far less applicable to *uncertainty* and *error* than to *variability* (as these terms are used by Oberkampf et al. 1998). Although Taguchi methods are effective for many problems, work still needs to be done to develop alternative approaches that overcome these limitations.

2.2.3.2. ***Robust Optimization Methods.*** For our purposes, robust optimization methods seek to improve a design by making it insensitive to small changes in the design values, and they exploit sequential numerical optimization techniques. One method for achieving robustness is to minimize both the mean and variance. Thus, the optimization problem is formulated as a multiobjective problem:

$$\min_{t \in \Omega} \quad w_1 c(t,\theta) + w_2 \sigma^2 (t,\theta) \tag{2}$$

where t are the design variables in the domain Ω, θ are the uncertain parameters that are described by one or more PDFs, c is the mean of the objective function, σ^2 is the variance of c due to the randomness of θ, and w_i are the user-defined weights. Depending on the choice of weights, this formulation will minimize the objective, minimize the variance in the objective, or discover some compromise between these two goals.

Robust optimization methods are effective if $c(t,\theta)$ is a good simulation of the performance or cost goals and if the PDF of θ is well characterized. For example, structural analysis codes can accurately predict the strains in metal truss structures given the loads. Moreover, the PDF of uncertain loading parameters such as wind speed or wave height have been collected. Therefore, robust optimization for sizing of civil engineering projects should result in safer and more cost-effective structures. Unfortunately, few simulation codes automatically predict the variance of the mean given a known PDF of the uncertain parameters. Tada, Matsumoto, and Yoshida (1988) provide a clear explanation of this method and its application to simple structural sizing problems.

2.2.3.3. Optimization for Reliability. Optimization for reliability methods are based on the assumption that the design space is divided into two regions: success and failure. The goal of the optimization is to find the best design that is sufficiently far from the failure region so that the probability of failure is acceptably small. Thus, the optimization problem is formulated as a constrained optimization problem:

$$\min_{t \in \Omega} \quad c(t,\theta) \tag{3}$$

subject to

$$P\left[g(t,\theta) \le 0\right] \le r \tag{4}$$

where r is the reliability requirement, $g(t,\theta) = 0$ defines the boundary (or limit surface) between success and failure, and $P[g \le 0]$ is the probability of failure for the current values of the design vector t.

Optimization for reliability can be attempted using standard constrained nonlinear optimization procedures. The major difficulty is the computational expense of calculating the probability of failure. A secondary difficulty is that the constraint $P_F \le r$ can be a highly nonlinear function of t even if $g(t,\theta)$ is linear in t.

The computational expense of optimization for reliability greatly hinders its acceptance. If an evaluation of the constraint $g(t,\theta)$ is computationally expensive or if the reliability requirement r is small, then Monte Carlo analysis can be prohibitively expensive since it requires thousands of evaluations of g at randomly sampled values of θ. An alternate approach is to (1) use the optimization code to find the most probable point of failure or MPP, (2) estimate the probability of failure using a linear approximation to the limit surface centered at the MPP, and (3) use the optimization code to minimize the objective for the required probability of failure. In this alternate approach, the optimization code is used twice, first to find the values of θ that define the MPP and then to find the values of t which reduce the objective without compromising safety. See Langley (2000) and Grooteman (1999) for a good overview of these methods.

3. Current Status and Barriers

3.1. Structural Analysis

3.1.1. Current Status

Traditionally, the approach to designing aerospace structures with uncertainties is to use statistically based material properties (e.g., yield strength) and to introduce design factors. The statistically based material properties are characterized as A-basis and B-basis material property values (Anon. 1997). An A-basis material property is one in which 99 percent of the material property distribution is above the basis value with a 95 percent level of confidence. A B-basis material property is one in which 90 percent of the material property distribution is above the basis value with a 95 percent level of confidence. Design factors can be placed into two categories and include safety factors and design knockdown factors for stability critical structures. Safety factors account for uncertainties in a "lump-sum" fashion by multiplying the maximum expected applied stress by a single safety factor. The FAA air-worthiness certification requires a design safety factor equal to 1.5 for man-rated aircraft structures; however, safety factors as low as 1.02–1.03 have been used in the past for non-man-rated structures such as missiles. The safety factor is intended to account for uncertainties such as uncertainty in aerodynamic load definition and structural stress analysis, variations in material properties due to manufacturing defects and imperfections, and variations in fabrication and inspection standards. The safety factor is generally developed from empirically based design guidelines established from years of structural testing of aluminum structures. For a historical review of the evolution of the 1.5 factor of safety in the United States, see Muller and Schmid (1978).

The traditional approach to designing thin-walled buckling-resistant structures is to predict the buckling load of the structure with a deterministic analysis and then to reduce the predicted load with an empirical design knockdown factor, which is intended to account for the difference between the predicted buckling load and the actual buckling load of the structure determined from tests. The differences between analysis and test results are mainly due to uncertainties in the structural geometry (e.g., imperfections), loading conditions, material properties, and boundary conditions. Design guidelines for stability critical isotropic structures can be found in several NASA documents including Weingarten, Seide, and Peterson (1968) for buckling of thin-walled circular cylinders, Weingarten and Seide (1968) for buckling of thin-walled truncated cones, and Weingarten and Seide (1969) for the buckling of thin-walled doubly curved shells.

Many of the aforementioned design practices have been carried over to composite structures for lack of better design methods. In addition, these design methods can potentially result in overly conservative or unconservative designs of aerospace structures. Furthermore, these design guidelines do not include any data or information related to uncertainty sensitivity.

3.1.1.1. Probabilistic Analysis and Design Methods. A probabilistic design methodology reported in Anon. (1997) accounts for uncertainties in material properties; external or operational loads; manufacturing processes and their effects on material strength; environmental effects on strength such as moisture or radiation exposure; environmental history during operation; flaw and/or damage locations, severity, and probability of occurrence and effects on strength; and predictive accuracy of structural models and analysis. The probabilistic approach uses the statistical characterization of parameter uncertainties and attempts to provide a desired reliability in the design. In the probabilistic approach, the uncertainties of the individual design parameters and loads are modeled by appropriate probability densities. These probability densities are combined into cumulative density functions by using transformation equations. In this case, the design parameters have an uncertainty that is quantified in terms of risk. The credibility of this approach depends on two factors: the accuracy of the analytical model used to predict the structural response, and the accuracy of the probabilistic techniques employed. This probabilistic methodology has shown some success in the design of composite structures where the parameter uncertainties are well-known. For example, the IPACS (Integrated Probabilistic Assessment of Composite Structures) computer code was developed at NASA Glenn Research Center (Chamis and Murthy 1991), and a probabilistic stability analysis for predicting the buckling loads of compression-loaded composite cylinders was developed at Delft University of Technology (Arbocz, Starnes, and Nemeth 2000).

3.1.1.2. Fuzzy Set or Possibilistic Analysis Methods. For situations in which sample data necessary to quantify parameter uncertainties are limited or nonexistent, fuzzy set analysis can be used to account for uncertainties. In these methods, uncertainties in input parameters (e.g., dimensions, Young's modulus) are defined by membership functions. An example of a membership function is shown in figure 8.

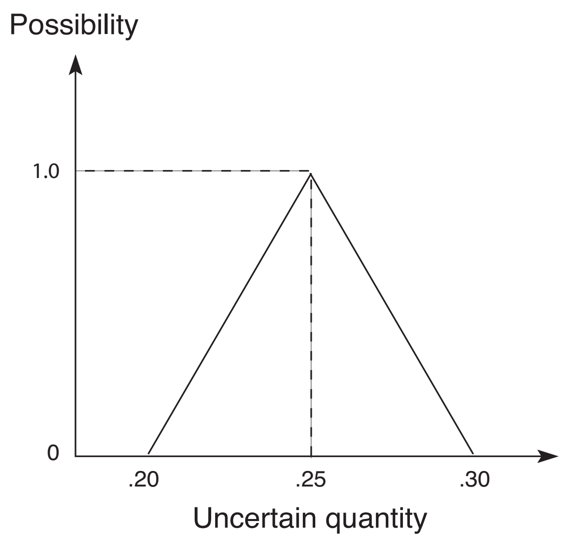

Figure 8. Example of membership function.

The vertical scale is the possibility that an uncertain quantity takes on a given value, and the horizontal scale shows values of the uncertain quantity. The possibility varies from zero (no possibility) to one (maximum possibility). In this example, the most likely value of the uncertain quantity is 0.25. The uncertain quantity is bounded by 0.20 and 0.30 at Possibility = 0.0. The objective is to use the membership functions of the input parameters to determine the corresponding membership functions for the response quantities (e.g., stress, buckling load). The membership functions for the response quantities are then compared with the membership functions of the allowable responses to determine the possibility of failure.

A subset of fuzzy set or possibilistic analysis is sometimes called interval analysis. In this approach, upper and lower bounds are placed on the uncertain input parameters, and the resulting upper and lower bounds are calculated for the response quantities. The objective is merely to bound the response rather than to indicate the likelihood of the response taking on a given value. This approach is equivalent to working with membership functions at a possibility of zero.

Fuzzy set or possibilistic analysis methods have been proposed by Noor, Starnes, and Peters (2000) and have been applied to structural problems such as the probabilistic strength predictions of bonded joints by Stroud, Krishnamurthy, and Smith (2001). In addition, interval analysis has been used to predict response bounds for compression-loaded composite shells with random imperfections, e.g., Hilburger and Starnes (2000).

3.1.1.3. Example. The example illustrated in figure 9 (from Fadale and Sues 1999) illustrates how quantitative design for reliability enables effective trade-offs between weight and reliability. An existing lap joint connecting two integral airframe panels was redesigned for minimum weight and to meet reliability requirements. Failure analyses (the limit state functions) involved fatigue and discrete source damage. Reliability-based design methods yielded an improved design that saved 19 percent in weight while providing the same reliability. In addition, this method provided sensitivity information that showed how weight varies with reliability. In this case, small increases in weight produced large increases in reliability. Weights are shown normalized with respect to the weight of the original joint.

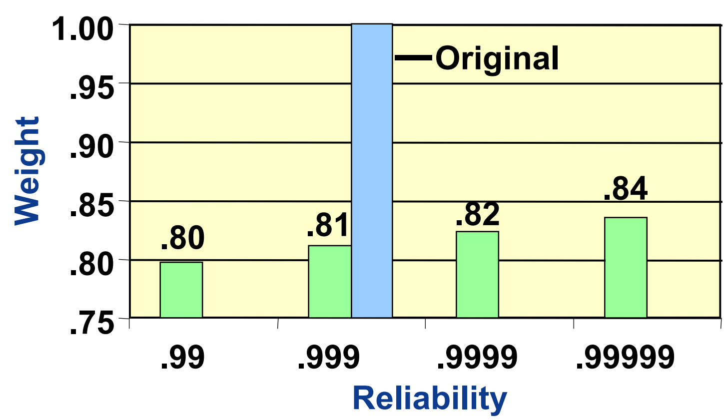

Figure 9. Reliability versus weight trade-off (from Fadale and Sues 1999).

3.1.2. Barriers

Most of the barriers to the use of uncertainty-based design methods in the structures discipline are shared with the other design disciplines.

B1. Industry feels comfortable with traditional design methods.

There is always inertia associated with existing processes. Certainly, traditional design methods have been very successful in the aerospace industry. Nevertheless, the traditional methods and processes are characterized by costs, schedules, and performance limitations that are significant problems in the modern business climate. A necessary condition for overcoming this barrier is ensuring that the transition by industry to the new uncertainty-based methods and processes is relatively painless.

B2. Few demonstrations of the benefits of uncertainty-based design methods are available.

The technology advocates of uncertainty-based design need to provide compelling demonstrations of the benefits of uncertainty-based design methods and a compelling business case for changing to the new processes. This case must demonstrate measurable benefits and must be couched in terms readily understandable by both technology managers and practitioners. Given the head start of the structures community on uncertainty-based design methods, this barrier is even greater for the other design disciplines.

B3. Uncertainty-based design methods are more complex and considerably more expensive than deterministic design methods.

Advances in computer hardware and software, especially in automation, are bound to help. However, orders of magnitude improvements are needed to overcome this barrier. Fundamental breakthroughs are needed in this area.

B4. Characterization of structural imperfections and uncertainties necessary to facilitate accurate analysis and design of the structure is time-consuming and is highly dependent on structural configuration, material system, and manufacturing processes.

To some extent this structures-specific barrier will naturally lessen with time as more and more such characterizations are done. However, methods must be established for generalizing the specific results that come out of tests of particular configurations, materials, and manufacturing processes.

3.2. Aerodynamic Testing and CFD

3.2.1. Current Status

For the purposes of discussing the risk associated with using the results obtained from experimental and/or computational aerodynamic simulations, it is convenient to think of a simulation as a single pass through a manufacturing process (Eisenhart 1969). The outputs of the "manufacturing" process are the numbers generated either by the instruments in an experiment or by the computer codes in a computation. It is the uncertainty (fuzziness) associated with those numbers that a simulation contributes to the overall risk in the design of an aerospace vehicle. Hence, the objective of any aerodynamic simulation effort must be to quantify the subprocess and overall process variation[4] and contain it to acceptable levels in the simulation results and thence into the final design.

Wheeler (1990) discusses the three stages involved in quantifying and containing variation in the making of an industrial product. These stages are useful for discussing the risk associated with both types of aerodynamic simulation: testing and CFD. The manufacturing stages, as presented by Wheeler, together with the analogous aerodynamic simulation stages are given in table 1. Usually, the three aerodynamic simulation stages are carried out simultaneously, at least in part (Rubbert 1998), but the strategies (objectives) of each for managing and minimizing risk are different.

[4] We will use the term "variation" to designate the scatter in replicated results. If the scatter is not known and controlled, it is not possible to consistently and credibly assess and correct the offset of the mean of the results from the true value.

Table 1. Stages for Minimizing Risk Associated With Manufacturing and With Aerodynamic Simulation

Manufacturing		Aerodynamic simulation	
Stage	Objective	Stage	Objective
Product design	Choose design parameters so that the product will be insensitive to variation in raw materials and manufacturing process conditions	Airframe design	Choose design parameters so that the simulation results will be insensitive to the simulation process
Manufacturing process design	Choose the manufacturing process conditions so that the product will be insensitive to variation in those conditions	Simulation process design	Design the simulation process to be insensitive to variation in the process parameters
Manufacturing	Control the manufacturing process to obtain desired product consistency	Simulating	Manage the level of variation so that the process variation has known and traceable bounds

This subsection addresses previous work and the current status of work in the three stages of simulation as described in table 1. The various efforts can be divided into three types: general strategies, *ad hoc* "example" evaluations, and systematic evaluations. It is beyond the scope of this section to report and evaluate all of the work in these areas. However, we will list certain publications that illustrate what we believe to be the state of the art.

Airframe Design. A usual design strategy is to choose airframe designs for which one has sufficient experience to be able to assess risk. In this capacity, CFD has made some inroads to the design process for over a decade (cf. Rubbert and Goldhammer 1989). Many issues still abound regarding the role of CFD in design (Rubbert 1990, 1994, 1998; Raj and Singer 1991, Raj 1998; Cosner 1994, 1995), not the least of which is the rigorous establishment of confidence in computational results.

Beyond the usual design strategy of choosing airframe designs for which one has sufficient experience to be able to assess risk, the pioneering work in this area seems to be optimization based on statistical modeling of the design criteria (Huyse 2001). Such modeling produces "softer" but more robust optima. There does not appear to be any work in CFD that attempts to produce aerodynamic designs that are inherently robust in the face of input uncertainties and discretization and modeling errors. Also, neither general strategies nor systematic evaluations for airframe design have been developed.

Simulation Process Design. General strategies have been developed for assessing and managing risk in both computational and experimental simulations. Examples of general strategies for computations are Cosner (2000), Mehta (1998), Oberkampf et al. (1998), Rizzi and Vos (1998), and Roache (1998). These strategies typically require (1) assessment and management of numerical error due to discretization of the governing differential equations and (2) a hierarchy of validation phases, primarily statistical comparisons with experimental results. These requirements are not unlike the conceptual distinction between CFD code "calibration" and "validation" from Waggoner et al. (1994) as part of an international effort to delineate a proper process for code validation and to provide a comprehensive series of test cases (AGARD 1994):

> <u>CFD Code Calibration</u>: The comparison of CFD code results with experimental data for realistic geometries that are similar to the ones of design interest, made in order to provide a measure of

the code's ability to predict specific parameters that are of importance to the design objectives without necessarily verifying that all the features of the flow are correctly modeled.

CFD Code Validation: Detailed surface- and flow-field comparisons with experimental data to verify the code's ability to model accurately the critical physics of the flow. Validation can occur only when the accuracy and limitations of the experimental data are known and thoroughly understood and when the accuracy and limitations of the code's numerical algorithms, grid density effects, and physical basis are equally known and understood over a range of specified parameters.

With this distinction, many prior cases of purported code validation should be considered a collection of specific code calibrations. Furthermore, this distinction makes clear that computational validation can only occur in conjunction with rigorous experimental uncertainty management. Results from this distinction have been published by Bussoletti (1994).

Promising efforts are underway by several research groups to reduce, manage, and assess the numerical error using adjoint equations (Giles and Pierce 1999; Habashi et al. 1998; Patera and Rönquist 2001; Roberts, Sidilkover, and Thomas 2000; Venditti and Darmofal 2000). Such ideas seem to have come of age and the use of such methods appears to be spreading. However, systematic evaluations of the methods, especially regarding the scatter due to variation in code and observer, appear to be lacking. Validation efforts at this stage appear to consist mostly of example problems. The most complete effort of this type may be the work of Aeschliman and Oberkampf (1998). Others have attempted to assess variation across several codes using several experimental data sets (Barber et al. 1998; Elsholz 1997; Georgiadis, Yoder, and DeBonis 1999).

Examples of general strategies for designing experimental simulations for managed risk are Aeschliman and Oberkampf (1998), Anon. (1995), and Mayo (1996). Overall, such strategies consist of one or more of the following three elements: (1) creation of a hierarchy of validation experiments, (2) evaluation of the effects of instrument errors using error propagation analysis, and (3) replications during the experiment to allow for statistical characterization of the data scatter for that test. Although it is clear that any competent research facility would follow these strategies, it is not at all clear how well the strategies can be counted on to fully characterize the "fuzziness" of the experimental results. The reason for this seems to be a general lack of systematic evaluation of the strategies themselves.

Simulating. Approaches are in place for both experimental and computational aerodynamic simulation for estimating a portion of the uncertainty in the results of any given simulation effort. The methods described in the previous paragraph for design of an experimental simulation process are used widely in the industry for estimating the uncertainty of experimental results (Belter 1996; Cahill 1996; Meyn 1998; Kammeyer and Rueger 2000), although their general effectiveness is not well understood, primarily because systematic evaluations across facilities are essentially unavailable. The need for managing and evaluating numerical error in individual computational simulations is well-known and is required by archival publications. As described previously, methods have been developed for estimating such errors. However, systematic evaluation of such schemes is lacking.

The only effort known to us that attempts to evaluate experimental simulation process *as a process* is that of Hemsch et al. (2000). The effort uses the methods of statistical quality control, check standard (surrogate) testing, and replicates during customer testing to evaluate and control the process for all tests conducted in a facility. The method is being used at Langley Research Center in eight wind tunnels and one nozzle test facility. We are not aware of any similar efforts associated with computational results. Moreover, the strategies have not yet been developed for evaluating and controlling processes from multiple facilities to produce consistent data.

Probably the leading work for addressing computational uncertainty as a process is being conducted by Oberkampf and his associates (Oberkampf and Blottner 1998; Oberkampf 1998; Oberkampf et al. 1998; Oberkampf and Trucano 2000). Significant contributions can also be found in the work of Roache (1990, 1998). These works could be heavily leveraged toward the current interest in uncertainty-based design.

3.2.2. Barriers

The main theme that seems to arise out of the previous discussion in this section is a lack of systematic, quantitative, and credible (traceable) evaluations of the available methods for minimizing, managing, and estimating the errors associated with the results of both experimental and computational simulation. Aerodynamics shares with structures the barriers of industry comfort with traditional design methods (B1), few demonstrations of benefits of uncertainty-based design (B2), and increased complexity and greatly increased cost for uncertainty-based design methods compared with deterministic design methods (B3). Indeed, the cost increase is even more of a barrier in aerodynamics because the nonlinear aspects of computational aerodynamics make the computation of gradients much more of a challenge than for computational structures.

3.2.2.1. Statistical Process Control. Additional barriers include the dearth of statistical process control activity, the lack of any current approach for characterizing the model form uncertainties associated with transition and turbulence, and the lack of a viable approach for characterizing uncertainties in sensitive nonlinear problems.

B5. There is a dearth of statistical process control activity in aerodynamics.

This barrier afflicts most disciplines. In the case of aerodynamics, two principal causes, or "sub-barriers," are involved:

a. Present and projected CFD code calibration, verification, and validation activities are expensive and insufficiently general to be applicable for predictive accuracy assessment.

b. Calibration and validation exercises need to include code developers (or analysts) and experimentalists, but these groups are not motivated to work together.

High-fidelity CFD computations (Reynolds-averaged Navier-Stokes) are notoriously expensive—runtime can last upwards of a day, even on a 32-processor cluster, for a full aircraft computation. This expense precludes, for example, the practical use of even the most sophisticated sampling methods for assessing the effects of *variability*. Part of B5(a) is a reinforcement of B4. The additional aspect is that the calibration, verification, and validation approaches currently in use by the CFD community need to be reconciled with the general verification and validation framework that has emerged in the past few years.

The second aspect of this barrier, B5(b), involves cultural and financial forces acting in concert, and certainly results in a dearth of statistical process control activity. Consider the following institutional groups:

Airframe Designers. These workers typically have little or no time to do any systematic work other than design. Their efforts are aimed at optimizing a design as fast as possible using both experimental and computational simulation. Unfortunately, their support groups involved in research, development, and testing have little funding with which to carry out evaluations that cross their institutional boundaries. Furthermore, any such systematic evaluations carried out are likely to be proprietary.

Simulation Process Designers. These workers typically have little funding to do any systematic work. Their day-to-day pressures are likely to be problem solving and extension of simulation capabilities rather than systematic evaluation. Notable exceptions are the adjoint equation work for estimating and managing numerical errors and the statistical quality control work for estimating and controlling data scatter in wind tunnels. Both types of simulations suffer from a lack of definitive systematic hierarchical experiments with which to evaluate modeling errors.

Simulation Users. Users of both types of simulations are under severe pressure to produce "good quality" results as quickly as possible for as little money as possible. Users very seldom have the time or funding to carry out systematic evaluations. They are typically quite willing, however, to carry out small efforts to help with such evaluations if they are organized and funded by others. A common language will need to be agreed to among the practitioners so that calibration, validation, verification, certification, uncertainty, and so forth have consistently defined meanings and contexts.

Systems Approach. A systems approach could be a useful context to develop computational and experimental aerodynamic methodologies for risk based design. Here the focus is drawn from top-level system requirements, such as the successful insertion of the space shuttle into orbit (fig. 10). One could just as well focus on other missions. Examples would include (but not be limited to) planetary entry, such as the Mars Lander, or aircraft performance, such as commercial transport cruise and high lift aerodynamics.

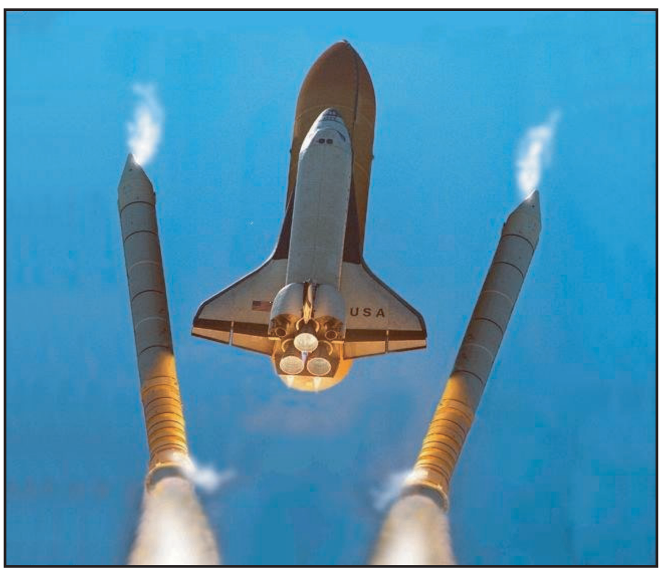

Figure 10. Systems approach to computational aerodynamics for uncertainty-based design.

All of these examples share a number of features from a design process perspective. Perhaps foremost is the need for simulating or modeling flow environments that cannot be fully reproduced by conventional experimentation. This approach leads to the use of computational tools of varying fidelity, experimental processes of varying approximation, and so forth. A necessary consequence is the amalgamation of differing fidelity technologies for the extrapolation to system-level conditions for performance predictions.

Easterling (2001) has proposed a process to quantify the uncertainty of computational predictions, and a summary figure from his report is presented in figure 11. The details of this work are quite extensive and beyond the scope of this white paper, but his approach could be influential in uncertainty-based design activities. One key result here is the Quantified Prediction Uncertainty—a product of computation, experiment, and analysis—that is used to assess system performance requirements.

Uncertainty quantification activities exist both among and within the elements of Easterling's model. Note that he distinguishes the *system environment* from the *testable environment,* explicitly recognizing the extrapolative nature of many computational physics or ground-based testing environments (think of Reynolds Number vis-à-vis aircraft performance).

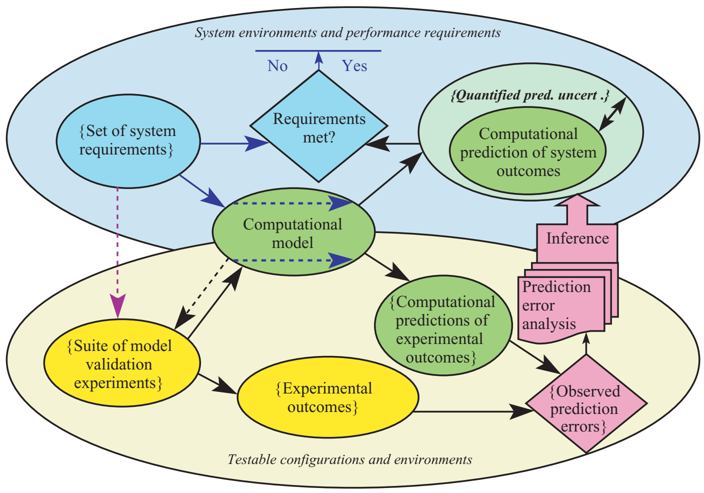

Figure 11. Quantifying the uncertainty of computational predictions (from Easterling 2001).

To view computation in the context of an overall design process, drawing on the work of Rubbert (1994) is useful. Figure 12 is taken from Rubbert as a characterization of the general design activity: rapid progress early in the design phase, asymptotic advancement late in the design activity, and an ever-reducing variation throughout the process. The range of usefulness for a particular CFD code is then shown in the context of this design process (fig. 13). Because of the inherent upstream limitations, such as setup time, and downstream limitations, such as accuracy, a hierarchy of methods is used through the design process: lower order faster methods early in the process and higher order slower methods late in the design process. This general reasoning would apply to other simulation technologies as well.

Several things can be done to more rigorously manage this risk, and some examples are shown in figure 14 and figure 15. Activities ranging from adaptive gridding to implementing expert systems could significantly improve the risk management for the utilization of any particular code. A rigorous means to link codes of varying fidelity could also significantly impact the risk associated with a design process.

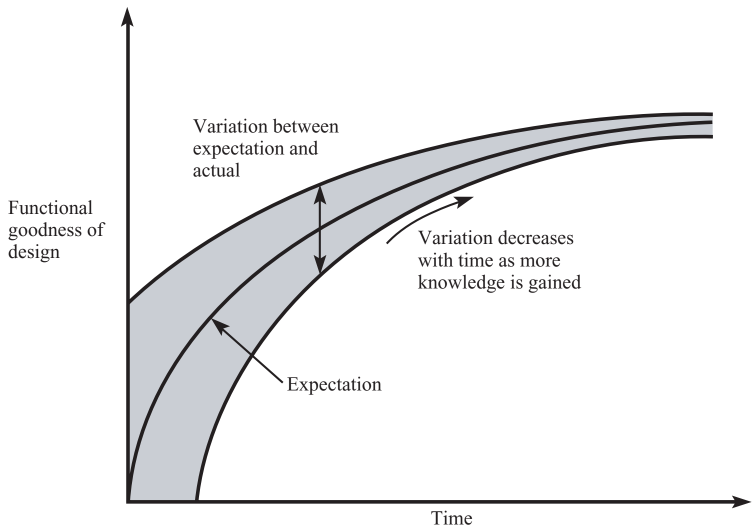

Figure 12. Variation associated with design process (from Rubbert 1994).

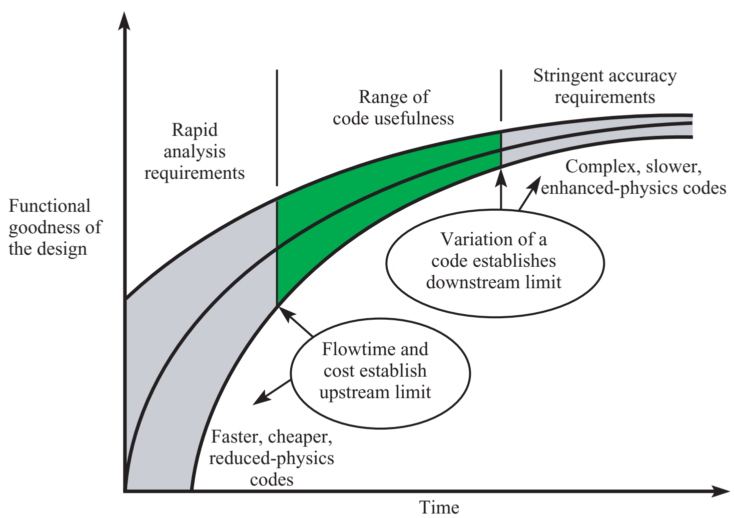

Figure 13. Range of usefulness of code within design process (from Rubbert 1994).

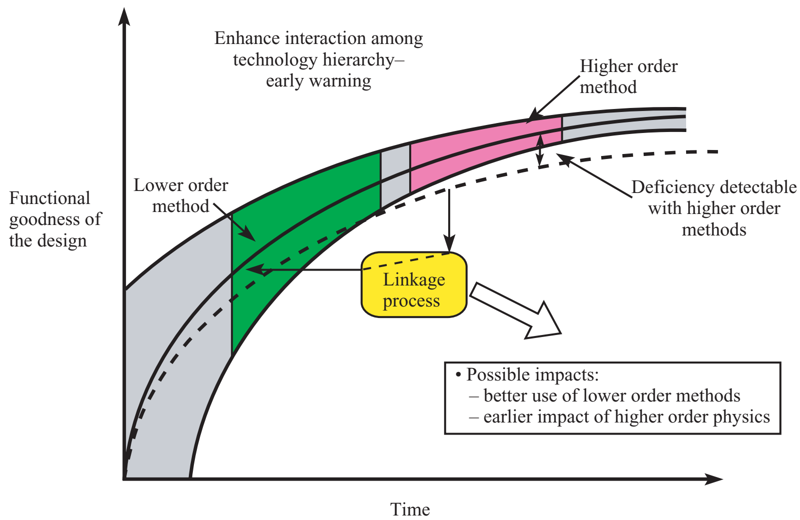

Figure 14. Within-code enhancements for design process.

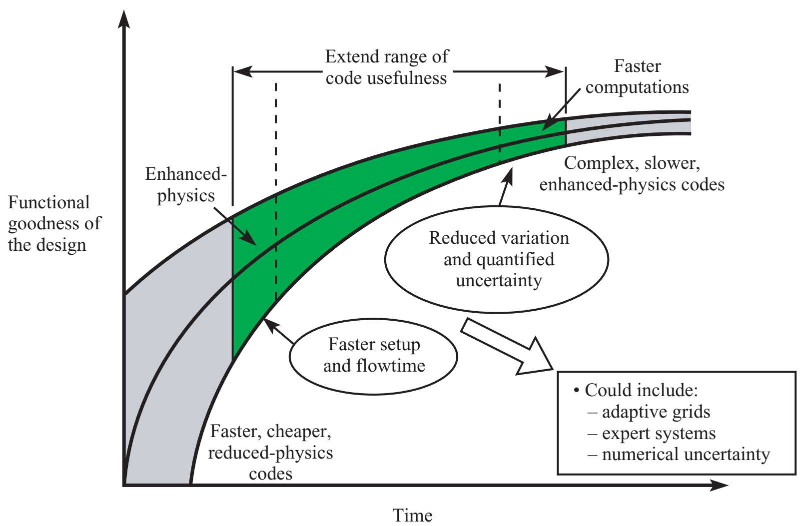

Figure 15. Cross-code interaction to enhance the design process.

3.2.2.2. Aerodynamics Model Form Uncertainty

B6. Effective approaches for characterizing model form error are lacking.

Undoubtedly the greatest challenge in characterizing the uncertainty associated with CFD computations is the characterization of the model form uncertainty. The aerodynamics models used in design include simple algebraic equations, linear aerodynamics (vortex-lattice and panel) methods, Euler methods, laminar Navier-Stokes methods, and Reynolds-averaged Navier-Stokes (RANS) methods. Most aerodynamics effects of design interest involve turbulent flow. Turbulence modeling has challenged aerodynamicists for decades. CFD calculations that resolve all spatial and temporal scales require $O(Re^{9/4})$ storage and $O(Re^{11/4})$ operations (see, for example, Rogallo and Moin 1984), where *Re* is the Reynolds number. Since such computations for flows of aerodynamic design interest are well beyond foreseeable computer resources, phenomenological turbulence models are a necessity. For preliminary and detailed design, aerodynamic codes utilize various 0-equation, 1-equation, 2-equation, algebraic Reynolds stress (second-order) closure, and full second-order Reynolds stress models.

The parametric uncertainties associated with the coefficients of a given turbulence or transition model can be (but almost never are) characterized with standard (but expensive) sensitivity analysis methods. The dearth of plausible strategies for characterizing the model form uncertainty associated with the structure of the turbulence model employed in RANS computations, as well as the simplifications associated with using laminar, Euler, linear, and algebraic aerodynamics models, inhibits many in the CFD community to tackle the more manageable aspects of computational uncertainty in CFD. The only work we have been able to find on this subject is by Coleman and Stern (1997).

For some aerodynamics design applications, the challenge of predicting the onset of laminar-turbulent transition and the associated modeling of the transitional region is also considerable. Here, too, characterization of model form uncertainty is a significant barrier. The same can be said of the models used in Large-Eddy Simulation and Detached-Eddy Simulation.

3.2.2.3. Sensitive Nonlinearities

B7. There are no dependable approaches to uncertainty quantification for nonlinear problems.

Aerodynamics is replete with situations in which small changes in parameters lead to drastic changes in the flow and therefore to drastic changes in the performance measures. Phenomena such as the transonic drag rise, flow separation and reattachment, shock-boundary-layer interactions, vortex bursting, limit-cycle oscillation, and boundary-layer transition suddenly change the whole character of the flow. Uncertainty characterizations performed for one flow regime do not extrapolate well to another regime. Presently, no strategy can be used with confidence for characterizing uncertainties for sensitive nonlinear problems. This lack of confidence on the uncertainty bounds often leads to restricting the design space to linear regimes for which designers have sufficient experience to trust their judgment on the uncertainties. This restriction can lead to lost opportunities for higher performing vehicles. Although it is encouraging that work on uncertainty quantification for strongly nonlinear problems is expanding, much remains to be done.

3.3. Control Systems

3.3.1. Current Status

Stability and performance robustness have long been considered significant issues in control system design and analysis. Researchers like Bode (1945), Nyquist (1932), and Evans (1948) were instrumental in developing some of the fundamental concepts for the analysis and design of feedback control systems. For the most part, their work focused on frequency domain graphical methods for single-input/single-output (SISO) systems. As a result of their efforts, quantifiable metrics for characterizing stability robustness were developed. Even today, stability robustness for SISO systems is typically characterized in terms of gain and phase margins. With the help of computers and powerful numerical software, the SISO concepts for analyzing robustness have been generalized to include multi-input/multi-output (MIMO) systems using loop-gain singular value analysis (Safonov 1977). Unfortunately, singular value analysis in its general form can, in many cases, result in very conservative designs that may not necessarily reflect the true nature of the parameter/model uncertainties. Although there has been much development since the introduction of singular values, e.g., structured singular-value (μ) (Doyle 1982, 1983) and μ-analysis (Weingarten and Seide 1969), the developments rely on frequency domain bounded uncertainty representations that may not adequately model the true nature of the uncertainty. In an attempt to overcome this limitation, researchers are now investigating methods for analyzing the stability of feedback systems with parameter uncertainties defined in terms of probability density functions. This approach is generally referred to as "probability of stability" (Stengel 1980; Lim and Junkins 1987;

Stengel 1991).

One of the first papers to employ probabilistic descriptions of parametric uncertainties for the analysis of stability robustness was Stengel (1980) with a follow-up by Stengel (1991). In these papers, the author employs the Monte Carlo simulation method to assess the effect of probabilistic parametric uncertainties on system stability. For linear time-invariant systems, stability may be evaluated by computing the eigenvalues of the system. Eigenvalues with negative real parts are stable; those with positive real parts are unstable. Since the value of the real part of the system eigenvalues has only two possible outcomes, i.e., positive (unstable) or negative (stable), the probability of instability, P[instability], may be defined mathematically as

$$P[\text{instability}] = 1 - \int_{-\infty}^{0} f_{\Sigma}(\sigma) d\sigma \tag{5}$$

where σ is vector of the real parts of the system eigenvalues and f_{Σ} is their joint probability density function. Note that f_{Σ} is almost never known analytically, but may be evaluated implicitly using Monte Carlo techniques. As an example, consider the characteristic equation for a typical second-order system under feedback control:

$$s^2 + 2\zeta\omega + \omega^2 \tag{6}$$

Assume that the closed-loop system damping ς and natural frequency ω are uncertain parameters with normal distributions. Specifically, let ς have a mean of 0.707 with a standard deviation of 0.5 and ω have a mean of 1.0 with a standard deviation of 0.2. A Monte Carlo simulation has been performed to assess the probability of instability. The results are presented in figure 16. In this figure, regions of highest eigenvalue density are shown in red and yellow and regions of lowest density in dark blue. Regions of zero eigenvalue density are shown in white.

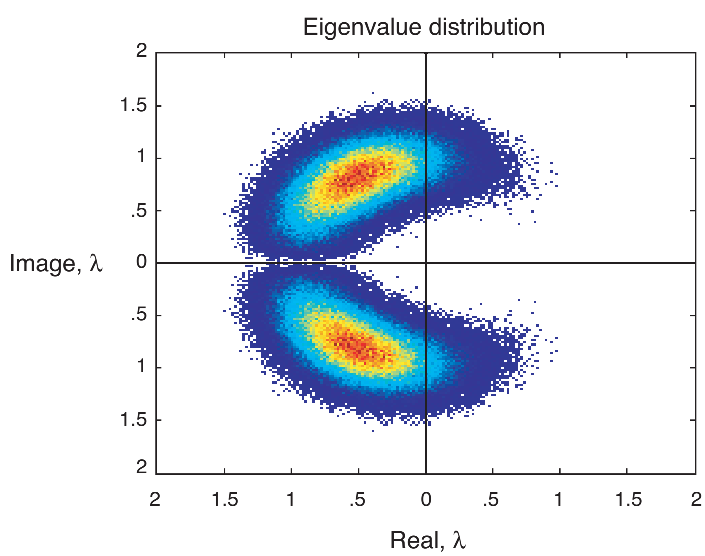

Figure 16. Probability of instability.

Using the data presented previously one can easily compute the probability of instability. In this example P[instability] = 7.82 percent. Lim and Junkins (1987) introduce a technique for approximating the probability of stability using linear perturbations of system eigenvalues and techniques from probability theory. This method belongs to the class of response surface methods because of the assumptions used for the system eigenvalue models. Specifically, the assumption is that the eigenvalues inside the failure domain may be represented by a first-order Taylor series expansion about some nominal point. This method may prove extremely valuable for a system in which parameter uncertainties have small variances and eigenvalues with near-linear behavior. For systems that do not satisfy these requirements, more research is needed to quantify the impact of the underlying assumptions.

Spencer (1994) and Spencer et al. (1992) explore the use of first-order and second-order reliability methods (FORM/SORM) for computing probabilistic stability/performance measures for structural control systems. This body of work addresses several interesting aspects of probability for controlled systems. Similar to the work of Stengel (1980) it addresses probability of stability using eigenvalue considerations, but extends the scope to include system RMS output response values and control system RMS input values, which are particularly useful metrics used in many control applications. In terms of its approach to the pure stability problem, i.e., eigenvalue considerations, it casts the problem as a classical reliability problem for a series of components with limit state functions made up of the individual eigenvalues. In series systems, if one of the components fails, the entire system fails. The analogy to stability is that if any one of the system eigenvalues has a positive real part then the entire system is unstable. An example of a family of three eigenvalue limit state functions with two uncertain parameters is given in figure 17.

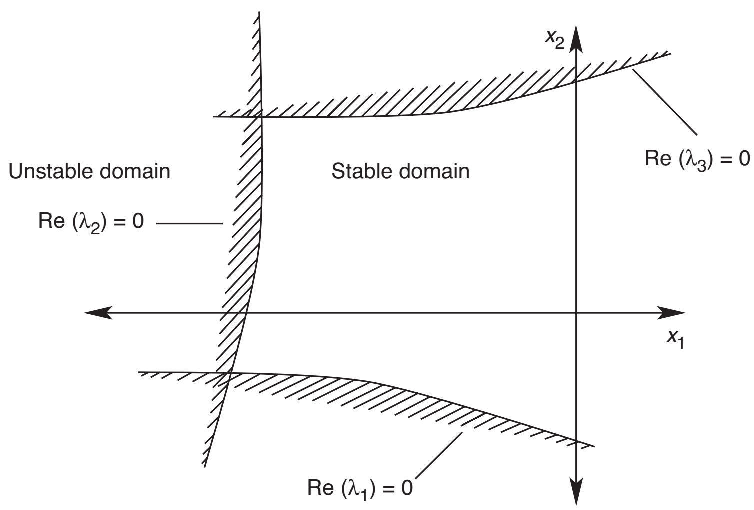

Figure 17. Eigenvalue limit state function.

The examples presented by Spencer (1994) and Spencer et al. (1992) provide an informative view of reliability methods applied to the area of active structural control. The types of uncertainties addressed in these examples included stiffness, damping, inertia, actuator effectiveness, and time delay. Although these examples are limited to low-order structural systems with corresponding low-order compensators, the basic theoretical structure of FORM/SORM should be capable of handling higher order controlled systems.

3.3.1.1. Bounded Uncertainty Design and Analysis. A typical control design with bounded uncertainty structure is presented by Balas et al. (1998). In this application, linear control designs for the F-14 aircraft lateral-directional axis during powered approach to a carrier landing are presented. The controllers are designed using the structured singular value (μ) framework (Balas and Packard 1996; Moser 1993; Balas and Doyle 1994; Gagnon, Pomerleau, and Desbiens 1999). The performance objective is to design robust controllers such that the true airplane (nominal model plus uncertainty) responds effectively to pilot command in the form of lateral stick and rudder pedal inputs. A block diagram, representing the various interconnections between the nominal model, the controller K, and the uncertainty Δ_G is presented in figure 18. The nominal model, designated as $F14_{nom}$, has four states, lateral velocity v, yaw rate r, roll rate p, and bank angle ϕ. This model is assumed to be linear and time-invariant for a trim condition of 10.5 degrees angle of attack and an air speed of 137 kn. For the purpose of control design, the aircraft is modeled as having three control inputs, differential stabilizer deflection δ_{dtab}, rudder deflection δ_{rud}, and differential spoiler deflection δ_{dsp}. Three measured outputs are used in the feedback loop: roll rate, yaw rate, and lateral acceleration y_{ac}. The dashed box in the figure represents the true airplane model, which includes the nominal model, actuator models, and W_{in} and Δ_G, which parameterize the uncertainty in the model. The model uncertainty Δ_G assumed here is called input multiplicative plant uncertainty. The uncertainty is modeled as three individual, complex, full-block multiplicative uncertainties at the input of the aircraft model. These uncertainties accommodate errors in differential stabilizer, differential spoiler, and rudder moment coefficients. The reasoning behind using three individual blocks to represent the uncertainty is based on an assumption that isolated errors in differential stabilizer, differential spoiler, and rudder moment do not couple into each other. Two linear μ controllers were successfully designed, implemented, and tested in pilot-in-the-loop simulations at the crewed flight simulator at the U.S. Naval Air Warfare Center in Patuxent River, Maryland. The test pilots both concluded that the μ controllers achieved all performance objectives, with a Cooper-Harper rating of 2 and 3, respectively.

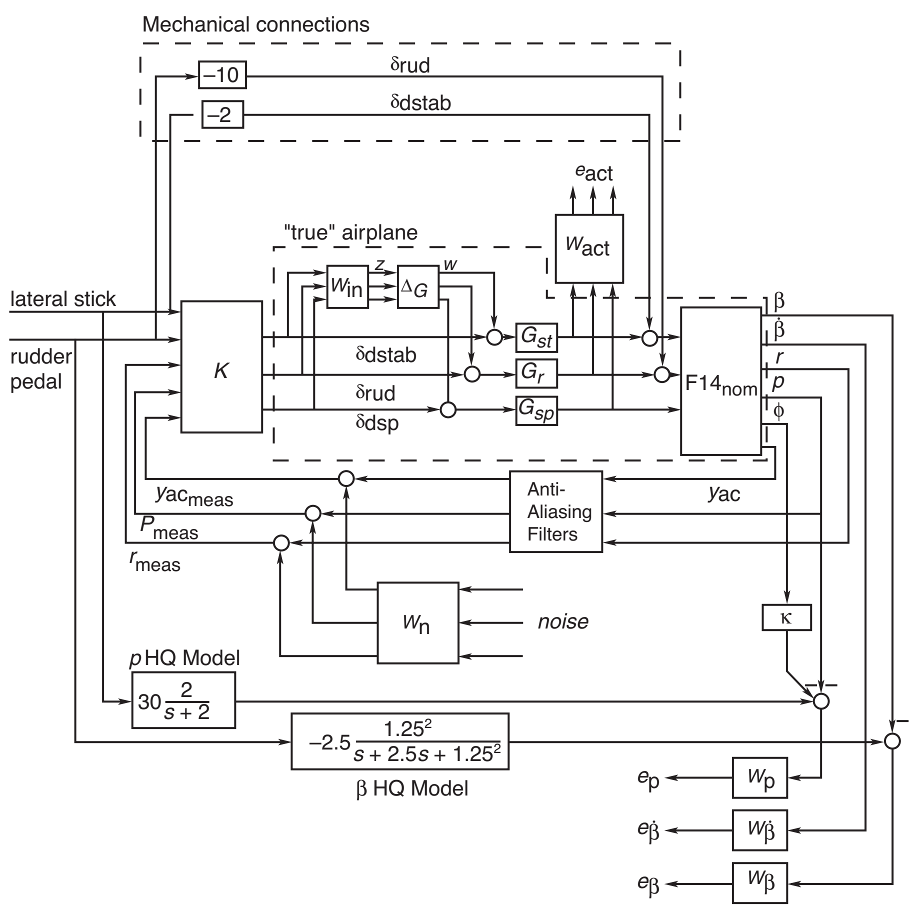

Figure 18. Block diagram of F14 robust controller (from Balas 1998).

3.3.1.2. Fuzzy Control. Ham, Qu, and Johnson (2000) describe a robust fuzzy control development for robot manipulators that guarantees both global stability and performance. In the approach taken here, a robust suboptimal control is designed first and fuzzified for each rule to guarantee stability in each fuzzy set. Then, individual fuzzy controls are blended to form the overall fuzzy controller. The procedure for designing a robust fuzzy controller is given as follows:

- Subsets F_i are chosen according to their proximity to hyper-balls of the auxiliary state ($z = z(x)$), reflecting the designer's choice for stability regions and performance. Membership functions $M_i(x)$ are chosen to make the sets F_i fuzzy. These functions are required to have their degree of membership between zero and one.
- Individual fuzzy controls are selected according to the fuzzy rule.
    - If $x \in F_i$, then control is given by $u = u_i(x)$, where $u_i(x)$ is a fuzzy control which depends on the bounds on the nonlinear part of the state matrix and the auxiliary state vector.
- The overall fuzzy control u_f is obtained by blending the individual control laws according to the standard fuzzifying rule.

This design procedure provides robustness, global asymptotic stability, and performance. It should be noted however that the robustness characteristic of this control approach is obtained from the Lyapunov stability theory, together with a norm-bounded approach to handle nonlinearities and uncertainties, and not as a specific implementation of the fuzzy set theory. The fuzzy control scheme was applied to control of a two degree-of-freedom robot manipulator. The bounds in the eigenvalues of the inertia matrix were chosen as 0.5 and 9, respectively. The nonlinearities in the state matrix are bounded from above by a quadratic function of the state vector norm. The desired trajectories for both joint angles are given by $1 - \cos(t)$. Three subsets of the state space F_i, $i = 1, 2, 3$ are defined: the states at or close to the origin; states either on, inside, or close to the hyper-ball defined by $|z| = 0.005$; and the states on the outside and not close to the hyper-ball. Figure 19 illustrates the triangular membership function used in this example; the simulation results for the robust fuzzy control are shown in figure 20. The tracking error time histories for each of the joint angles are shown, indicating that the fuzzy controller provides good tracking performance. It even provides slightly better performance than a pure nonlinear robust controller does.

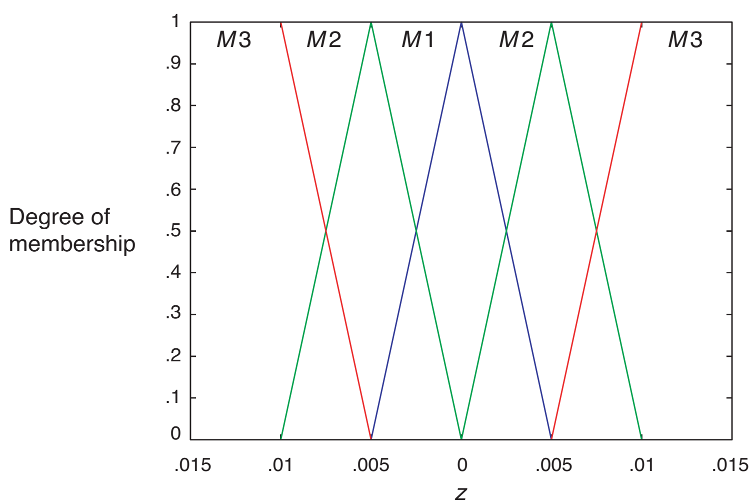

Figure 19. Symmetric triangular membership functions.

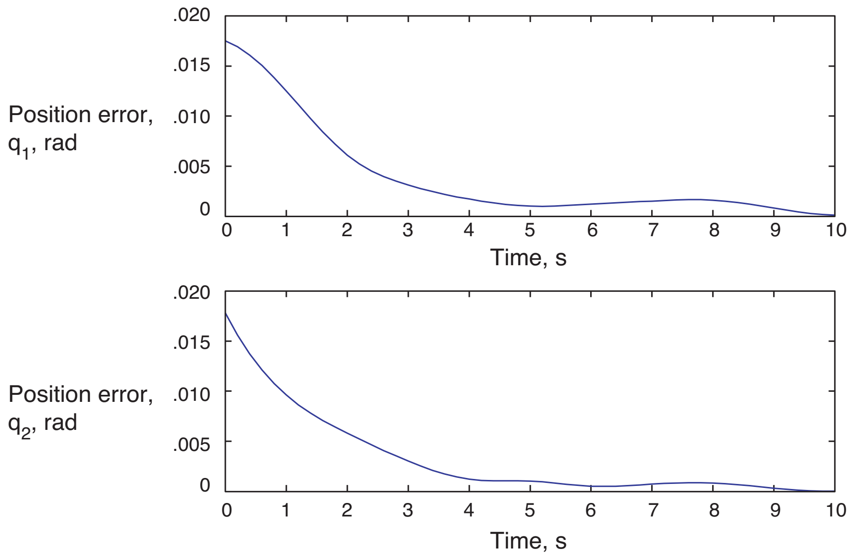

Figure 20. Position error time histories.

3.3.2. Barriers

The controls discipline is afflicted by barriers B1–B3, B6 and B7. In the controls context B6 would be phrased in terms of unmodeled dynamics. In a sense the controls counterpart of B7 presents an even greater challenge because the low-dimensional aircraft models used in controls represent a much more drastic simplification of the detailed physics than the models of concern in aerodynamics.

The following are some barriers that are specific to applying probabilistic methods to the design and analysis of closed-loop dynamical systems:

B8. Characterization of uncertainties for use in control is inadequate.

Control design obviously requires the characterization of parameter and model form uncertainties from a broad range of disciplines. Clearly, the uncertainty characterization activities in such disciplines as structures and aerodynamics need to take into account the requirements flowing from the controls community.

B9. Methods for mapping probabilistic parameter uncertainties into norm-bounded uncertainties do not exist.

Conventional robust control approaches rely on norm-bounded descriptions for uncertainties in both analysis and design. An enormous amount of work has been done in this area and it is highly desirable to leverage this work by finding ways to incorporate probabilistic uncertainties into the robust control design and analysis processes. This barrier implies that insertion of probabilistic information into controls analysis and design processes requires a substantial overhaul of these processes.

B10. Existing probabilistic analysis tools are not well suited to handle the time and frequency domain response quantities that are typically used in the analysis of closed-loop dynamical systems.

Existing FORM and SORM methods are geared towards steady problems. Clearly, similarly effective methods are needed for unsteady problems with the high modal densities (zeros and poles) that are common in the control of dynamical systems.

3.4. Optimization

3.4.1. Current Status

Multidisciplinary Design Optimization (MDO) is increasingly important to the aerospace community. For example, Giesing and Barthelemy (1998) summarize presentations at the 7th AIAA Multidisciplinary Analysis and Optimization Symposium addressing the uses of MDO in industry. The industry representatives provided many examples of successful MDO applications but also produced a list of new methods that the industry requires. One of those emerging areas was robust design or optimization methods that produce solutions insensitive to variability in input parameters.

The need for robust design methods appears in many contexts. During the preliminary design process, the exact value of input parameters is not known. It may be possible to make an educated guess or provide bounds for these unknown parameters but they are not deterministic quantities. Faced with uncertain parameters, traditional optimization techniques tend to "over-optimize". Like the curve labeled "Sharp" in figure 21, solutions produced by these techniques perform well at the design point but have poor off-design characteristics. As noted by Young, Anderson, and Yurkovich (1998), the aerospace industry favors designs that have room to grow. Like the curve labeled "Robust" in figure 21, designs required by the industry must be adaptable to new missions or new business climates without a marked decrease in performance and is often willing to sacrifice a sharp optimum for this flexibility.

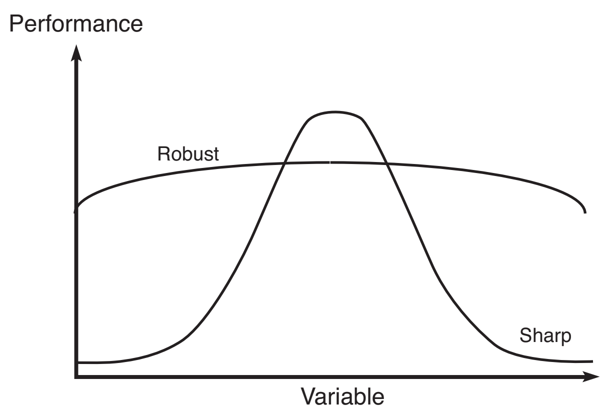

Figure 21. Illustration of robust optimum.

The present research seeks optimization methods that are robust in the sense that they produce solutions insensitive to small changes in the input parameters. As an additional requirement, the methods must be able to find successful designs using a moderate number of high-fidelity disciplinary analyses. This second requirement acknowledges the fact that disciplinary analyses (e.g. CFD) can be computationally expensive and an optimization method that requires thousands of function evaluations has limited usefulness in the current design environment.

An equally important research area is optimization for reliability, which is not a new idea. Some of the earliest examples of structural optimization include reliability constraints. Today, the open issues in reliability-based structural optimization involve testing and validating the optimization procedures and demonstrating the benefits of reliability-based methods over conventional methods. Other interesting areas for study involve a comparison of possibilistic methods with probabilistic methods. Chen et al. (1999) conclude that possibilistic methods are preferred when there is insufficient data to build accurate probabilistic models of the uncertainties.

3.4.1.1. Sampling-Based Methods. Response surface methods and other sampling-based methods are widely admired and often used but are seldom systematically applied. For example, Taguchi parameter design methods are popular because they prescribe both experimental test matrices and the objective function and they provide detailed instructions about how to determine the best design. The popularity of Taguchi methods has encouraged several researchers to use them as the basis for optimization with uncertainty. For example, Lee et al. (1996) describe their use for solving unconstrained engineering problems, and Unal, Stanley, and Joyner (1993) used Taguchi methods as a tool for conceptual design of propulsion systems. Like Taguchi methods, Latin hypercubes and other random sampling methods have been used for optimization with uncertainty. For example, DeLaurentis and Mavris (2000) demonstrate robust design on a high-speed civil transport and Booker et al. (1998) apply pattern search methods to optimize rotor blades. These methods all prescribe data points for evaluation and approximate responses from simulations.

These methods also share a common weakness by ignoring bias errors in simulation or experimental results. Booker et al. (1998) emphasize that sampling-based optimization methods are useful if the simulation produces anomalous results for some combinations of input. Torczon and Trosset (1998) explain that pattern search optimization methods rarely converge to local minima that are caused by truncation, rounding or other numerical errors in simulation codes. Thus, these authors recommend their methods for optimization with uncertainty. However, none of the authors acknowledge that bias errors in the predicted responses can invalidate the optimization results. For example, the Taguchi method ignores the possibility that variations in data collected by different facilities or by the same facility in different circumstances may not be due solely to random noise. Similarly, data sampling methods ignore the possibility that simulations include bias errors due to a different fidelity of analysis or different grid generation techniques. Applying sampling to a single source of data avoids some of the bias error issues but can produce useless optimization results as the optimization procedure exploits weaknesses in the approximate model. On the other hand, applying optimization to data from a mixture of experimental and mathematical simulation sources requires an *ad hoc* procedure. Romero (1999) discusses the bias error problem and suggests a global-local approach that works well on some demonstration problems. Patera (1997) discusses errors in experimental and simulated data and devises a method to estimate the resulting error in the optimization results.

The most promising work in this area is coordinated by Sandia National Laboratories ASCI Verification and Validation program (Alvin et al. 2000). The first step is to identify sources of *variability*, *uncertainty*, and *error* in simulations. The next step is to develop both approximation and sampling methods that properly account for this uncertainty. Once uncertainty is characterized, then currently available optimization procedures can be applied. Romero et al. (1995) demonstrate the power and potential of these methods by using optimization to identify worst-case thermal loading conditions. They conclude that a warehouse fire might compromise the fail-safe mechanisms on military stores unless the proposed design of the firing system is modified to account for uncertainty. A similar technique could be effective in aerospace design, for example, by identifying worst-case aeroelastic loads or by discovering wind tunnel test matrices that exaggerate the difference between turbulence models.

3.4.1.2. Robust Optimization Methods. Robust optimization methods similar to equation (2) have been proposed for many years but have seldom been evaluated for practical applications. Yoon, Jung, and Hyun (1999) propose robust optimization as a way to specify machine tolerances for simple structural sizing problems. And Teng, Free, and Parkinson (1992) demonstrate the value of these methods for simplified active and passive vibration control systems. Similarly, Darlington et al. (1999) consider batch chemical reactors and use robust optimization to design the thermal control system. Du and Chen (2000a, 2000b) extend these ideas to MDO problems. They argue that most MDO procedures assume that each disciplinary analysis predicts with equal certainty and that very different solutions will result if these problems are posed using robust optimization.

Robust optimization methods have two major weaknesses: the difficulty in choosing weights and the lack of confidence in the estimate of variance. Messac and Sundararaj (2000) address the difficulty in choosing weights. They explain that multiobjective formulations that depend on a weighted sum of objective functions are designed to find a compromise that reduces each objective. However, this weighted sum method often fails because no set of weights allows the optimization procedure to find the best compromise. Moreover, even if a good choice of weights does exist, the user has no way to know those weights. Messac and Sundararaj (2000) demonstrate an alternative approach called Physical Programming. Frangopol and Iizuka (1992) suggest another approach called ε-constraint method and show how this method can be used in structural designs with many failure modes.

Even if a superior multiobjective formulation is discovered, the lack of confidence in σ^2 will remain a weakness of these methods. Current methods such as Monte Carlo analysis are computationally expensive and often require human intervention in order to operate reliably. Some researchers seek better ways to predict σ^2. For example, Taylor (2000) suggests using automatic differentiation techniques to predict first and second derivatives of c with respect to θ. Taylor compares the resulting estimates of variance using this new method and using Monte Carlo analysis. Similarly, Archetti, Gaivoronski, and Stella (1997) consider efficient gradient estimation procedures and their impact on robust optimization.

Several researchers are exploring new avenues in robust optimization. For example, Huyse and Lewis (2001) suggest a formulation

$$\min_{t \in \Omega} \int_{\theta} c(t,\theta) f_{\theta}(\theta) \partial\theta \tag{7}$$

where $f_\theta(\theta)$ is the PDF that describes the uncertain parameters θ. Chosen design variables should minimize the expected value of the objective function. As an example, the shape of an airfoil profile and the angle of attack needed to provide required lift are optimized for free stream Mach numbers ranging from 0.7 to 0.8. The Mach number range can be a uniform distribution if all Mach numbers are equally important or it can be a Beta distribution centered on the design cruise Mach number. This new formulation is exciting because it avoids the over-design phenomena seen in single point designs, yet it requires no more function evaluations than the multipoint designs currently used by the airframe industry.

3.4.1.3. Optimization for Reliability. Optimization for reliability is the most studied and used of the methods for optimization with uncertainty. Civil engineering and aerospace structural analysts are highly motivated to produce designs with a small probability of failure. Simulations that predict structural response as well as reliability are becoming commercially available. Moreover, new materials such as composite polymers and metal matrices require new design tools that take advantage of their special properties without compromising safety (Abumeri, Kuguoglu, and Chamis 2000).

Gas turbine design and other aerospace propulsion systems design have benefited the most from current research. Abumeri and Chamis (2000) provide an overview of an extensive capability for optimization of engine structures. Grandhi and Wang (1999) show the benefit of designing turbine blades for reduced weight and increased reliability. Kowal and Mahadevan (1998) demonstrate the surprising conclusion that extremely tight tolerances in manufacturing turbine blades can be counterproductive; they use manufacturing tolerances as design variables and conclude that a certain amount of irregularity actually improves the reliability of turbines.

In addition to optimization tools, the aerospace community has also provided validation cases, which increase the credibility of these methods. For example, Boeing engineers report cost savings due to reliability studies related to the redesign of the Shuttle docking bay for use in Shuttle-Mir rendezvous (Torng and Yang 1994; Torng, Funk, and Stephenson 1999).

3.4.2. Barriers

The one glaring feature of the survey of methods for optimization under uncertainty is that all existing methods are designed for probabilistic descriptions of uncertainty. Few researchers work on optimization under uncertainties characterized by other descriptions, such as by intervals or by membership functions. Yet Chen (1999) suggests that probabilistic methods are only effective if sufficient data exists to build accurate probabilistic models. Hence,

B11. No methods are available for optimization under nonprobabilistic uncertainties.

This barrier is especially formidable because plausible probabilistic descriptions are never likely to be available for most effects due to *uncertainties* and *errors*.

Even within the realm of probabilistic characterizations of uncertainty, barrier B3 is even more formidable for optimization under uncertainty than for the individual disciplinary uncertainty analyses. It is worth paraphrasing it here with special emphasis on the optimization technology challenge:

B12. Current methods for optimization under probabilistic uncertainty are too expensive for use with high-fidelity analysis tools in many disciplines.

Clearly, a breakthrough in algorithms for optimization under uncertainty would have wide ranging impact because it would ameliorate the barrier of computational expense for uncertainty analysis in many disciplines.

B13. Extending uncertainty analysis and optimization to applications involving multiple disciplines compounds the complexity and cost.

Most (perhaps all) current approaches to multidisciplinary uncertainty analysis and optimization treat the entire multidisciplinary analysis as a unit—no attempts have been made to apply decomposition techniques to improve the efficiency. In the realm of deterministic problems, MDO methods have been developed that decompose the full multidisciplinary problem into more manageable components, usually along disciplinary lines. These decomposition approaches have produced more computationally efficient schemes than one gets by simply slapping a generic optimizer on top of a fully integrated multidisciplinary analysis code. (No comprehensive survey of these approaches exists. See Alexandrov 2001 for a review of multilevel decomposition approaches and Alexandrov and Lewis 2000 for some work on distributed optimization.) Hopefully similarly creative approaches to problem decomposition can mitigate this barrier, both for uncertainty analysis and for optimization under uncertainty.

3.5. Summary of Barriers

The preceding sections have mentioned a number of barriers to the adoption of uncertainty-based design methods for aerospace vehicles. In summary:

B1. Industry feels comfortable with traditional design methods.

B2. Few demonstrations of the benefits of uncertainty-based design methods are available.

B3. Current uncertainty-based design methods are more complex and much more computationally expensive than deterministic methods.

B4. Characterization of structural imperfections and uncertainties necessary to facilitate accurate analysis and design of the structure is time consuming and is highly dependent on structural configuration, material system, and manufacturing processes.

B5. There is a dearth of statistical process control activity in aerodynamics.

B6. Effective approaches for characterizing model form error are lacking.

B7. There are no dependable approaches to uncertainty quantification for nonlinear problems.

B8. Characterization of uncertainties for use in control is inadequate.

B9. Methods for mapping probabilistic parameter uncertainties into norm-bounded uncertainties do not exist.

B10. Existing probabilistic analysis tools are not well suited to handle the time and frequency domain response quantities that are typically used in the analysis of closed-loop dynamical systems.

B11. No methods are available for optimization under nonprobabilistic uncertainties.

B12. Current methods for optimization under uncertainty are too expensive for use with high-fidelity analysis tools in many disciplines.

B13. Extending uncertainty analysis and optimization to applications involving multiple disciplines compounds the complexity and cost.

B14. Researchers and analysts lack training in statistical methods and probabilistic assessment.

This last barrier has not been mentioned previously. We list it here because it is a very real, pervasive barrier that must be tackled. The developers of uncertainty-based design methods must substantially increase their knowledge of these subjects. Moreover, the intended end users of uncertainty-based design methods—the analysts—must become more acquainted with this area.

4. Potential Benefits of Uncertainty-Based Design

Previous sections have mentioned a number of potential benefits of uncertainty-based design, most of which apply to all the disciplines as well as to the multidisciplinary system (though not necessarily to the same degree).

P1. Confidence in analysis tools will increase.

Uncertainty-based design methods are arguably the enabling technology for turning the use of analysis tools from an art into a science. To accomplish this transformation, a comprehensive strategy for assessing uncertainty must be developed. The focus today within most computational disciplines is on quantifying and managing discretization and convergence error and on calibrating codes against experimental data. This narrow view must be greatly expanded in order to provide the complete picture of uncertainty that is essential for inspiring confidence in analysts and project managers. As one disciplinary example, CFD is a critical design tool which will have increased use if variations can be quantified and contained, together with quantifying and containing the variation of experimental results used for code and solution (conceptual/preliminary design) validation.

P2. Design cycle time, cost, and risk will be reduced.

One key to reducing the design cycle time is to avoid computational overkill. Knowing the uncertainty associated with codes of various fidelities would permit identification of the fastest codes that met the uncertainty requirements of the project. In other words, uncertainty-based design methods would enable quantifiable trade-offs between computational uncertainty and computational expense. Moreover, upfront knowledge of where the uncertainties in the design tools are greatest can lead to more efficient use of risk-reduction experiments.

P3. System performance will increase while ensuring that reliability requirements are met.

Aerospace vehicles are as safe as they are today in large part because of the conservative approach to their design. Uncertainty-based design methods provide a means to increase system performance while ensuring that the reliability or safety requirements are still met. Certainly other fields of engineering have demonstrated that structural weight can be reduced without sacrificing safety requirements. Also, greater performance can potentially be obtained from MIMO control systems by replacing the norm-bounded approach to uncertainties (structured singular values) in control system design and analysis with genuine probabilistic methods.

P4. Designs will be more robust.

Uncertainty-based optimization methods can identify good designs that minimize the impact of uncertainties arising from the system operating conditions, manufacturing variabilities, and the design tools themselves.

P5. The methodology can assess systems at off-nominal conditions.

Uncertainty-based design methods provide a systematic means to address and analyze systems or subsystems that may operate in abnormal, unusual, or damaged conditions. Such approaches can be used to address the degraded performance or failure of such systems.

P6. The use of composite structures will increase.

This benefit is the one discipline-specific benefit that we call out in this list. The payoff for application of probabilistic design is greater for composite structures than for metallic structures because of the greater variability of the materials used in composites.

5. Proposed LaRC Uncertainty-Based Design Research

The proposed role for NASA Langley Research Center in uncertainty-based design is:

> Evaluate and improve methods for management of uncertainty with applications to multidisciplinary aerospace vehicle design by developing and validating strategies, algorithms, tools and data to
>
>> characterize and manage the uncertainties from the individual aerospace vehicle design disciplines, especially aerodynamics, structures, and controls, based on the best available experimental and computational results;
>>
>> characterize the norm and distribution of the resulting uncertainties in system metrics; and

account for uncertainties in the design of aerospace vehicles at the conceptual through the detailed design stages.

The key phrases for the NASA LaRC role are “multidisciplinary,” “aerospace vehicle design disciplines,” “experimental and computational,” “system metrics,” and “at the conceptual through the detailed design stages.” Certainly some aspects of uncertainty management require sophisticated information technology; the role of LaRC is to exploit mature information technologies as applied to the airframe design disciplines but not necessarily to perform fundamental research on new information technologies.

Obviously, research is much needed in these broad areas. The essential needs are presented in tables in the next three subsections. Our assessment of the current Technology Readiness Level (TRL) is given in the third column of each table. The definitions of the TRLs can be found in appendix A. The items selected for emphasis in a LaRC uncertainty-based design program are chosen for their potential to overcome the various barrier issues described in section 3 and because their TRLs must be raised before they become candidates for application to focused programs.

5.1. Characterizing and Managing Disciplinary Uncertainties

Uncertainty characterization begins at the individual discipline level. Uncertainty management can only be effected at the discipline level, although it can be directed (or budgeted) at the system level. The general needs for the structures, aerodynamic and controls disciplines are to given in tables 2, 3, and 4.

Table 2. Characterizing and Managing Structural Uncertainties

Goal	Description	Current TRL
S1	Develop fundamental experimental testing methods to characterize structural responses with an emphasis on managing uncertainties	**2**
S2	Develop and validate fundamental algorithmic enhancements to high-fidelity structural analysis codes and to implement these codes in an uncertainty-based design framework	**3**
S3	Develop and validate modeling error estimation capabilities in structural analysis codes	**2**
S4	Characterize the structural response of aircraft for use in reliability-based structural design, including aerodynamic and nonaerodynamic loads	**2**
S5	Characterize the structural parameter uncertainties of aircraft for use in robust structures and control design	**2**

Table 3. Characterizing and Managing Aerodynamics Uncertainties

Goal	Description	Current TRL
A1	Refine and extend the use of statistical process control and modern design of experiments strategies in experimental aerodynamics for data from individual facilities	**4**
A2	Develop new statistical process control strategies for data from multiple facilities	**3**
A3	Develop statistical process control strategies for computational aerodynamics	**3**
A4	Develop efficient global sensitivity analysis algorithms and second-order local sensitivity analysis algorithms to characterize parameter uncertainties from nonlinear aerodynamics tools	**3**
A5	Develop and validate strategies to characterize the model form uncertainties associated with transition and turbulence, vortical flows, separation from smooth surfaces, jets, wakes, reattaching flows, re-laminarizing flows, shock-boundary-layer interaction, unsteadiness, etc.	**2**
A6	Develop strategies to characterize the aerodynamic loads on aircraft for use in structural reliability-based design	**2**
A7	Develop strategies to characterize the aerodynamic uncertainties on aircraft for use in robust control design	**2**

Table 4. Characterizing Controls Uncertainties

Goal	Description	Current TRL
C1	Characterize the uncertainties in sensors and actuators, e.g., sensor and actuator noise drift, and bias	**2**
C2	Characterize uncertainties in the control design models obtained by using system identification techniques	**2**

5.2. Characterizing Uncertainties in System Metrics

The general needs in multidisciplinary analysis are presented in table 5.

Table 5. Characterizing System Uncertainties

Goal	Description	Current TRL
V1	Characterize the uncertainties in the controls performance measures	**2**
V2	Develop strategies to obtain efficient uncertainty propagation characterizations using disciplinary codes equipped with efficient sensitivity derivatives	**3**
V3	Develop strategies to produce system uncertainty characterizations based on a combination of computational and experimental uncertainty characterizations	**2**

5.3. Accounting for Uncertainties in Airframe Design

The general needs for airframe design are presented in table 6.

Table 6. Accounting for Uncertainty in Airframe Design

Goal	Description	Current TRL
M1	Partner with industry and the FAA in the application and validation of probabilistic reliability-based design methods for composite airframe structures	**2**
M2	Develop viable uncertainty-based design methods that span the design cycle from conceptual through detailed design	**2**
M3	Develop and validate robust aerodynamic design methods for aerodynamic performance optimization	**3**
M4	Develop and validate reliability-based aerodynamic design methods for control effectiveness	**1**
M5	Develop and validate probabilistic-based algorithms and tools for robust control design and analysis of aerospace systems	**2**
M6	Develop and validate probabilistic-based algorithms and tools for reliability-based optimization and robust optimization	**2**
M7	Develop strategies to characterize confidence in optimal solutions	**2**
M8	Educate the engineering community at LaRC on nondeterministic problem formulations of their engineering problems, the potential benefits of nondeterministic approaches, and the exciting research opportunities in this field	**NA**

5.4. Approach

The approach to meet the listed needs will depend on the maturity of uncertainty-based design technology in the various disciplines. Early studies may be exploratory, pathfinding studies that explain procedures and indicate possible benefits of RBD. These early studies may not involve complex mathematical models. Later studies will involve realistic mathematical models and high-fidelity analyses for single disciplines—then multiple disciplines. These later studies will include strategies for incorporating high-performance computing.

6. Conclusions

6.1. Expected Results

The expected concrete results from a 5-year uncertainty-based design research activity are shown in table 7. In addition to providing a short goal statement with the expected output and outcome, we also furnish our estimate of the Research and Development Degree of Difficulty (R&D^3) using the scale developed by Mankins (1998):

- **R&D^3 – Level I:** A very low degree of difficulty is anticipated in achieving R&D objectives for this technology. Probability of success in normal R&D effort—99 percent

- **R&D^3 – Level II:** A moderate degree of difficulty should be anticipated in achieving R&D objectives for this technology. Probability of success in normal R&D effort—90 percent

- **R&D^3 – Level III:** A high degree of difficulty anticipated in achieving R&D objectives for this technology. Probability of success in normal R&D effort—80 percent

- **R&D^3 – Level IV:** A very high degree of difficulty anticipated in achieving R&D objectives for this technology. Probability of success in normal R&D effort—50 percent

- **R&D^3 – Level V:** The degree of difficulty anticipated in achieving R&D objectives for this technology is so high that a fundamental breakthrough is required. Probability of success in normal R&D effort—20 percent

An expected intangible outcome of the concrete results of this activity will be the conversion of dozens of other LaRC engineers to nondeterministic approaches to airframe design.

We also expect substantial interim benefits such as

1. New, inexpensive strategies for quantifying and controlling computational and experimental uncertainties in the disciplines.
2. New, less-expensive strategies for verifying and validating computational codes and solutions.
3. Significant insight into the process of Measuring Predictive Capability.
    a. What is it?
    b. How do we carry it out in the face of severe nonlinearities and inference domains separated by different physics?

6.2. Opportunities for LaRC

LaRC has a window of opportunity to be in the vanguard of uncertainty-based methods for multidisciplinary airframe design. Momentum is gathering in the engineering community for this technological leap. LaRC has tremendous advantages in this nascent field, and can facilitate the adoption of uncertainty-based methods by industry and NASA programs.

Table 7. Expected Results from Uncertainty-Based Design Research

Goal	**Output**	**Outcome**	**R&D[3] Level**
Affordable probabilistic analyses	Augment high-fidelity structures and aerodynamics tools with efficient probabilistic output	Codes provide estimates of mean and standard deviation and/or probability of failure	II
Possibilistic uncertainty quantification	Develop fundamental possibilistic strategies and algorithms for multidisciplinary uncertainty quantification	Reduces system risk by enabling uncertainty quantification and design for uncertainty strategies at the conceptual design stage	IV
Aerodynamics uncertainty quantification	Develop efficient uncertainty quantification and control strategies and algorithms for aerodynamics performance, loads, and stability and control predictions	Increases design confidence and aircraft safety by measuring and controlling uncertainty in aerodynamics performance predictions and by enabling reliability-based structural design, stochastic control design, and reliability-based aerodynamic controllability analysis	III
Robust aerodynamic optimization	Develop 3-D, aerodynamic shape optimization algorithms that provide designs which are robust with respect to uncertainties in geometry, operating conditions, and CFD code accuracy	Controls and reduces risk by providing designs with aerodynamic performance that is insensitive to intrinsically uncertain quantities	III
Reliability-based structural design	Extend CSM and experimentally verify to predict probability of failure for composite structures	Airframe components designed with consistent levels of reliability	IV
Probabilistic controls analysis and design	Develop MIMO designs that use probabilistic input data	Safer and less conservative active control of aircraft	III
Multidisciplinary uncertainty-based design	Demonstrate multidisciplinary uncertainty-based airframe design incorporating the aerodynamics, structures and controls disciplines	Increases design confidence, controls and reduces design risk, and increases aircraft safety by enabling interdisciplinary design trade-offs that explicitly account for uncertainty, risk, and safety	V

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Appendix A.

Technology Readiness Levels

The Technology Readiness Levels (TRLs) are defined as follows:

TRL 9: Actual system "mission proven" through successful mission operations. Thoroughly debugged software readily repeatable. Fully integrated with operational hardware/software systems. All documentation completed. Successful operational experience. Sustaining software engineering support in place. Actual system fully demonstrated.

TRL 8: Actual system completed and "mission qualified" through test and demonstration in an operational environment. Thoroughly debugged software. Fully integrated with operational hardware and software systems. Most user documentation, training documentation, and maintenance documentation completed. All functionality tested in simulated and operational scenarios. Verification and validation completed.

TRL 7: System prototype demonstration in high-fidelity environment (parallel or shadow mode operation). Most functionality available for demonstration and test. Well integrated with operational hardware/software systems. Most software bugs removed. Limited documentation available.

TRL 6: System/subsystem prototype demonstration in a relevant end-to-end environment. Prototype implementations on full-scale realistic problems. Partially integrated with existing hardware/software systems. Limited documentation available. Engineering feasibility fully demonstrated.

TRL 5: Module and/or subsystem validation in relevant environment. Prototype implementations conform to target environment/interfaces. Experiments with realistic problems. Simulated interfaces to existing systems.

TRL 4: Module and/or subsystem validation in laboratory environment. Stand-alone prototype implementations. Experiments with full-scale problems or data sets.

TRL 3: Analytical and experimental critical function and/or characteristic proof-of-concept. Limited functionality implementations. Experiments with small representative data sets. Scientific feasibility fully demonstrated.

TRL 2: Technology concept and/or application formulated. Basic principles coded. Experiments with synthetic data. Mostly applied research.

TRL 1: Basic principles observed and reported. Basic properties of algorithms, representations, and concepts. Mathematical formulations. Mix of basic and applied research.

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14. ABSTRACT
This report consists of a survey of the state of the art in uncertainty-based design together with recommendations for a Base research activity in this area for the NASA Langley Research Center. This report identifies the needs and opportunities for computational and experimental methods that provide accurate, efficient solutions to nondeterministic multidisciplinary aerospace vehicle design problems. Barriers to the adoption of uncertainty-based design methods are identified, and the benefits the use of such methods are explained. Particular research needs are listed.

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