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ENHANCED AIRCRAFT DESIGN CAPABILITY FOR THE AUTOMATED STRUCTURAL OPTIMIZATION SYSTEM

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13. ABSTRACT *(Maximum 200 words)*

This report documents the results of an STTR Phase I feasibility study to investigate potential enhancements to the "Automated Structural Optimization System (ASTROS)." The scope of this feasibility study included (1) developing a robust design capability through probabilistic design optimization, (2) expanding the multidisciplinary optimization (MDO) capabilities of ASTROS, and (3) linking the three primary design stages, i.e., conceptual, preliminary, and detail design. A new method for reliability-based optimization was devised to account for modeling uncertainty in design optimization. Modeling uncertainty is quantified on the basis of ground vibration test and analysis data for generically similar structures. The new method yields the same degree of accuracy as existing methods for a small fraction of the cost. A framework for including manufacturing detail and manufacturing constraints in ASTROS was formulated. A genetic optimization algorithm for optimizing the layout and sizing of structural framing members was demonstrated, thereby helping to automate the interface between conceptual and preliminary design.

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SUMMARY REPORT

The purpose of this project is to enhance the preliminary design capability of ASTROS through (1) probabilistic design optimization, based on modeling uncertainty data from previous ground vibration tests (GVT) and analysis, (2) extension of ASTROS' multidisciplinary design optimization (MDO) capabilities, and (3) improved interfaces between conceptual, preliminary and detail design.

Phase I investigated the effects of modeling uncertainty on design optimization (a) when incorporated in the objective function, (b) when used to reduce, orthogonalize and scale the design space, and (c) when used to define probabilistic performance constraints. Alternative MDO extensions were explored, including the use of manufacturing detail and cost information to estimate costs at the preliminary design level, and implement joint strength and fatigue life constraints. The state-of-the-art (SOA) in parametric modeling was assessed as a basis for improving the interface between the conceptual and preliminary design.

The originally proposed probabilistic safety margin (PSM) approach to probabilistic design optimization was implemented in ASTROS and demonstrated by numerical example. Minimizing a probabilistic measure of structural weight tends to bias the search toward design variables with less uncertainty. Transformation of the design variables to a reduced, uncorrelated set of design variables is necessary when basing modeling uncertainty on GVT data. Comparison of the PSM approach for handling probabilistic constraints with existing reliability-based optimization (RBO) methods showed the RBO approach to be superior in terms of accuracy. However, existing RBO methods are prohibitively expensive for practical application. A new RBO method was devised that combines the accuracy of the RBO approach and computational efficiency of the PSM approach.

A framework for incorporating manufacturing detail in ASTROS for the evaluation of joint strength and fatigue life constraints, and the estimation manufacturing costs and nonstructural weight was formulated.

The SOA in parametric modeling was not found to be sufficiently mature to support this project. However, discrete optimization for the layout and preliminary sizing of structural framing members was demonstrated as a transitional step in generating a finite element model from surface geometry. An overview of the aircraft design paradigm and an assessment of future needs for the integration of conceptual, preliminary and detail design is presented.

Implementation of the ASTROS enhancements recommended in this study will significantly advance the utility of ASTROS. Applicability of ASTROS to the design of military and commercial aircraft in the 21st century, as well as the design of other automotive vehicles and civil structures will be improved accordingly. The automotive industry has embarked on a similar path of robust design technology and has already expressed an interest in this project.

EXECUTIVE SUMMARY

This report documents the results of an STTR Phase I feasibility study to investigate potential enhancements to the "Automated Structural Optimization System (ASTROS)." The scope of the study was initially broad, including (1) the development of a robust design capability through probabilistic design optimization, (2) expanding the multidisciplinary optimization (MDO) capabilities of ASTROS, and (3) linking the three primary design stages, i.e. conceptual, preliminary and detail design. As the project evolved, the effort focused more on the development of methods for probabilistic design optimization, and less on integrating the different design stages. Emphasis on the former was motivated by recent efforts at Wright State University to implement a method for probabilistic design optimization in ASTROS. The latter was de-emphasized when it became evident that critical technology in the area of parametric modeling was not as well developed as originally believed. The following paragraphs briefly summarize the results of investigations conducted during this study.

Probabilistic Design Optimization

A major effort was devoted to the investigation and development of methods for probabilistic design optimization. This began with the development of originally proposed probabilistic safety margin (PSM) methods, i.e. adding probabilistic safety margins to the constraints and the objective function, and using modeling uncertainty to reduce, orthogonalize and scale the probabilistic design variables. The relative importance of these methods was examined through numerical examples. These examples indicate that, while the incorporation of modeling uncertainty in the objective function does tend to bias the optimization in favor of design variables with less uncertainty, the primary effect of modeling uncertainty is to move the design away from the active constraints, thereby creating a more conservative design.

An initial investigation compared the results of probabilistic design optimization, using hypothetical modeling uncertainty derived from assumed coefficients of variation (COV) on the design variables, with results using databased modeling uncertainty derived from ground vibration test and analysis data. For applications with few design variables (e.g. the Cantilever Box Beam), the results from using the generic database were comparable to those where a 5% to 10% coefficient of variation was assumed for all design variables. See Figure 1. For applications with many design variables, (e.g. the Intermediate Complexity Wing), the equivalent coefficient of variation was much larger, on the order of 30%. However, the ICW problem is poorly formulated for this application. The use of global (modal) uncertainty data to represent the uncertainty of very localized design variables is improper. A more realistic formulation of the Intermediate Complexity Wing application would be one where the design variables representing skin thickness are linked over larger regions of the wing surface, not just the top and bottom opposing quadrilateral elements of the finite element model. This experience suggests that design variable linking should be guided in part by an understanding of the modeling uncertainty database.

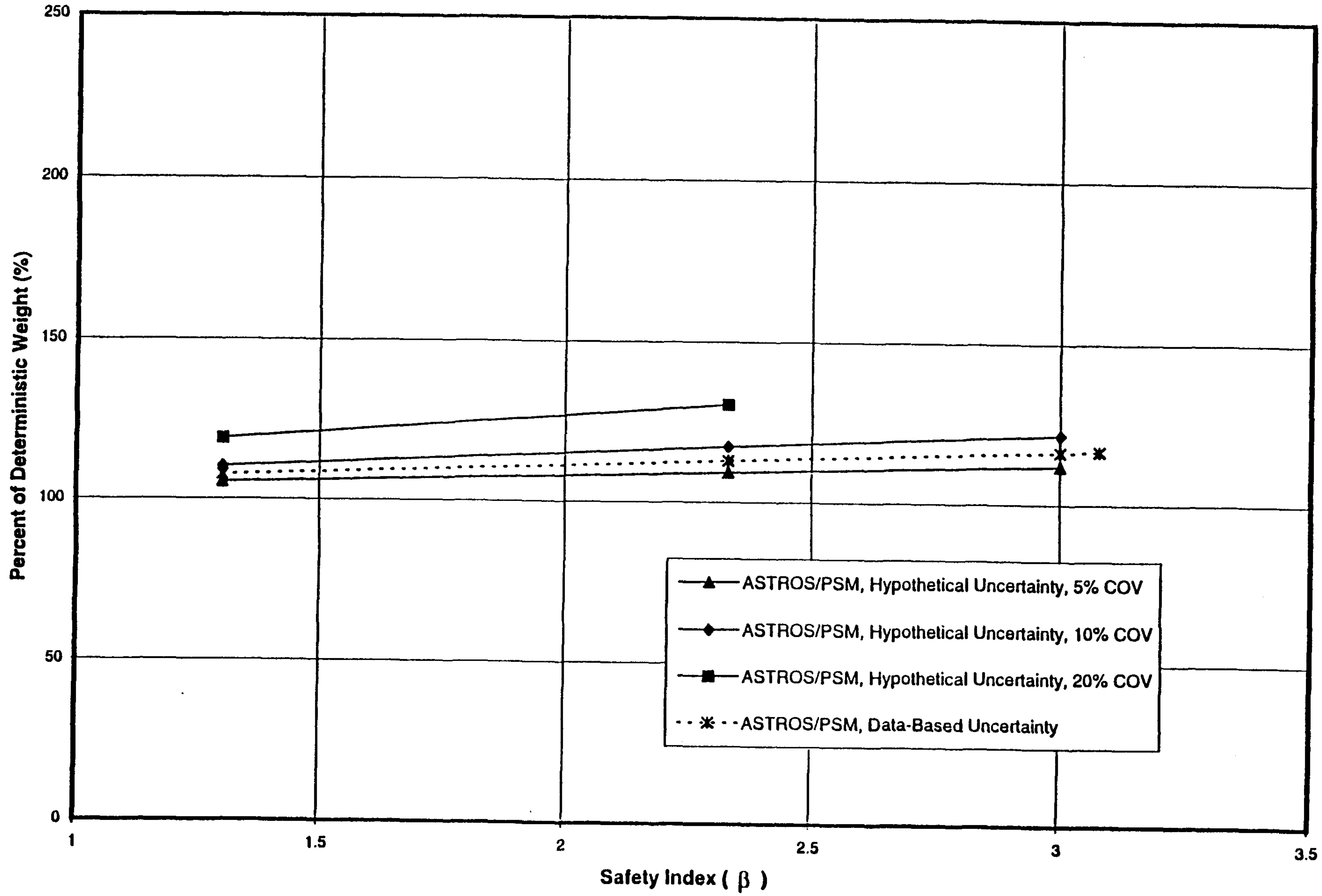

Figure 1. Comparison of Uncertainty Models for Cantilever Box Beam, Hypothetical vs. Data-based Uncertainty.

Preliminary inquiries have been made of several aircraft manufacturers to determine the availability of the data required to compile a generic modeling uncertainty database, and the willingness of manufacturers to provide data for this project. Inquiries so far have been made to both the military and commercial aircraft sides of McDonnell Douglas in Long Beach, CA, Rockwell Aerospace in Seal Beach, CA, and Boeing Commercial Airplane Company in Seattle, WA. Positive responses have so far been received from Rockwell and both sides of McDonnell Douglas, as well as the C-17 program office. In the case of the C-17, for example, several data sets have been identified as shown in Table 1. This is typical of what may be expected for other aircraft. Much more data are believed to be available. Table 2 contains a list of manufacturers of military aircraft currently in design, in production or recently in production, that will be contacted in Phase II.

Table 1. Ground Vibration Test/Analysis Data Sets Available for the C-17 Military Transport Aircraft from McDonnell Douglas.

Test Article	DTIS No.	Test Report No.
Complete C-17, T-1 Aircraft		MDC-J9180, Addendum II
H/S Elevator	L1602-01	MDC-K1954
Aileron	L1602-03	MDC-K1951
Flap	L1602-04	MDC-K1997
Spoiler	L1602-05	MDC-K1955
Landing Gear	L1602-06	MDC-K1988
Rudder	L1602-07	MDC-K1988
Cargo Door	L1602-08	MDC-K1988
J/D Air Defl.	L1602-09	MDC-K1988
Gear Doors	L1602-10	MDC-K1988
Slat	L1602-02	MDC-K1988

Direct comparisons were made between the probabilistic design optimization results published by Grandhi and his colleagues and students at Wright State University, and those obtained by the PSM method. A standard ASTROS demonstration problem, the Intermediate Complexity Wing shown in Figure 2, was the basis for this comparison. The two approaches gave nearly the same results. Further investigation revealed, as shown in Figure 3, that while the two approaches yielded similar weight penalties for small degrees of modeling uncertainty, the PSM approach tended to underestimate the weight penalties in cases where the modeling uncertainty was greater, especially when a high degree of reliability, e.g. 99% or higher was sought.

Table 2. Candidates for Suppliers of Modeling Uncertainty Data*

(a) Fighter/Attack Aircraft

Lockheed Martin/Boeing, Marietta, GA; Seattle, WA		
•	F-22	
Lockheed Martin Tactical Aircraft Systems, Ft. Worth, TX		
•	F-16 A/B	"Fighting Falcon"
•	F-16 C/D	"Fighting Falcon"
•	F-16 N	"Fighting Falcon"
McDonnell Douglas, St. Louis, MO		
•	F-15 A/B	"Eagle"
•	F-15 C/D	"Eagle"
•	F-15 E	"Eagle"
•	F-18 A/B	"Hornet"
•	F-18 C/D	"Hornet"
•	F-18 E/F	"Hornet"
•	AV-88	"Harrier 2"
Northrop Grumman, Los Angeles, CA		
•	F-14 A	"Tomcat"
•	F-14 B	"Super Tomcat"
•	F-14 C	"Super Tomcat"
Rockwell/Daimler-Benz, Seal Beach, CA		
•	X-31	Research Aircraft
•	B-1B	(Bomber)

(b) Military Transport Aircraft

Lockheed Martin Aeronautical Systems, Marietta, GA		
•	C-130 H	"Hercules"
•	C-130 J	"Hercules"
•	C-130 T	"Hercules"
McDonnell Douglas, St. Louis, MO; Long Beach, CA		
•	C-17 A	
•	KC-10A	"Extender"

* Reference: *Aviation Week Aerospace Source Book*, Jan. 8, 1996.

No. of Nodes	No. of Elements		No. of DOF's	
88	39	Rods	294	Constrained
	55	Shear Panels	234	Unconstrained
	62	Quadrilateral Membrane	528	Total
	2	Triangular Membrane		
	158	Total		

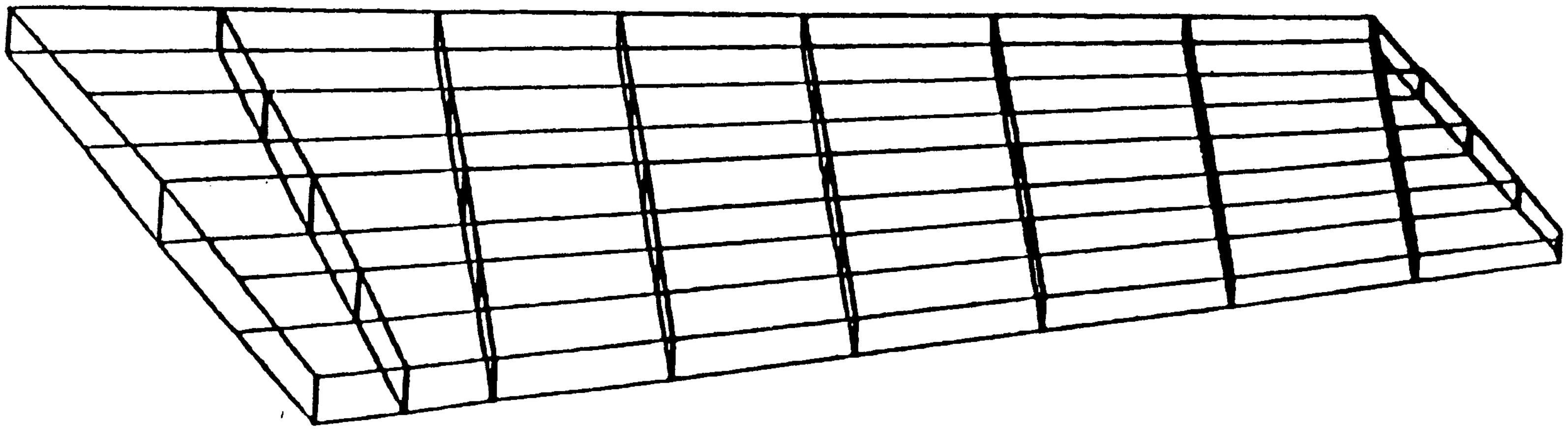

Figure 2. The Structural Model for the Intermediate Complexity Wing.

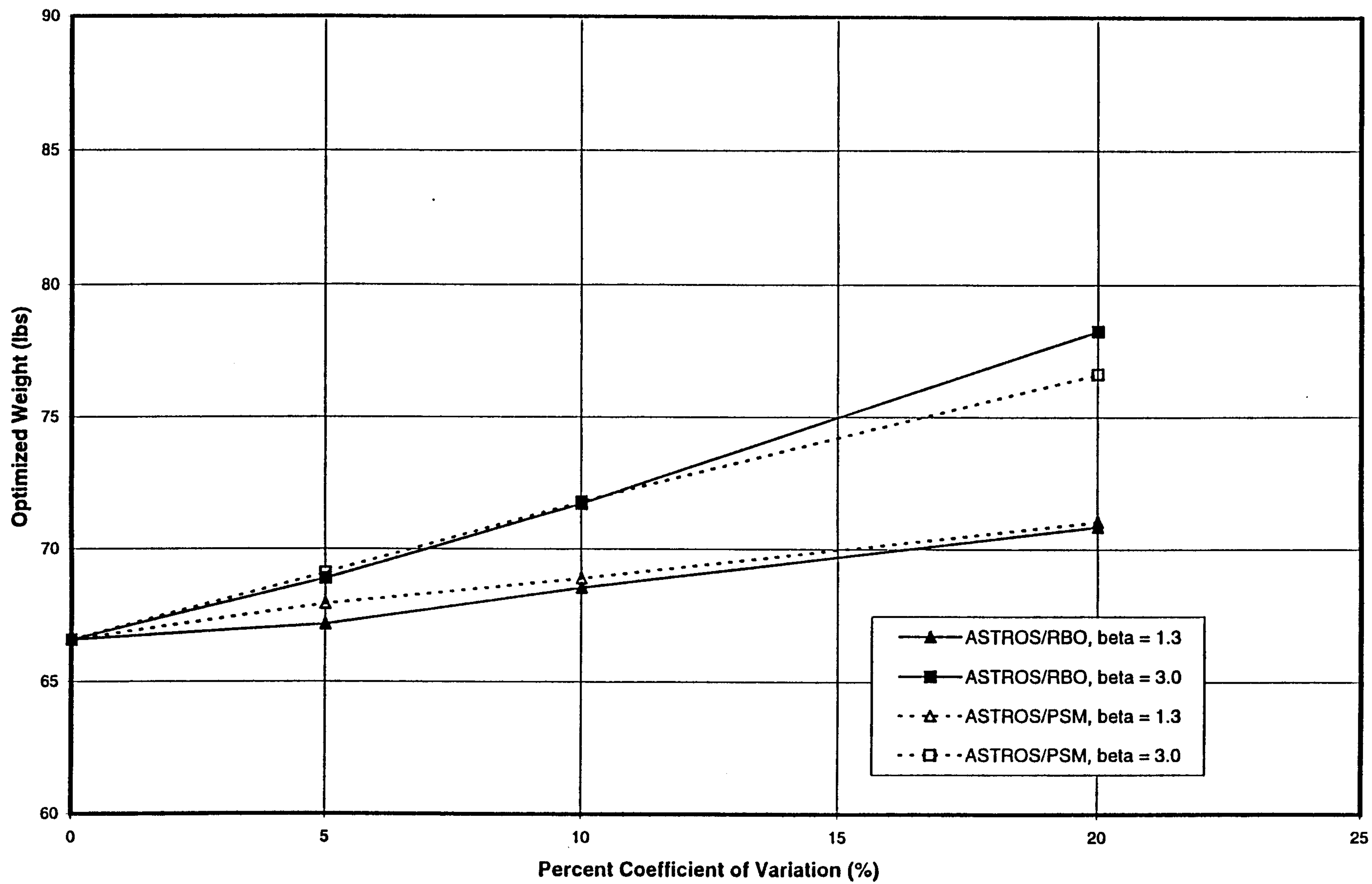

Figure 3. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Intermediate Complexity Wing

Unfortunately, the RBO method which had been implemented in ASTROS by Luo and Grandhi turned out to be *extremely* inefficient for practical applications involving many design variables and many performance constraints. It involves an iterative solution to achieve the desired safety margin for every active constraint, within each major design cycle of ASTROS, each iteration requiring a separate "exact analysis." This method is referred to as a "double loop" method because of the nested arrangement of optimization loops. Another published method instead doubles the number of design variables for each constraint while employing only a single optimization loop. This method, referred to as a "double-design-vector" method, is likewise unsuitable for practical applications. Both methods require much more computational effort than a deterministic optimization solution, by orders of magnitude!

In the process of researching these two RBO methods, a third method was devised. This method involves neither a double-loop nor a double-vector formulation, but is rather a single-loop-single vector (SLSV) method as opposed to the double-loop-single-vector (DLSV) method or the single-loop-double-vector (SLDV) method. It is conservatively estimated to require less than twice the computational effort as deterministic optimization (perhaps significantly less) compared with the other two methods which can require orders of magnitude more. The new SLSV method was implemented and found to yield results identical to those of the SLDV method. A comparison between the new RBO and the previous PSM methods for the Cantilever Box Beam example is shown in Figure 4. The weight penalties are unrealistically large in this example because of the simplicity of the model. With the only three design variables being the height, width and wall thickness of the beam over its entire length, a large weight penalty is paid for stiffening the beam near its fixed end.

Expansion of ASTROS' MDO Capabilities

The feasibility of expanding the MDO capabilities of ASTROS by adding a manufacturing detail capability was investigated and confirmed. A framework for incorporating manufacturing detail in the early design process was devised by Professor Ewing at the University of Kansas. The basis of the framework is a hierarchy of input bulk data "cards" which specify manufacturing processes used for bulk parts as well as for joined parts. Manufacturing data include both cost data and detail information which can be used, for example, to apply fatigue constraints on the structure. A method for defining fatigue constraints in terms of stress constraints was outlined. The cost data can be used in two ways. They can be used directly in the optimization process by including cost as part of (or as) the objective function. A secondary objective is to make manufacturing-related data available in the ASTROS database (CADDB) for use in interfacing with conceptual design.

Improved Interfaces Between Design Stages

The feasibility of extending the preliminary design capabilities of ASTROS through improved interfaces with conceptual and detail design stages was investigated. One of the studies performed by the University of Kansas in this area was the use of discrete optimization, in particular a genetic optimization algorithm (GOA), to optimize the layout and sizing of substructure elements such as bulkheads, frames, longerons and stringers. This is a step that would take the surface geometry determined in conceptual design, and produce an optimum

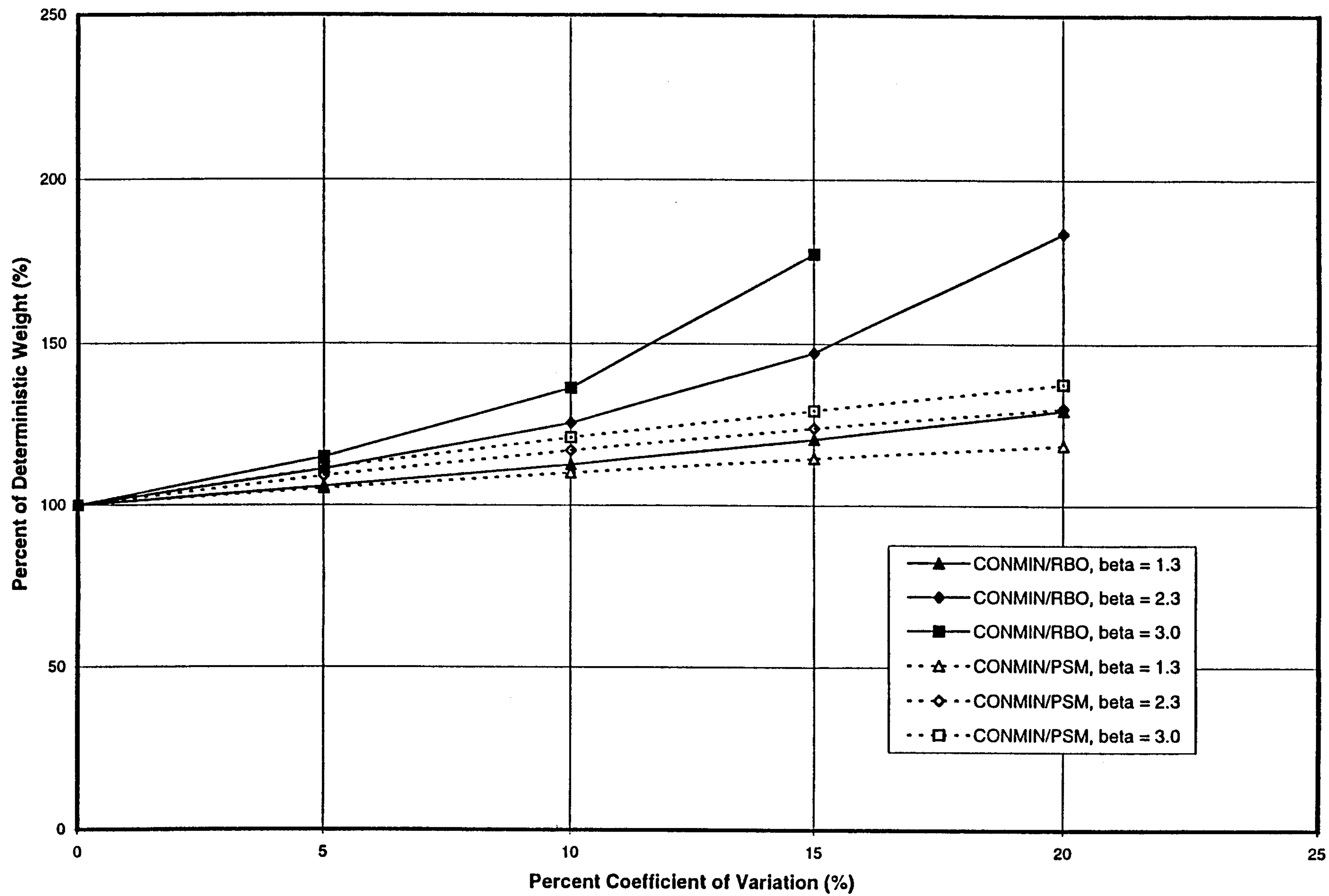

Figure 4. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Cantilever Box Beam

arrangement of framing elements as a basis for subsequent parametric modeling and the generation of a finite element model. Numerical examples were presented to demonstrate the approach, and a FORTRAN code implementing the GOA was delivered to ACTA.

Recommendations

Recommendations based on the analysis and conclusions of this study are grouped into three categories: (1) recommendations for the development of a probabilistic design optimization capability for ASTROS, (2) recommendations for the extension of ASTROS' MDO capabilities, and (3) recommendations for improving the interfaces between conceptual, preliminary and detail design. Detailed recommendations are contained in Section 8. Key recommendations for Phase II are highlighted below:

1. Implement the RBO/SLSV method for treating probabilistic constraints in ASTROS.

2. Compile databases of modeling uncertainty based on the difference between analytically predicted and experimentally measured vibration mode shapes and frequencies, from ground vibration tests and analysis of military and commercial aircraft.

3. Implement joint strength and fatigue life constraints in ASTROS as outlined in Section 3 and Volume II of this report.

4. A limited system identification capability, called ASTROS-ID, has been incorporated as a separate run option in ASTROS. This type of capability contributes to an improved interface between preliminary and final design in the sense that data from prototype testing of the final design can be assimilated back into the preliminary design model through the process of system identification. ACTA has developed a more powerful Structural System ID code (SSID) in cooperation with Sandia National Laboratories. It is recommended that ASTROS-ID be upgraded to include the capabilities of SSID, or be replaced by SSID, thereby further enhancing the ability of ASTROS to interface with final design.

5. ACTA also has a predictive accuracy code (PDAC) that operates in conjunction with SSID. PDAC would use the generic modeling uncertainty database assembled for aircraft structures to evaluate the predictive accuracy of preliminary design models for purposes of ASTROS-based analysis. This analysis is used to determine internal loads for detail design. The incorporation of PDAC in ASTROS would enable these internal loads to be quantified probabilistically to facilitate reliability-based design at the detail design level.

These recommendations have shaped the objectives and overall Phase II work plan outlined in the Phase II proposal submitted earlier. The most significant achievement of the study is the formulation and numerical testing of the new RBO/SLSV method for probabilistic design optimization. The inherent efficiency of the method suggests that for the first time, probabilistic design optimization can be implemented in a commercial code. The complimentary ability to

derive realistic modeling uncertainty data from previous ground vibration tests and analyses on aircraft structures means that the probabilistic designs produced by ASTROS will be fundamentally and traceably grounded in real data.

Finally, although not a recommendation for Phase II, the idea of using a GOA as a link between conceptual design and parametric modeling in the interface between conceptual and preliminary design should be pursued further. Clearly, the scope of such an effort goes well beyond the simple examples investigated in this study, but the ability to automate the structural framing process, currently performed on an ad hoc basis, appears to be a crucial link in bridging the gap between conceptual and preliminary design.

1. INTRODUCTION

1.1 Background

The design of modern aircraft, especially military aircraft which push the performance envelope, is still very much an art. Automated design tools have been developed over the years which facilitate the design process at all three levels (or stages) of design: conceptual, preliminary and detail design. One of the problems is that the different design levels are not yet well integrated; while automation has been introduced within each design level, the transfer of information back and forth between design levels is intuitive and manual.

Another difficulty with current design practice is that there is no formalism for treating modeling uncertainties in a consistent and rigorous manner. Uncertainties are typically treated in an *ad hoc* fashion using safety factors derived from past experience. Part of the problem is that past experience involving comparison of predicted results versus actual performance has not been statistically quantified in a way that is easily extrapolated to new situations. This requires a means of normalizing the data so that it can be processed statistically, and a complimentary means of scaling the normalized statistics to new but generically similar configurations. A rigorous treatment of modeling uncertainty in an optimum design process would utilize the statistics of modeling uncertainty to (1) quantify the degree of uncertainty in the objective function, e.g. weight, cost, etc., (2) transform the space of design variables to a reduced, uncorrelated, normalized parameter space, and (3) adjust constraint equations to account for parameter uncertainty and correlation.

A third problem is the integration of multidisciplinary analysis tools at the preliminary design level. For example, aerodynamic, structural, controls and propulsion analysis tools are highly developed in their own rights, but are difficult to integrate into a single system because of the independent nature of the development efforts. More progress has been made toward integrating these tools at the conceptual design level because the models are simpler. The recognized need for such a multidisciplinary design capability at the preliminary design level was a primary motivation behind the development of ASTROS [1-1, 1-2, 1-3]. The architecture of ASTROS was designed to accommodate multidisciplinary analysis and design optimization; however, only aerodynamic loads and structural modeling have so far been implemented.

Phase I of this project has addressed a number of issues related to these concerns, the intent being to evaluate the feasibility of various ways in which the effectiveness of ASTROS might be enhanced, and select those most promising for development in Phase II. The remainder of Section 1 reviews the original Phase I objectives and outlines the scope of research conducted in Phase I.

1.2 Phase I Objectives

The goal of this project as stated in the Phase I proposal [1-4] is to develop a preliminary structural design capability that optimizes the structural design within a system of internally coupled components including structures, aerodynamics, propulsion, controls, avionics and observables. This goal is consistent with the role originally envisioned for ASTROS which

serves as the foundation and environment for proposed software development. Phase I objectives were stated as follows:

1. To formulate and demonstrate an improved interface with conceptual design, both in terms of information flowing forward from conceptual to preliminary design, and information feedback from preliminary to conceptual design.

2. To extend the multidisciplinary capabilities of existing ASTROS software and thereby demonstrate the suitability of ASTROS for an expanded role in multidisciplinary optimization.

3. To formulate and demonstrate the use of generic modeling uncertainty in the design optimization process to achieve a robust design.

Phase I tasks were defined to pursue these objectives, beginning with initial feasibility studies, and where those studies showed promise, proceeding with the preliminary formulation of methods and presentation numerical examples for purposes of demonstration. The following subsection describes the scope of research conducted during Phase I, and serves as an introduction to the remainder of the report.

1.3 Scope of Phase I Research

Eight tasks were defined in the original Phase I Proposal [1-4]. A ninth task was subsequently added (with no increase in cost) to investigate a new method for treating modeling uncertainty in automated structural optimization. The need for a new method become apparent when it was realized that existing Reliability-Based Optimization (RBO) methods were prohibitively expensive for practical application, and the originally proposed Probabilistic Safety Margin (PSM) method might not yield sufficiently accurate results for desired levels of reliability and realistic levels of modeling uncertainty. The new method satisfies the dual objectives of computational speed and accuracy.

The first two tasks addressed the interface between preliminary and conceptual design and are interrelated to the extent that the second task involving feedback from preliminary to conceptual design, depends on the first which involves feedforward. One of the critical feedforward functions is parametric modeling, where quantitative relationships between conceptual and preliminary design geometries are established. Without these quantitative relationships, feedback is severely limited. Unfortunately, parametric modeling for airframe structures was found to be insufficiently well developed to facilitate the type of enhancement originally envisioned for this interface. Further discussion of these findings is contained in Section 2. Discussion of the total aircraft design paradigm and an assessment of needs for better integrating conceptual, preliminary and detail design is contained in Appendices A and B.

The third task investigated the use of discrete optimization methods for the optimization of discrete parameters such as the number of bulkheads, frames, ribs, etc. A genetic optimization

algorithm, GENDES was developed by the University of Kansas (KU) and is documented in Appendix B. Genetic optimization algorithms, such as GENDES show considerable promise for helping to link conceptual and preliminary design. In the conceptual-to-preliminary design interface, discrete *optimization* can be used with a coarse flexibility model to select the optimum size and spacing of bulkheads or frames in one direction, and longerons or stringers in the other direction. In the preliminary-to-conceptual design interface, discrete parameter *estimation* can be used to update the coarse model based on preliminary design information from the optimization of a finer grained finite element model derived from the coarse model by parametric modeling. Although the KU study concluded that it would be feasible to include GENDES in the ASTROS preliminary design environment, discrete optimization (and estimation) appear better suited for application in the interface between conceptual and preliminary design. Because of present limitations in the state-of-the-art of parametric modeling, this potential was not developed further.

Task 4 addressed the extension of Multidisciplinary Optimization (MDO) capabilities in ASTROS in two respects: (1) in the formulation of an electromagnetic observables (EMO) module that would use ASTROS aerodynamic panel elements to define aircraft external geometry, upon which reflectivity, absorption and transmission analysis are based, and (2) in the formulation of a module to consider manufacturing details, such as rivet lines, bolt connections and bond lines, in the optimization of a design to minimize life cycle cost at the preliminary design level. Since the EMO design problem entails the optimization of surface geometry which is primarily a conceptual design task, or perhaps a task to be addressed in the interface between conceptual and preliminary design, it was not pursued beyond a cursory review of the issues. However, the prospect of optimizing the design of manufacturing details to minimize life cycle cost was pursued. This effort led to the formulation of an approach for implementing fatigue constraints in ASTROS. The extension of ASTROS MDO capabilities is discussed in Section 3, which summarizes the KU effort documented in Appendix B.

The primary emphasis of this Phase I feasibility study was on the investigation, formulation and demonstration of methods for incorporating modeling uncertainty in structural design optimization. This effort encompassed the work performed under Tasks 5 through 7, and the additional Task 9. The initial investigation followed the outline of Task 5 where the effects of modeling uncertainty on the objective function, constraints and their gradients are explored. This investigation is discussed in Section 4. A comparison of the probabilistic design optimization method proposed in [1-4] with an alternative method published recently by Luo and Grandhi at Wright State University is presented in Section 5. A third alternative that combines the advantages of the first two is developed in Section 6. Section 6 documents the results of Task 9.

One of the important differences between the present approach and that adopted by other investigators lies in the source of modeling uncertainty data. Whereas other investigators have made arbitrary assumptions to quantify the uncertainty of individual design parameters, such as assumed coefficients of variation, the present approach is based on the direct comparison of actual ground vibration test data, and analysis predictions based on detailed finite element models. This approach is envisioned to have significant consequences for practical application for two reasons: firstly because the modeling uncertainty that will inevitably increase the weight

of a structure is based on actual data rather than conjecture, and secondly because the data are available from standard ground vibration tests routinely performed on all new airframe designs.

The final section of the report summarizes the conclusions and recommendations drawn from this Phase I study.

2. INTEGRATING DESIGN STAGES

2.1 Interfacing Conceptual and Preliminary Design

As a result of preliminary findings in the Phase I effort, a decision has been made to eliminate the activities that involve automating the linkage between conceptual and preliminary design from proposed Phase II work. This conclusion was reached after significant technology gaps were identified in the Phase I evaluation of a number of archetypal conceptual aircraft synthesis programs and how they would fit into an automated design process using uncertainty and preliminary design feedback (see Figure 2-1). The two major aircraft conceptual design systems studied were the Flight Optimization System (FLOPS) developed by the NASA Langley Research Center, [2-1] and the ACSYNT system, originally developed by NASA also [2-2].

The MDO Aircraft Synthesis Process (Figure 2-1), begins with the designer attempting to conceptualize a vehicle that can meet certain mission requirements. These may be range and payload requirements, return on investment, cost-per-revenue-passenger-mile, cruise speed, or other high level performance measures. Tools to perform this evaluation using everything from formal optimization methods to Monte Carlo methods exist in industry. A common trait among all the tools is that a set of conceptual design variables is selected that will satisfy the mission requirements. These variables are quantities such as wing area, t/c ratio, fuselage diameter, tail area, number of engines, etc. The variables are topological in nature and can be used to define gross characteristics of the vehicle's geometry, although very few of the synthesis tools actually attempt to do so.

Given a concept, a preliminary design model is required to evaluate the performance of the vehicle in its operating environment. Generally, this requires that CAD models of the concept be created. From these, finite element (FE) models are generated to evaluate the internal loads, stresses and dynamic stability of the system. This step was identified as a major technological gap, because there are no robust tools that can transform a conceptual design (enumerated as a set of conceptual design variables) to a CAD model with sufficient detail to be used in the generation of an appropriately complex FE model. Only a few tools even attempt to generate a parameterized outer mold line model, and none allow the generation, update and maintenance of the increasingly sophisticated models that result from the application of MDO to the combined conceptual/preliminary design process. While some work has been done in this area it is not sufficiently well developed for application in this project. Perhaps the greatest impediment to solving this problem is the inherent *messiness* of real aircraft models. It is one thing to have a push-button modeler for a flat plate or an axisymmetric shell, and quite another to have one for bulkheads with cutouts and arbitrary numbers of ribs and spars in a wing substructure!

It is important to understand that it is a requirement of design optimization that the Conceptual/CAD/FE relationship be highly automated and refineable. Over the course of the process outlined in Figure 2-1, it is not enough to loop over disjoint concepts and generate *thumbs-up* or *thumbs-down* preliminary design evaluations of acceptability. It has also been demonstrated that such uncoupled attempts to optimize systems result in suboptimal results [2-

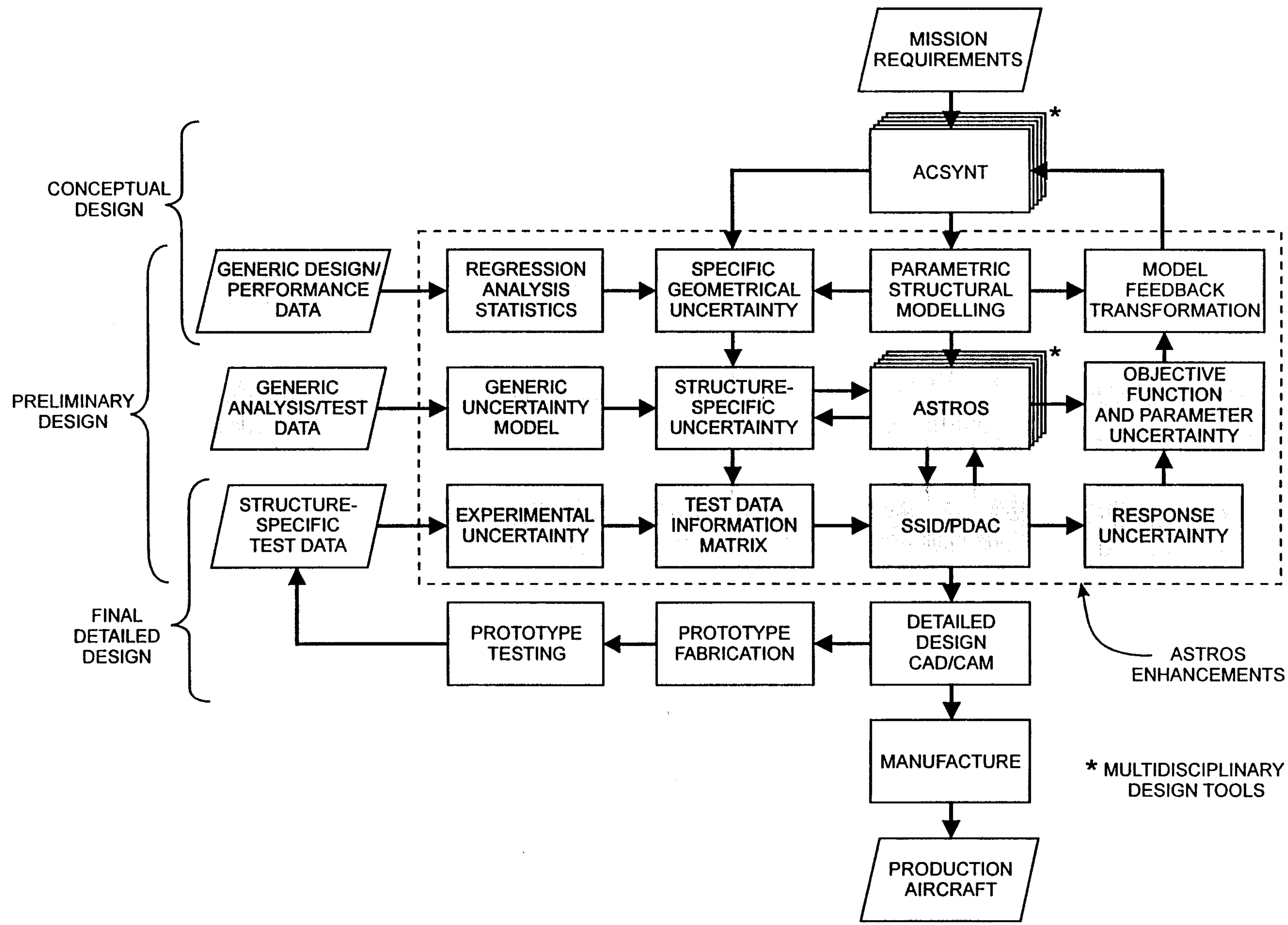

Figure 2-1. Flow Diagram of Multidisciplinary Aircraft Design and Development Process

3]. The envisioned design process requires that the concept become increasingly refined *subject to* the preliminary design level MDO.

While the first few iterations may result in disjoint concepts, eventually the process will settle on a single concept that will then require increasing refinement in its CAD representation and FE models. It is this refinement process that is completely missing from the current technology.

Finally, to support feedback and feedforward between the conceptual and preliminary design stages, the relationship between the conceptual design variables and the preliminary design variables must be a known mathematical relation. In the view of Figure 2-1, this means that the algorithms used to generate the CAD, and then the FE models, must be known so that the design sensitivity and the model uncertainty data can be combined in the solution of the augmented optimization problems that arise in this multi-level design process. Whether using formal multi-level optimization algorithms or a single augmented optimization problem, both conceptual and preliminary variables and constraints and interrelationships must be handled in an automated manner.

Current design practice, in which each of these steps is performed manually, avoids the problem because, at best, a pseudo-random search approach is used to find a feasible concept. In fact, the concept is typically *not* checked for feasibility with respect to preliminary design criteria. Instead, *a posteriori* methods are utilized to *fix* the inadequacies at the preliminary level. Any attempt to build a software tool around this process undermines the gains in robust aircraft designs that are the vision of the proposed effort. Thus, for the purposes of improving the aircraft design process by implementing new processes in software tools, the vision of Figure 2-1 is best served by avoiding the critical technology gap and concentrating development efforts in other areas.

2.2 Discrete Optimization as a Link in Parametric Modeling

Discrete optimization has been investigated as a possible link in a chain which may eventually connect conceptual to preliminary design. As envisioned here, discrete optimization would be used to optimize the layout and coarse sizing of framing elements in an aircraft structure. Parametric modeling might be used on both sides of the discrete optimization, at the front end to translate surface geometry into a coarse frame-and-skin type finite element model, and at the back end to take the optimized frame design and generate more detailed finite element model for preliminary design.

The investigation into discrete optimization techniques for aircraft design, specifically genetic search, has revealed more than just the usefulness of the technique, but also the areas of aircraft design for which it is most well suited. The robustness and ability to handle non-convex design spaces makes it ideally suited for the conceptual design environment. As a result, the application of genetic search methods to conceptual design is the focus of a related Master's Thesis effort at the University of Kansas. The use of genetic optimization algorithms (GOAs) in preliminary design analyses is felt to be less appropriate. The nature of preliminary design tends not to be one of exploration of options, but rather structural sizing. As a result, *genetic search may be*

more useful in the "gap" between conceptual and preliminary design where preliminary structural layout and sizing are accomplished.

2.2.1 Review of Discrete Parameter Optimization Techniques

Most numerical techniques for optimization commonly used today are well grounded in years of experimental application to engineering problems, and their effectiveness is well documented. The majority of these numerical techniques, and certainly the more efficient of the methods, require the use of gradient information. The gradient information is obtained in the derivatives of both the objective function (what is being optimized) and all the constraint functions (the requirements and limitations on the design variables). All of these numerical methods require the derivatives to be at least first-order and many of the more powerful techniques require the use of second-order derivatives to be effective. The evaluation of these derivatives for the objective and constraint functions at each iteration is computationally intensive, and therefore expensive, and cumbersome for even moderately complex engineering design problems. A further handicap to these traditional numerical methods is their limitation to continuous variables and convex design environments. The gradient methods (hill climbing or slope descending) locate the nearest optimum point to the initial estimate with no guarantee that point is the global optimum if the design space is not convex. It is no wonder then that the amount of experimental research into alternative discrete parameter methods of optimization has increased in recent years with the increased emphasis on process cost minimization.

Discrete parameter optimization algorithms, including genetic search and simulated annealing have been considered for many optimization tasks in engineering. They both appear to be particularly useful for the conceptual design task in aircraft design. Simulated annealing [2-4] has been used to solve a variety of engineering optimization problems. It has also been used in conjunction with neural networks for aircraft design [2-5].

One popular alternative that is presently being explored at major airframe companies [2-6] and is being researched in depth at institutions across the world is the genetic optimization algorithm. GOA, or genetic search, research has been around for decades in the social and pure sciences, dating back to the late 50's and early 60's, mainly as a tool to evaluate human problem solving and learning methods and to simulate biologic systems [2-7]. Only within the last decade have genetic algorithms stepped out of the research labs and into the engineering labs as actual problem solving tools as companies begin to recognize their potential. GOA's are simple, adaptable systems for problems solving that are more robust in their application than any numerical method and more appealing because they require no information about the environment, or search space, in which they are working. GOA's remain general and robust by exploiting information available in any search problem. Genetic search techniques have received even greater attention for solving a wide range of engineering problems. They have been shown to be effective in multicriterion design environments [2-8], and in particular, for aircraft design [2-6].

The design applications just cited, along with all others explored, have handled constraints by imposing a penalty on the objective function for constraint violation. However, a recent

extension of the genetic search process [2-9] handles constraints by selectively replacing the genetic code of infeasible designs with genetic code of feasible designs. This process is effected by an "expression operator," one which tends to "express" the genetics of feasible designs in place of infeasible designs.

2.2.2 Demonstration of Genetic Search Techniques in Wingbox Design

In order to demonstrate the usefulness of the new constraint-handling approach, a wingbox design problem has been solved with the new technique and compared with solutions from more traditional, two spar wingbox cross-section subjected to user-selected shear forces and moments. A set of hierarchical buckling requirements forms the constraint set. In particular, no skin buckling is allowed at the limit load, no stringer buckling is allowed at the ultimate load, and no spar cap buckling is allowed at 120% of the ultimate load. In all cases, as well, no yielding is permitted. Figure 2-2 details the wingbox configuration.

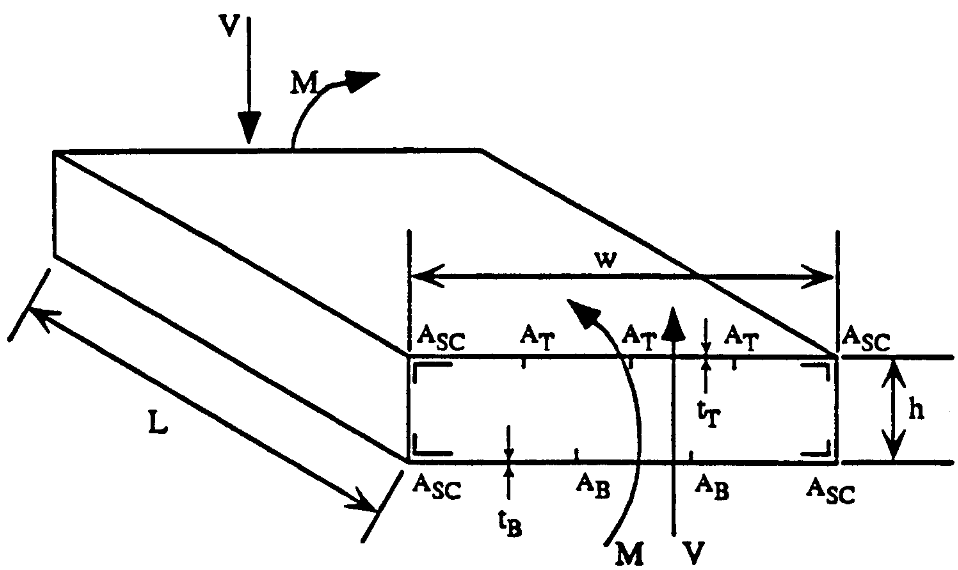

Figure 2-2. Wingbox Structural Layout and Loading

The structural component design variables are:

top and bottom skin thicknesses, t_T, t_B
the number of stringers on the top and bottom skin, n_T,n_B
the schedule number of the top and bottom stringers, I_T, I_B
the schedule number of the four spar caps, I_{SC}

In the problem solved here the "schedule number" is the standard equal-length leg right angle extrusion number for a stringer or spar cap. The schedule numbers are directly related to the cross-section of the top and bottom stringers (A_T, A_B) and the spar caps (A_{SC}). Based on these design variables, the objective function can be most simply defined as the cross-sectional area of the wingbox:

$$f(x) = (t_T + t_B)w + 4A_{SC} + n_T A_T + n_B A_B \tag{2-1}$$

The constraints are based on pure bending stress which is compared to allowable buckling stress or yield. For the purpose of this simplified example, the stiffened panel, stringer and spar cap buckling loads were written as a linear function of schedule number. However, the use of more complex equation or a look-up table does not increase the complexity of using the GOA.

The wingbox optimization problem has been solved for a single set of applied loads and moments using the following techniques:

NCONF: a quadratic programming algorithm with an augmented Lagrangean objective function using finite difference gradients; devised by [2-10], as implemented in the IMSL subroutine library;

NCONG: same as NCONF, except gradients;

NEWSUMT: a sequential unconstrained minimization technique with an exterior penalty function for constraint handling using finite difference gradients [2-11];

NEWSUMTG: same as NEWSUMT, except with exact gradients;

GENDES4: a genetic algorithm based on Hajela's constraint-handling with feasible design gene expression operator;

Table 2-1 summarizes the solutions (i.e., the "optimum" solution for the design variables" from the aforementioned solution algorithms. Note that the traditional solutions based on exact gradient calculations perform the best. The genetic algorithm results shown are for the best solution achieved in 5 tries. Note that the genetic search solution compares favorably with the traditional finite-difference-based solutions. This is significant because in many design applications, such as the conceptual design environment discussed in the next section, exact gradients will not be available, and finite difference gradients will be the only ones available. This *fact seems to favor the use of genetic search techniques for conceptual design. At the very least, GOA algorithms have been established as appropriate for combined layout and sizing optimization.*

Table 2-1. Comparison of alternative methods of wingbox design

method	area	n_T	n_B	I_{SC}	I_T	I_B	t_T	t_B
NCONF	22.8	15	15	30	30	30	.24	.05
NEWSUMT	30.6	12	12	26	25	26	.279	.32
NCONG	15.1	15	1	29	8	28	.254	.071
NEWSUMT-G	15.3	15	2	15	8	1	.259	.082
GENDES4	15.9	13	3	16	8	8	.29	.08

2.2.3 Genetic search techniques in ASTROS

Although preliminary design may not be the most suitable place for discrete optimization, implementing GENDES in the ASTROS environment is entirely feasible. The bulk Data entries necessary to incorporate the algorithm have been devised. For example, a bulk data "card" titled GENETIC allows the user to, for instance, select either "gene expression" (EXPRESS) or "cost function augmentation" (COSTAUG) for constraint application. The COSTAUG card allows the user to select either a linear or inverse cost augmentation function. The associated input data templates and relation entries also have been devised (for inclusion into the TEMPLAT.DAT and RELDEF.DAT files required by ASTROS at build-time).

2.2.4 Linking Conceptual and Preliminary Aircraft Design

Two ways in which improvements in the way conceptual and preliminary design tasks are linked will now be presented.

Improving the ability to devise appropriate finite element models

One of the key impediments to linking conceptual and preliminary design is the difficulty in devising a finite element model to represent the structure. At the very least, a set of geometric parameters is available from the conceptual design phase. In a better case, various cross-sectional profiles of fuselage and wings are known. However, the finite element analyst needs to make elements of specific sizes "on" the surfaces provided at the conceptual level. Typically, a skin panel element would span between bulkheads or frames in one direction and between longerons or stringers in the other. Without knowing the spacing, the analyst is forced to use an *ad hoc* procedure.

Using the same algorithm described earlier for a wingbox layout and sizing, a fuselage, a vertical stabilizer or any structure made with skin and substructure structural concepts could be laid out and sized. This would form a vital link between a conceptual design and a preliminary design. The enormous benefit is that the preliminary designer then gets a reasonable starting point for bulkhead, frame and rib locations as well as longeron and stringer placements. Using these structural placements, a finite element model can be made rather easily. Also, after preliminary sizing with a traditional sizing algorithm like ASTROS, the structure should be lighter than one based on an *ad hoc* layout.

Providing feedback from preliminary design to conceptual design

Many conceptual design algorithms are based on either tabular or response surface representations of the relationships between design parameters and performance. For instance, wing weight can be found in many sources, e.g., [2-12] as a function of surface area. In other cases, wing weight can be found as a function of multiple parameters, like surface area, aspect ratio, etc. In both cases, the functionality is based on *historical databases*. Such data have a high confidence associated with them. However, as preliminary designs are accomplished--based on user requirements generally different that those associated with aircraft in the database--

it seems appropriate to use the weight and cost data from preliminary designs to update the database, at least until a design has been finalized. In this way, the very rudimentary techniques used for weight and cost estimation in conceptual design will be updated, with some finite level of confidence, to include information from preliminary designs.

3. EXTENSION OF ASTROS MDO CAPABILITIES

3.1 Manufacturing Detail Capability for ASTROS

A framework for incorporating manufacturing detail in the early design process has been devised. The basis of the framework is a hierarchy of input bulk data "cards" which specify manufacturing processes used for bulk parts as well as for joined parts. The manufacturing data would include cost data, but also detail information which could be used to apply, for instance, fatigue constraints on the structure. In particular, if a rivet joining process is prescribed, the number and size of rivets needed could easily be determined along with the skin thickness. One of the factors in such a sizing process would be the avoidance of a fatigue life less than that prescribed.

3.1.1 Cost accounting with ASTROS

All manufacturing processes have costs associated with them, and they can be dealt with directly. For bulk parts, the cost is specified, for instance, on a per pound basis. For joining operations, some costs are allocated to specified machines, jigs and clamps. For rivets, for instance, the number and size of the rivets can be automatically calculated.

The key objective of including cost information in ASTROS is to provide cost information to the preliminary design algorithm, especially if cost is part of (or is) the objective function. Currently ASTROS uses weight as the objective function, but this may not always be the case. For instance, if ASTROS were augmented to select rivet sizes and numbers, the cost association would allow gradient information to guide the optimizer to structural designs which result in reduced overall costs and failure avoidance associated with rivet selection.

A secondary objective is to provide an opportunity for manufacturing-related data to be available in the ASTROS database (CADDB) for use in a conceptual design algorithm. The conceptual design algorithm being used by a user, would then have an organized, documented database with which to interface. This was discussed briefly in Section 2.2.4.

3.1.2 Failure modeling associated with manufacturing detail

The manufacturing method used in a design often imposes strength and life limitations on the resulting structure. Traditional preliminary design using ASTROS, MSC/NASTRAN or Dessault/ ELFINI is based on strength constraints, that is the avoidance of stresses too high for the structure to withstand, as well as flexibility constraints. ASTROS has some capability to impose buckling constraints, but to impose fatigue life or fracture constraints, the user is forced to pose them artificially as strength constraints.

The goal of this subtask is to implement strength and fatigue life constraints in ASTROS. Failure modes associated with manufacturing detail need to be included for two distinct reasons. First, their inclusion increases the constraint set to be more representative of the service environment. Secondly, accounting for life-limiting design details allows a better life cycle cost to be computed.

Rivet strength

Constraints on rivet shear strength and sheet (skin) bearing strength can be developed by slight modifications to existing strength constraints. Sensitivities of these constraints can be used during subproblem optimization looping. Formal riveted connection sizing algorithms can be installed in ASTROS for "outer loop" resizing. It is well known that differences exist between manufacturers and product classes (e.g., military and civilian) in the fitting and bearing factors used for resizing. However, the proposed constraints can be made sufficiently general to accommodate any product- or manufacturer-specific rules in use. The goal is to establish an algorithm for strength design of riveted connections.

Fatigue due to rivet holes

A second area of concern in rivet selection is fatigue failure, typically in a sheet or skin which the rivet is used to secure. The proposal is to use Miner's cumulative damage rule based on user-defined load spectra. Other rules could be used with little change in the difficulty of implementation. Using Miner's rule, failure occurs when:

$$\sum \frac{n_i}{N_i} = 1 \qquad (3\text{-}1)$$

First, the user specifies either a set of representative time histories or a set of "number of occurrence" load spectra for a set of load factor ranges. If a history of load factors is given, ASTROS will compute a load spectrum. Either time histories or load spectra can be combined by the user to represent the estimated service environment of the aircraft design. Given the life goal for the aircraft, say in hours, the number of times the "*ith*" load range will occur in the design life, n_i, can be calculated. Load spectra sets are tied to specific load cases so that, for instance, a load spectrum representing the load factor variations associated with gust loading can be tied to a load case with symmetric loading on the wings. Each load spectra-load case combination is tied to a set of elements, possibly all of the elements in the model. In this way, the user controls to which parts of the aircraft fatigue constraints are associated. This could save a good deal of processing time if applied carefully. Using stress range-cycles to failure curves ("S-N curves"), the predicted cyclic life at each load range, N_i, can be determined based on the load range "R-ratio", where:

$$R = \frac{\sigma_{\min}}{\sigma_{\max}} \qquad (3\text{-}2)$$

and the notch sensitivity factor for the set of elements under consideration. A great deal of data is required. An S-N curve must be available for each stress ratio, R, each notch sensitivity ratio and each material under consideration. This information will be sought from the open literature, for instance, the Air Force Materials Laboratory.

Details of the existing rules for design, for instance the proper notch sensitivity factor selection, typically vary only in the numerous design factors used. Therefore, the goal will be to establish a general algorithm for fatigue constraints on riveted connections.

In order to provide ASTROS with the ability to design with fatigue constraints, analytical sensitivities will be devised for "inner loop" resizing. For a constraint of the form:

$$g(\bar{x}) = \Sigma \frac{n_i}{N_i} - 1 \leq 0 \tag{3-3}$$

the sensitivities with respect to design variables are:

$$\frac{\partial g}{\partial x_j} = \Sigma \frac{\partial g}{\partial N_i} \frac{\partial N_i}{\partial \sigma_i} \frac{\partial \sigma_i}{\partial x_j} \tag{3-4}$$

The gradient of g with respect to N_j is easily found, from Miner's rule. The gradient of the log-number of cycles until failure with respect to σ can either be calculated from a table of values or expressed analytically. For instance, if $N(\sigma)$ is assumed to be of the form:

$$N = ae^{-b\sigma}$$

then the desired gradient is:

$$\frac{\partial N}{\partial \sigma} = -abe^{-b\sigma}$$

The gradient of σ with respect to all design variables is already available within ASTROS.

For the later version of ASTROS, in which development cost is an admissible objective function, sensitivities of cost as a function of rivet design variables will be derived. Rivet design variables, such as skin thickness and rivet diameter, for various types of rivets and skin preparations (e.g., countersunk holes, polished skin, anodized skin, etc.) would then be selected in the optimization scheme based on overall cost. As with weight minimization design, however, constraints on shear strength, bearing strength, and fatigue life would still be appropriate.

3.1.3 Manufacturing Detail Bulk Data Items

The basis for finite element property information in ASTROS (and NASTRAN) is the hierarchy of Connectivity, Property and Material. So, for instance, a bar element has connectivity specified with a CBAR card, which references a specific PBAR property card. The PBAR card specifies properties like cross-sectional area, but also references a specific MATi material card. For instance, a MAT1 card specifies the modulus of elasticity and Poisson's ratio. The idea for including manufacturing detail is to reference manufacturing detail information with the ASTROS property cards.

The strategy is two-fold. First, the property cards for all finite elements will have an associated manufacturing process. This could be as simple as an anodizing process or as complicated as a peening operation. Secondly, the process for joining all parts must be specified.

As an example, the following summary of proposed changes and additions to ASTROS bulk data entries is provided. The names of data items and relations were selected to be an evocative as possible.

The following additions to bulk data relations would allow a manufacturing process and a joining process to be added to both bar and shell elements, the most common elements in a preliminary design finite element model:

PBAR

add:	MANIDi	id of the manufacturing method(s)
	JOINID	id of the joining method
	NSMPU	non-structural mass per unit length (e.g., for a leading edge assembly attached to a front wing spar)

PSHELL (specifies properties for a shell element)

add:	MANIDi	
	JOINID	
	NSMPU	non structural mass per unit area (e.g., for interior wall in a fuselage)

The values of the MANID entries would "point" to new MANUF bulk data relations. The JOINID entries would point to new PJOIN and CJOIN relations. The NSMPU entries allow mass for non-structural items to be added to the model.

Some of the new bulk data relations introduced above are shown in Appendix B. These relations tie a manufacturing process to a finite element model and provide for the needed jigs and special tools to be used in the manufacturing process.

3.2 Electromagnetic Observable Analysis (EOA)

This task was addressed in sufficient detail to allow only a cursory review. Although ASTROS models and solvers could be modified to allow an analysis of the electromagnetic reflectivity and absorptivity of a structure, a more appropriate place for EOA is at the conceptual design level where the geometric layout is typically set. Since the decision has been made not to address multilevel design optimization in this project, the EOA task was not pursued further. Additional discussion is contained in Appendix B.

4. STEPS TOWARD A ROBUST DESIGN METHODOLOGY

The Phase I Proposal [1-4] outlined a series of steps directed toward achieving a robust design methodology based on the recognition and treatment of modeling uncertainty in design optimization. Three steps were suggested: (1) incorporating modeling uncertainty in the objective function being optimized, (2) scaling the design parameter space to bias the search in the direction of those parameters which are less uncertain, and (3) accounting for modeling uncertainty in the performance constraints that ultimately determine the design. This section expands the concepts originally proposed, and illustrates their relative effects on the outcome of a design using simple numerical examples. The steps are addressed in reverse order, beginning with the effect of modeling uncertainty on performance constraints.

4.1 Effect of Modeling Uncertainty on Performance Constraints

4.1.1 Probabilistic Safety Margin Approach

Reference [1-4] suggested that one way to introduce modeling uncertainty in the optimum design process is by applying probabilistic safety margins to performance constraints. Performance constrains can involve frequency limits, stress limits, displacement limits, and other measures of performance relative to the structure and its interaction with aerodynamics, propulsion and controls. The simplest may be a global displacement constraint, such as a wing tip displacement under static loading. In this report, the design variables are considered to be random variables denoted by x_i. The unsubscripted letter, x, denotes a vector of the random variables, x_i. A performance constraint can be written as

$$g(x) \geq 0 \tag{4-1}$$

For example, a constraint on the static displacement, u, of a structure might be written

$$g(x) = u_0 - u(x) \geq 0 \tag{4-2}$$

where in this case u and u_0 are scalar quantities. If x is a vector of random variables, $u(x)$ will be a scalar random variable. First order second moment (FOSM) methods are used in this approach, so that the random variables are characterized by their means and standard deviations. The means and standard deviations of the design variables, x_i, are denoted by μ_{x_i} and σ_{x_i}, respectively. The means and standard deviations of other random variables, such as u, are subscripted accordingly, e.g. μ_u and σ_u. It is assumed that the mean values of u and x are related as

$$\mu_u = E[u(x)] = u(\mu_x) \tag{4- 3}$$

Consistent with the FOSM approach, the standard deviation of u, σ_u, is given by

$$\sigma_u^2 = E\left[(u-\mu_u)^2\right] = E\left[\Delta u^2\right]$$

$$= E\left[T_{ux}\Delta x \Delta x^{\mathrm{T}} T_{ux}{}^{\mathrm{T}}\right]$$

$$= T_{ux} E\left[\Delta x \Delta x^{\mathrm{T}}\right] T_{ux}{}^{\mathrm{T}} = T_{ux} S_{xx} T_{ux}{}^{\mathrm{T}} \tag{4-4}$$

where

$$\mathrm{T}_{\mathrm{ux}} = \frac{\partial \mathrm{u}}{\partial \mathrm{x}} = \left\{\frac{\partial \mathrm{u}}{\partial \mathrm{x}_1}, \frac{\partial \mathrm{u}}{\partial \mathrm{x}_2}, \ldots, \frac{\partial \mathrm{u}}{\partial \mathrm{x}_n}\right\} \tag{4-5}$$

is the matrix (in this case a row vector) of partial derivatives of u with respect to x, and S_{xx} is the covariance matrix of x.

A probabilistic safety margin, Δu_p may be incorporated in the performance constraint of Eqn. (4-2) by defining the response $u(x)$ in terms of the mean response, $\mu_u = u(\mu_x)$, where

$$u(x) = \mu_u + \Delta u_p \tag{4-6}$$

The safety margin, Δu_p, can be quantified in terms of an assumed normal (Gaussian) distribution where

$$P = \Phi(\beta); \quad \beta = \Phi^{-1}(P) \tag{4-7}$$

where Φ denotes the cumulative normal probability distribution, P is the probability of survival, i.e. the probability that the constraint will not be violated, and β is a safety index defined as

$$\beta = \frac{u_o - \mu_u}{\sigma_u} \tag{4- 8}$$

from Equation (4-2). This leads to the safety margin

$$\Delta u_p = \beta \sigma_u \tag{4- 9}$$

For example, a 98% probability of survival corresponds to a safety factor of $\beta = 2$, referred to as a "two-sigma" design.

To illustrate the probabilistic safety margin approach, one may consider the simple two-spring "structure" shown in Figure 4-1. A static force is applied at the free end of the two springs connected in series. the state equation specifies that the displacement, u, at the end of the two springs is the sum of deflections across the two springs.

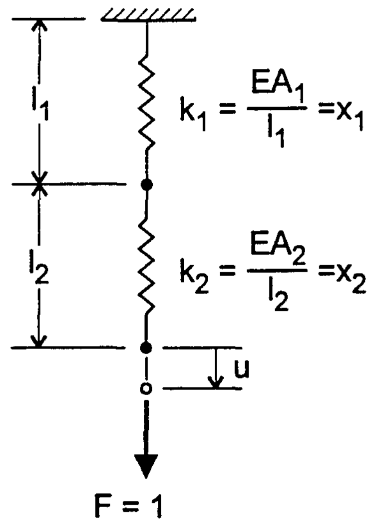

Figure 4-1. Two Spring Example

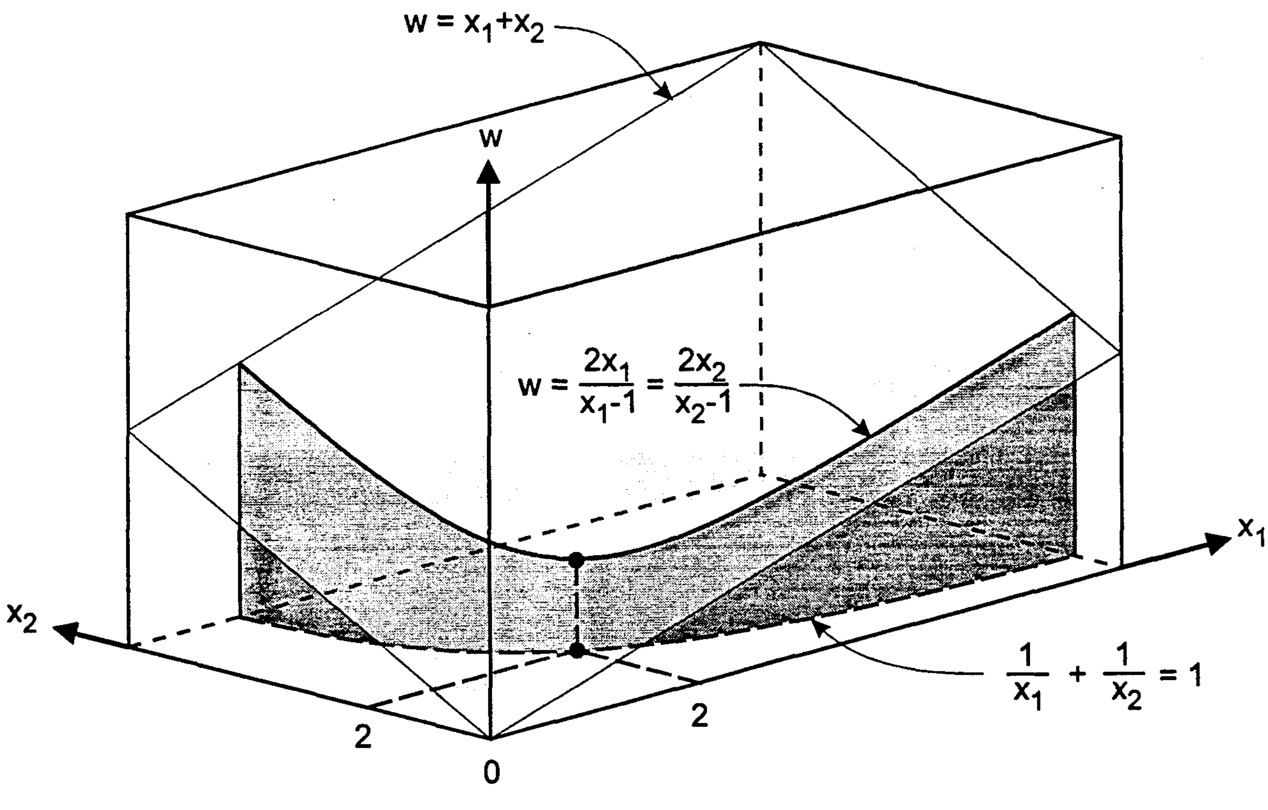

Figure 4-2. Illustration of Deterministic Design Optimization

$$u = \frac{F}{k_1} + \frac{F}{k_2} \tag{4- 10}$$

where the individual spring stiffnesses, k_i, are defined in terms of their respective areas, A_i, lengths, ℓ_i, and a common modulus of elasticity, E. The weight of the "structure" is

$$W = \left(A_1\ell_1 + A_2\ell_2\right)\gamma \tag{4-11}$$

where γ is a material density. For notational simplicity, one may define the design variables as $x_i = A_i$, with unit values for E, ℓ_i, γ, F and u_0. Then (4-10) and (4-11) become

$$u(x) = \frac{1}{x_1} + \frac{1}{x_2} \tag{4-12}$$

$$W(x) = x_1 + x_2 \tag{4-13}$$

The deterministic design optimization problem may be stated as follows:

$$\textit{Minimize}\text{: } W(x) \tag{4-14a}$$

$$\textit{Subject to}\text{: } u_0 - u(x) \geq 0 \tag{4-14b}$$

The solution is easily visualized as the minimum weight point on the intersection of two surfaces bnnnnnnnin 3D space, where x_1 and x_2 are the design parameters defining the x_1, x_2 plane, and W is the dependent variable defined over the x_1, x_2 parameter space. See Figure 4-2.

For positive stiffness, the deterministic solution must lie in the ($x_1>0$, $x_2>0$) quadrant of the x_1, x_2 plane. The asymptotes are x_1, = 1 and x_2, = 1, and the minimum weight intersection of the two surfaces occurs at $x_1 = x_2 = 2$. The displacement of structure is then

$$u(x) = \frac{1}{2} + \frac{1}{2} = 1$$

which satisfies the constraint equation $u(x) = 1$, and the minimum weight is $W = 4$.

If modeling uncertainty is represented in terms of the random design variables x_1 and x_2, where the actual stiffness can be less than or greater than the nominal (mean) value of 2, one would expect to have to "over-design" the system in order to achieve a reliable design, i.e. one that not only achieves a minimum weight, but does so in a way that the desired level of performance is achieved with a specified degree of probability. Intuitively, if the performance constraint is

$$g(x) = u_0 - u(x) \geq 0 \tag{4-2}$$

one might add a probabilistic safety margin, Δu_p, to u and write the constraint as

$$g(x) = u_0 - \left[u(x) + \Delta u_p\right] \geq 0 \tag{4-15}$$

The safety margin, Δu_p, is easily calculated if modeling uncertainty is due to parameter uncertainty where the probability distribution of each parameter is known. In practical applications, the mean of each distribution is typically assumed to be the nominal parameter value, μ_{x_i}, and the standard deviation, σ_{x_i}, is defined by a coefficient of variation, Ω_i such that

$$\sigma_{x_i} = \Omega_i \mu_{x_i} \tag{4-16}$$

If the design variables have uncorrelated distributions, their covariance matrix, S_{xx}, will be diagonal. Linear covariance propagation may be used to estimate the uncertainty in response (performance) u, due to this parameter uncertainty.

If S_{xx} is diagonal, then (4-4) gives

$$S_{uu} = \sum_i \sigma_i^2 \left(\frac{du}{dx_i}\right)^2 = \sigma_u^2 \tag{4- 17}$$

If a 10% coefficient of variation is assumed for both x_1 and x_2, then $\sigma_{x_1} = \sigma_{x_2} = 0.2$, given the mean values $\mu_{x_1} = \mu_{x_2} = 2.0$.

The derivatives of u with respect to x_1 and x_2 from Eqn (4-12) are

$$\frac{\partial u}{\partial x_1} = -\frac{1}{x_1^2} = -\frac{1}{4}$$

$$\frac{\partial u}{\partial x_2} = -\frac{1}{x_2^2} = -\frac{1}{4}$$

when evaluated at the nominal values $x_1 = x_2$. This gives

$$\sigma_u = \left[2\left(\frac{.04}{16}\right)\right]^{1/2} = 0.05\sqrt{2}$$

For a safety factor of $\beta = 2$, corresponding to a 98% probability of survival, (4-9) gives

$$u(x) \leq u_0 - \Delta u_p = 1 - 0.1\sqrt{2} \tag{4- 18}$$

In this simple case, the symmetry of the problem again leads to a minimum weight design where $x_1 = x_2$.

Substitution of Equation (4-12) into (4-18) gives

$$\frac{1}{x_1}+\frac{1}{x_2}=\frac{2}{x_i}=1-0.1\sqrt{2}$$

or

$$x_1=x_2=x_i=\frac{2}{1-0.1\sqrt{2}}=2.329 \tag{4-19}$$

Because of the form of Equation (4-18) the safety margin approach may also be thought of as a "constraint padding" approach. This approach may be used when there are many design variables and multiple constraints, but instead of first finding the deterministic solution, calculating the "safety margin", Δu_p, (assumed to be constant) and then determining the design variables required to satisfy (4-18), the optimization problem is changed from (4-14) to

$$\textit{Minimize: } W(x) \tag{4-20a}$$

$$\textit{Subject to: } g_j(x) \mp \Delta g_j \geq 0 \tag{4-20b}$$

where

$$\Delta g_j = \beta \sigma_{g_j} \tag{4-20c}$$

$$\sigma^2_{g_j} = \left[\partial g_j / \partial x\right]\left[S_{xx}\right]\left[\partial g_j / \partial x\right]^T \tag{4-20d}$$

$$\beta = \Phi^{-1}(P) \tag{4-20e}$$

The values of the design variables, x, are treated as the nominal (mean) design variables and the constraint derivatives are evaluated at these values at every step of the iterative solution. The plus or minus sign in (4-20b) depends on whether the constraint is, respectively, a lower bound or an upper bound.

4.1.2 Reliability-based Optimization Approach

There is another way to approach the probabilistic design optimization problem. Instead of taking the mean values of the design variables as the point of reference and calculating probabilistic safety margins to adjust each of the performance constraints, which in effect moves the constraint surfaces relative to the current design point in parameter space, the constraint surfaces instead are considered to be fixed in parameter space, and the mean values of the design variables are moved to position the design point far enough from the constraint surfaces to achieve the desired probability of survival. This approach is referred to in the literature as "reliability-based optimization," c.f. References [4-1 to 4-5].

It is easiest to consider first a problem with only a single performance constraint, and follow the development of Ang and Tang [4-1]. They begin with the case where the basic design variables, x_i, are uncorrelated. A set of reduced, uncorrelated, normalized variates is defined as

$$y_i = \frac{x_i - \mu_{x_i}}{\sigma_{x_i}} \tag{4-21}$$

where, as before, μ_{x_i} and σ_{x_i} are the mean and standard deviation of the random variable x_i. By this definition, the reduced variates, y_i, have zero mean and unit standard deviation.

In the case of nonlinear performance constraints, a first-order approximation of the function $g(x)$ expanded about the most probable failure point, x^*, on the constraint surface may be written as

$$g(x) = g(x^*) + \sum_i (x_i - x_i^*)\left(\frac{\partial g}{\partial x_i}\right)^* \tag{4-22}$$

where the derivatives are evaluated at x^*. By definition, however, $g(x^*) = 0$ on the constraint surface. From (4-21) one finds that

$$\begin{aligned} x_i - x_i^* &= (\sigma_{x_i} y_i + \mu_{x_i}) - (\sigma_{x_i} y_i^* + \mu_{x_i}) \\ &= \sigma_{x_i}(y_i - y_i^*) \end{aligned} \tag{4-23}$$

$$\frac{\partial g}{\partial x_i} = \frac{\partial g}{\partial y_i}\frac{dy_i}{dx_i} = \frac{1}{\sigma_{x_i}}\left(\frac{\partial g}{\partial y_i}\right) \tag{4-24}$$

Then (4-22) becomes

$$g(x) = \sum_i (y_i - y_i^*)\left(\frac{\partial g}{\partial y_i}\right)^* \tag{4-25}$$

The expected (or mean) value of $g(u)$ to first order approximation is therefore

$$\mu_g = -\sum_i y_i^*\left(\frac{\partial g}{\partial y_i}\right)^* \tag{4-26}$$

since by definition the expected value of $y_i = 0$. It can further be shown that to first order approximation, the standard derivation of g is

$$\sigma_g = \left[\sum \left(\frac{\partial g}{\partial y_i}\right)^{*2}\right]^{1/2} \tag{4- 27}$$

The ratio of μ_g to σ_g is then

$$\frac{\mu_g}{\sigma_g} = \frac{-\sum y_i^*\left(\frac{\partial g}{\partial y_i}\right)^*}{\left[\sum_i \left(\frac{\partial g}{\partial y_i}\right)^{*2}\right]^{1/2}} \tag{4-28}$$

Ang and Tang [4-1] show that

$$\alpha_i^* = \frac{\left(\frac{\partial g}{\partial y_i}\right)^*}{\left[\sum_i \left(\frac{\partial g}{\partial y_i}\right)^{*2}\right]^{1/2}} = \frac{\left(\sigma_i \frac{\partial g}{\partial x_i}\right)^*}{\left[\sum_i \sigma_i^2 \left(\frac{\partial g}{\partial x_i}\right)^{*2}\right]^{1/2}} \tag{4-29}$$

are the direction cosines of the gradient vector, $\Delta_y g(\mu_x + \sigma_x y^*)$ evaluated at the most probable failure point, x^* or y^*, and the ratio μ_g / σ_g is the safety index, β, defined as the shortest distance from the origin of the y-coordinate axes to the limit surface

$$g(x) = g(\mu_x + \sigma_x y) = 0 \tag{4-30}$$

Ang and Tang also show that

$$y_i^* = -\alpha_i^* \beta \tag{4-31}$$

by satisfying Kuhn-Tucker necessary conditions at x^*.

It is instructive to return to the simple two-spring problem, beginning with the deterministic solution, $x_1 = x_2 = 2$. By definition, this point in design space lies on the limit surface. If x_1 and x_2 are now treated as random variables, their mean values, μ_{x_1} and μ_{x_2} can be obtained from Eqns (4-21) and (4-31).

$$\mu_{x_i} = x_i^* - \sigma_{x_i} y_i^* \tag{4-32}$$

on the constraint surface. Substitution of (4-31) into (4-32) gives

$$\mu_{x_i} = x_i^* + \sigma_{x_i} \alpha_i^* \beta \tag{4-33}$$

If σ_{x_i} is expressed in terms of the mean and a coefficient of variation, Ω_i, then (4-33) becomes

$$\mu_{x_i} = x_i^* + \Omega_i \mu_{x_i} \alpha_i^* \beta$$

$$\mu_{x_i}(1 - \beta\, \Omega_i \alpha_i^*) = x_i^*$$

$$\mu_{x_i} = \frac{x_i^*}{1 - \beta\, \Omega_i \alpha_i^*} \tag{4-34}$$

The deterministic solution $x_1 = x_2 = 2$ gives values of x_i on the constraint surface. Thus $x_i^* = x_i = 2$. For this example,

$$g(x) = 1 - \frac{1}{x_1} - \frac{1}{x_2}$$

$$\left(\frac{\partial g}{\partial x_i}\right)^* = \frac{1}{x_i^{*2}} = \frac{1}{4}$$

Then for $\Omega_1 = \Omega_2 = \Omega$, and $\mu_{x_1} = \mu_{x_2} = \mu$,

$$\alpha_i^* = \frac{4\Omega\mu}{4\left(\Omega^2\mu^2 + \Omega^2\mu^2\right)^{1/2}} = \frac{1}{\sqrt{2}} \qquad (4\text{-}35)$$

From (4-33) with $\Omega = 0.1$ and $\beta = 2$,

$$\mu_{x_1} = \mu_{x_2} = \frac{2}{1 - 2(0.1)/\sqrt{2}} = 2.329 \qquad (4\text{-}36)$$

which, in this particular case, happens to be identical to the result obtained from the probabilistic safety margin approach in (4-19).

4.2 Use of Modeling Uncertainty to Scale the Parameter Space

The second suggestion of using modeling uncertainty to enhance structural design optimization was to scale the parameter space based on with the covariance matrix of design variables. This was thought to accomplish two objectives: (1) reduce the parameter space to the rank of the covariance matrix, and (2) scale the parameter space so as to bias the search in favor of those design variables having the least uncertainty. The former is true, however, the latter is not. In fact, parameter scaling has no effect on the solution if applied consistently.

Having said that, it is recognized that the transformation of design parameters to a set of reduced uncorrelated, normalized (scaled) design variables is a fundamental technique used in the formulation of reliability-based optimization as reported in the literature, e.g. References [4-1 to 4-5]. It is particularly relevant when the covariance matrix characterizing design variable uncertainty is derived from structural vibration analysis and test data as proposed herein, because that covariance matrix will always reflect correlation among the design variables, and may be rank deficient depending on the number and type of design variables defined, and the quantity of data available to generate the covariance matrix.

The design variable scaling transformation outlined in [1-4] is applicable. In terms of the present notation, the scaling transformation is derived by performing a singular value decomposition (SVD) [4-6] on the covariance matrix, S_{xx}. This procedure decomposes S_{xx} into the triple matrix product

$$S_{xx} = \theta D^2 \theta^T \qquad (4\text{-}37)$$

where D^2 is a diagonal matrix of positive singular values. These singular values are the variances of the transformed, uncorrelated design variables, and θ is the corresponding matrix of orthonormal eigenvectors such that

$$\theta^T\theta = I \tag{4-38}$$

where I is an identity matrix. The number of (nonzero) singular values is equal to the rank of S_{xx}. For example, if S_{xx} is of dimension 100 x 100 but has a rank of only 20, then D^2 will be of dimension 20 x 20 and θ will be 100 x 20. The transformation

$$x = \theta D^{-1} y \tag{4-39}$$

transforms S_{xx} to an identity matrix of dimension 20 x 20 as follows:

$$D^{-1}\left(\theta^T S_{xx}\theta\right)D^{-1} = D^{-1}\left(D^2\right)D^{-1} = I \tag{4-40}$$

The inverse transformation,

$$y = D\theta^T x = Tx \tag{4-41}$$

is the transformation that transforms x to the "standard, uncorrelated and normal variates" referred to in Equation (2) of Reference [4-5]. Further discussion of S_{xx} and the significance of this transformation are contained in Sections 6 and 7.

4.3 Incorporation of Modeling Uncertainty in the Objective Function

The third way to account for modeling uncertainty in design optimization is to include it in the objective function. In this way, the optimizer searches for a design that minimizes a probabilistic measure of the total weight of a structure, in addition to satisfying the performance constraints under conditions of modeling uncertainty. For example, if global stiffness were a performance goal, and that stiffness alternatively could be achieved by stiffening different parts of the structure, the optimizer would tend to favor that part of the structure with less uncertainty, other things being equal.

To include modeling uncertainty in the objective function using the probabilistic safety margin approach, Equations (4-20a) and (4-20b) are modified as follows:

$$\textit{Minimize:}\ W_P(\mu)_x = \mu_W + \beta\sigma_W \tag{4-42a}$$

$$\textit{Subject to:}\ g_j(\mu_x) - \Delta g_j \geq 0 \tag{4-42b}$$

where

$$\sigma_W^2 = [\partial W / \partial\mu_x][S_{xx}][\partial W / \partial\mu_x]^{\mathrm{T}} \tag{4-43}$$

and Equations (4-20c, d, e) apply to the evaluation of Δg_j and β as before.

To illustrate the effect of this modification, one may reexamine the simple two-spring problem of Figure 4-1. In this case,

$$W_P(\mu_x) = \mu_{x_1} + \mu_{x_2} + \beta\left(\Omega_1^2\mu_{x_1}^2 + \Omega_2^2\mu_{x_2}^2\right)^{1/2} \tag{4-44a}$$

and

$$g(\mu_x) = C - \frac{1}{\mu_{x_1}} - \frac{1}{\mu_{x_2}} \tag{4-44b}$$

where

$$C = 1 - \Delta g = 1 - \Delta u_p \tag{4-44c}$$

The optimization problem is solved by defining the Lagrangian, L, as

$$L = W_P(\mu_x) + \lambda g(\mu_x) \tag{4-45}$$

and setting the derivatives of L with respect to μ_{x_1}, μ_{x_2} and λ equal to zero.

$$\frac{\partial L}{\partial \mu_{x_1}} = \frac{\partial W_P}{\partial \mu_1} + \lambda \frac{\partial g}{\partial \mu_x} = 0 \tag{4-46a}$$

$$\frac{\partial L}{\partial \mu_{x_2}} = \frac{\partial W_p}{\partial \mu_{x_2}} + \lambda \frac{\partial g}{\partial \mu_{x_2}} = 0 \tag{4-46b}$$

$$\frac{\partial L}{\partial \lambda} = g(\mu_x) = 0 \tag{4-46c}$$

These three equations are solved (in closed form) for λ, μ_{x_1}, and μ_{x_2}. When $\Omega_1 = \Omega_2 = 0.1$, the optimized design variables are exactly the same as they were before, i.e. when there was no uncertainty in the objective function. However, with $\Omega_1 = 0.1$, $\Omega_2 = 0.2$, the resulting values for μ_{x_1}, and μ_{x_2} are

$$\mu_{x_1} = 2.717;\ \mu_{x_2} = 2.449$$

With no uncertainty in the objective function and $\Omega_1 = 0.1$, $\Omega_2 = 0.2$ the values of μ_{x_1} and μ_{x_2} are

$$\mu_{x_1} = 2.576;\ \mu_{x_2} = 2.576$$

It is of interest to note that, as expected, adding uncertainty to the objective function did in fact have the result of increasing the stiffness of the less uncertain parameter more than the other. The mean weight,

$$\mu_W = \mu_{x_1} + \mu_{x_2}$$

is approximately the same in the two cases, 5.166 in the first case and 5.152 in the second, while the probabilistic weights (98% probability of nonexceedence) are 6.286 in the first case, and 6.304 in the second.

The second set of probabilistic weights includes a double weight penalty for modeling uncertainty, because on the constraint side of the problem, one is adding a safety margin to account for the possibility that the structural members may be too small, thereby allowing too much deflection under static loading, whereas on the objective function side, one is adding a safety margin to account for the possibility that the members may be too large, thereby causing the structure to be overweight. If modeling uncertainty is defined by known probability distributions on member sizes, this doubling of the weight penalty is appropriate. However, if modeling uncertainty is defined in terms of the difference between the analytical and experimental evaluation of vibration modes, as proposed here, the uncertainty represents more than uncertainty in member sizes, and doubling the full weight penalty is not appropriate.

Although the effect of adding uncertainty to the objective function appears to be significant, ASTROS is not presently structured to allow easy implementation of this modification. It would require computing second derivatives of weight with respect to the design variables, where only the first derivatives are presently computed. The first derivatives are used to compute σ_W in (4-43). Computing the derivatives of W_p in (4-46) requires derivatives of σ_W, and therefore the second derivatives of weight.

Even though ASTROS could not be modified in Phase I to further explore the effect of adding modeling uncertainty to the objective function, further consideration will be given in Phase II. Cost-benefit tradeoffs will be made to determine the extent of modification required to achieve significant benefit for more realistic applications. It is important to recognize that this modification can be applied regardless of which approach is used to handle the probabilistic constraints, i.e. the probabilistic safety margin approach or the reliability-based optimization approach.

5. ASTROS IMPLEMENTATION OF THE PROBABILISTIC SAFETY MARGIN METHOD

5.1 ASTROS Modifications

Under this activity, two ideas were investigated within the ASTROS paradigm: the use of generic model uncertainty data to (1) augment the objective function; and (2) to augment or pad the design constraints. In the first case, the design would be biased to minimize the uncertainty; in the second, the design would impose a certain confidence level on the constraint satisfaction.

To implement these ideas within the ASTROS environment, several new FORTRAN modules were developed and changes were made to the ASTROS execution sequence to make use of the generic uncertainty database. The starting point was to transform the generic model uncertainty database into a scaled covariance matrix of parameters corresponding to the upper triangle of the generalized mass and stiffness matrices.

The generic modeling uncertainty is represented by the normalized covariance matrix

$$S_{\bar{r}\bar{r}} = \begin{bmatrix} S_{mm} & S_{m\tilde{k}} \\ S_{m\tilde{k}}^{T} & S_{\tilde{k}\tilde{k}} \end{bmatrix} \tag{5-1}$$

where m and $\tilde{k}$ represent the modal mass and frequency-normalized modal stiffness of generically similar structures [5-1,5-2,5-3]. This covariance matrix is derived from corresponding sets of modal analysis and test data gathered from previously analyzed and tested structures. Differences between analysis and test modes are expressed in terms of eigenvalue differences, $\Delta\lambda$, and the cross orthogonality between analysis and test modes, ψ. From these differences, differences between the analysis and test modal mass matrices

$$\Delta m = (I-\psi) + (I-\psi)^{T} \tag{5-2}$$

and modal stiffness matrices

$$\Delta k = {}^{o}\Delta\lambda + {}^{o}\lambda(I-\psi) + (I-\psi)^{T}\,{}^{o}\lambda \tag{5-3}$$

are computed, both referenced to the modes of the analytical model. The matrix, ${}^{o}\lambda$, in (5-3) is a diagonal matrix of the analytical eigenvalues. The matrix, Δk, is normalized to remove frequency dependence by pre- and post-multiplying Δk by the inverse of the diagonal matrix of modal frequencies, ${}^{o}\lambda^{-1/2}$. The resulting normalized matrix is

$$\Delta\tilde{k} = {}^{o}\lambda^{-1/2}\ \Delta k\ {}^{o}\lambda^{-1/2} \tag{5-4}$$

The upper triangular portions of Δm and $\Delta\tilde{k}$ are then vectorized to obtain the vector

$$\Delta\tilde{r} = \begin{Bmatrix} \text{vec}\,(\Delta m) \\ \text{vec}\,(\Delta\tilde{k}) \end{Bmatrix} \tag{5-5}$$

The covariance matrix, $S_{\tilde{r}\tilde{r}}$, is then computed by averaging the outer product of $\Delta\tilde{r}$ vectors from generically similar structures.

$$S_{\tilde{r}\tilde{r}} = \frac{1}{N}\sum_{i=1}^{N}\left(\Delta\tilde{r}_i\Delta\tilde{r}_i^{\mathrm{T}}\right) \tag{5-6}$$

This normalized generic covariance matrix can be used to represent the modeling uncertainty of any other structure belonging to the same generic family. This is done by rescaling $S_{\tilde{r}\tilde{r}}$ to obtain

$$S_{rr} = \begin{bmatrix} S_{mm} & S_{mk} \\ S_{mk}^T & S_{kk} \end{bmatrix} \tag{5-7}$$

where

$$S_{m_{ij}k_{hl}} = {}^o\omega_h {}^o\omega_l S_{m_{ij}\tilde{k}_{hl}} \tag{5-8a}$$

$$S_{k_{ij}k_{hl}} = {}^o\omega_i {}^o\omega_j {}^o\omega_h {}^o\omega_l S_{m_{ij}\tilde{k}_{hl}} \tag{5-8b}$$

and ${}^o\omega_i = {}^o\lambda_i^{1/2}$. Computation of the S_{xx} matrix was coded using a combination of MAPOL and new modules that perform the operations:

$$S_{xx} = \left[T_{rx}^T S_{rr}^{-1} T_{rx}\right]^{-1} \tag{5-9}$$

where T_{rx} is the matrix of sensitivities of the upper triangular components of the generalized mass and stiffness matrices referenced to the analytical modes, ${}^o\phi$.

$$T_{rx}\,\big|_{\text{mass}} = {}^o\phi^T \frac{\partial m}{\partial X}\,{}^o\phi \tag{5-10a}$$

$$T_{rx}\,\big|_{\text{stiffness}} = {}^o\phi^T \frac{\partial k}{\partial X}\,{}^o\phi \tag{5-10b}$$

Special ASTROS modules were written to perform these operations, since $\partial m / \partial x$ and $\partial k / \partial x$ do not exist as matrix entities in ASTROS.

These steps allowed the use of the S_{xx} matrix to perform the two studies. In the first case, the changes could be made within the DESIGN module by simple code modifications. In the second

case, new modules were written that computed a probabilistic displacement safety margin (constraint pad) to reach a certain level of confidence.

For each displacement component, the variance of a response variable, u is computed as:

$$\sigma_u^2 = E\left[\Delta u^2\right] = T_{ux} S_{xx} T_{ux}^T \tag{5-11}$$

where T_{ux} is the matrix of derivatives of the response, u, with respect to the design variables, x_i .

$$T_{ux} = \left[\frac{\partial u}{\partial x_1}, \frac{\partial u}{\partial x_2} \cdots \frac{\partial u}{\partial x_n}\right] \tag{5-12}$$

The first approach proved inconclusive within the ASTROS paradigm, since the design sensitivity of the weight uncertainty could not be computed from the existing ASTROS sensitivity information. The weight uncertainty itself is a function of the first derivative of the generalized mass and stiffness of the participating normal modes. ASTROS currently does not compute the higher derivatives, which would be needed to compute a first order approximation to the objective pad's derivative. Consequently, the optimal design point is not affected by adding a probabilistic safety margin to the objective function, since none of the objective or constraint derivatives are aware of the safety margin's effects. The safety margin methodology applied to constraints worked well, however, and new designs were obtained that satisfied the padded constraints.

This study prompted comparisons with an existing reliability-based optimization approach. One approach was implemented in ASTROS Version 11 by Luo and Grandhi [4-5]. In support of this effort, the Luo and Grandhi implementation was obtained and ported to ASTROS Version 12. Successful executions were obtained using the same ASTROS system that was used for the objective and constraint safety margin approaches. These comparisons led to a new method for reliability-based design optimization using a database of previously derived modeling uncertainty.

5.2 Numerical Example — Cantilever Box Beam

The first numerical example examined with the modified ASTROS code is based on the simple ten-element box beam shown in Figure 5-1. The box beam has a length, L, height, h, width, b, and wall thickness, t. The length is fixed but the height, width and thickness are design variables to be optimized for minimum weight. The performance constraint is that the static deflection at the free end of the beam is not to exceed u_0 under a tip load of F. Numerical values for the constant terms are:

F = 1000 lb.
u_0 = 0.2 in.
L = 120 in.
E = 1×10^7 lb./in.^{2}
γ = 0.1 lb./in.^{3}

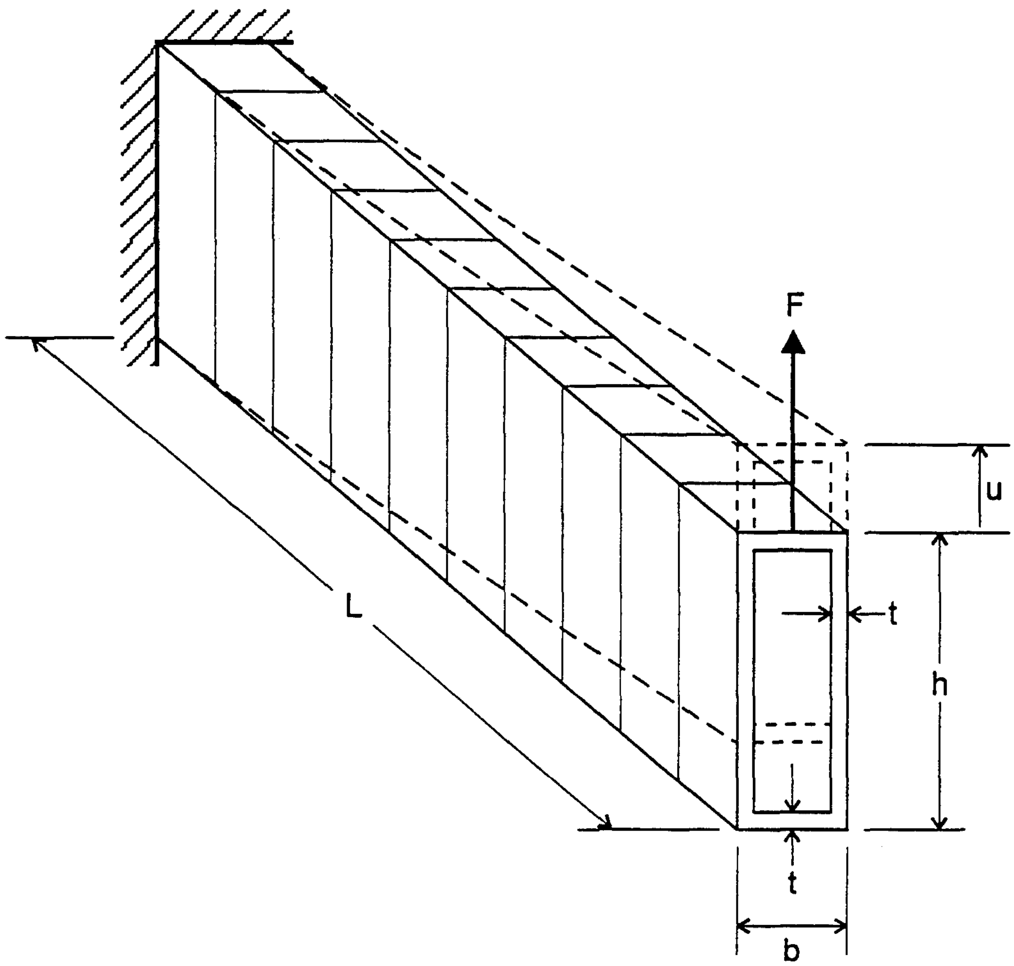

Figure 5-1. Geometry of Cantilever Box Beam

Numerical ranges for the design variables are:

$$x_1 = t = (0.1, 1.0) \text{ in.}$$
$$x_2 = b = (6, 30) \text{ in.}$$
$$x_3 = h = (6, 30) \text{ in.}$$

Three series of ASTROS runs were made. The first was a single deterministic optimization run to determine the optimum design under conditions of no modeling uncertainty. The results of deterministic optimization are:

t = 0.1 in.
b = 6.0 in.
h = 21.47 in.

W = 65.44 lb.
u = 0.194 in.

The second series was based on the assumption that the three design variables are uncorrelated, and that their respective uncertainties are defined by equal coefficients of variation (COV), i.e.

$$\Omega_1 = \Omega_2 = \Omega_3 = \Omega \qquad (5\text{-}13)$$

Several runs were made with COV's ranging from 5% to 20%. In addition several levels of reliability were chosen, including 90% ($\beta_0 = 1.3$), 99% ($\beta_0 = 2.3$), and 99.9% ($\beta_0 = 3.0$). The results of this series are summarized in Table 5-1.

The third series used a correlated parameter covariance matrix derived from a generic database of modeling uncertainty for space structures [5-1]. In this case, modeling uncertainty is determined by the $S_{\overline{rr}}$ matrix and the operations performed to obtain S_{xx} presented in Section 5.1. All three values of β_0 were run for this series. The results are summarized in Table 5-2.

The results of probabilistic design optimization using ASTROS for the Cantilever Box Beam are illustrated in Figure 5-2, where mean weights from the probabilistic design optimization are plotted as percentages of the weight obtained by deterministic design optimization. The three solid lines plot weight as functions of the safety index, β_0 , for 5%, 10%, and 20% coefficients of variation. The dotted line plots weight as a function of β_0 for the case where generic modeling uncertainty based on $S_{\overline{rr}}$ was used to quantify modeling uncertainty. It is of interest to note that modeling uncertainty based on real data (even though they were not box beam data) gave results corresponding to an equivalent parameter COV of about 7.5%.

It is also noted that the ASTROS run corresponding to a COV of 20% and a safety index of β_0 = 3.0 failed to converge. This evidently has something to do with the assumption of a constant COV, combined with high levels of modeling uncertainty and reliability. When constant standard deviations were specified instead of constant COV's, the optimization converged. With the constant COV approach, the standard derivations increase as the means of the design variables increase, leading to a potentially unstable solution.

This phenomenon was further explored with a specialized code using CONMIN as the optimization engine [5-4]. In this case the box beam was modeled as a single element with only 2 degrees of freedom (DOF) instead of the ten-element 20-DOF model in ASTROS. By limiting the code to constant COV and constant standard deviation applications (excluding the $S_{\overline{rr}}$ approach) it was not necessary to compute the modal frequencies so that only a purely static solution was required. A suite of runs with this code was made for comparison with the ASTROS results. This comparison is shown in Figure 5-3. The CONMIN results were slightly lower in all cases than the ASTROS results, but did converge for the 20% COV, $\beta_0 = 3.0$ case whereas the ASTROS solution did not. Even the deterministic CONMIN solution was slightly lower than that of ASTROS as indicated by the horizontal dashed line just below 100%. However, the differences between ASTROS and CONMIN are considered to be negligibly small, tending to corroborate both analyses.

Table 5-1. Mean Values of ASTROS-Optimized Design/Response Variables for the Cantilever Box Beam Using the PSM Method with Constant COV.

(a) Safety Index $\beta_o = 1.3$ ($P = 90\%$)

Design/Response Variables	Coefficient of Variation		
	5%	10%	20%
t in.	0.1	0.1	0.1
b in.	6.0	6.0	6.0
h in.	22.90	24.23	26.59
W lb.	68.93	72.15	77.90

(b) Safety Index $\beta_o = 2.3$ ($P = 99\%$)

Design/Response Variables	Coefficient of Variation		
	5%	10%	20%
t in.	0.1	0.1	0.1
b in.	6.0	6.0	6.0
h in.	23.97	26.13	29.80
W lb.	71.45	76.72	85.40

(c) Safety Index $\beta_o = 3.0$ ($P = 99.9\%$)

Design/Response Variables	Coefficient of Variation		
	5%	10%	20%
t in.	0.1	0.1	did not converge
b in.	6.0	6.0	
h in.	24.61	27.26	
W lb.	73.21	79.52	

Table 5-2. Mean Values of ASTROS-Optimized Design/Response Variables for the Cantilever Box Beam Using the PSM Method with Generic Modeling Uncertainty.

Design/Response Variables	Safety Index β_o , Reliability P		
	β_o 1.3, $P = 90\%$	$\beta_o = 2.3$, $P = 99\%$	$\beta_o = 3.0$, $P = 99.9\%$
t in.	0.1	0.1	0.1
b in.	6.0	6.0	6.0
h in.	23.55	24.99	25.74
f_1 Hz.	59.22	62.23	63.80
f_2 Hz.	315.82	327.79	333.87
f_3 Hz.	409.32	409.32	409.32
W lb.	70.45	73.89	75.71

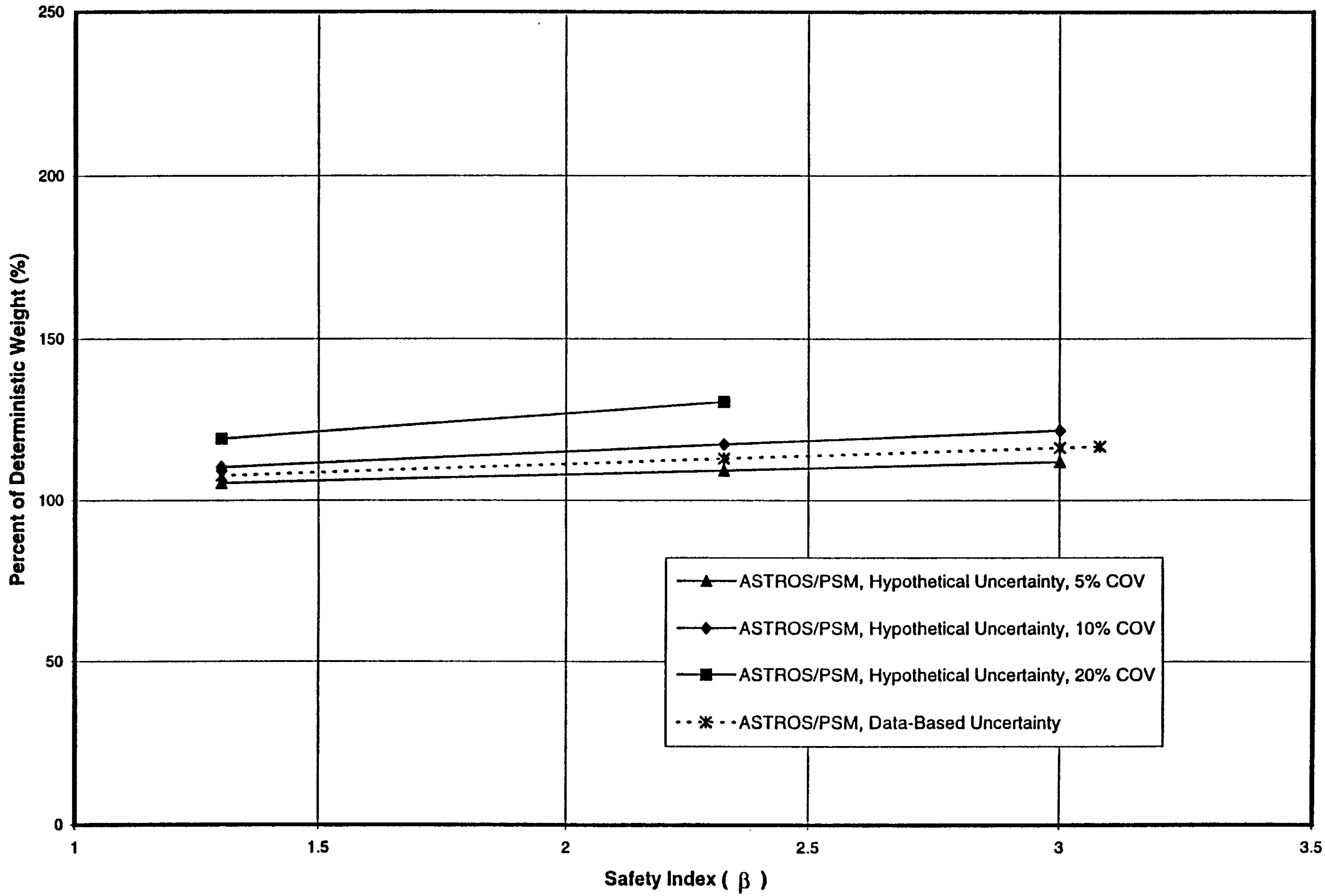

Figure 5-2. Comparison of Uncertainty Models for Cantilever Box Beam, Hypothetical vs. Data-Based Uncertainty

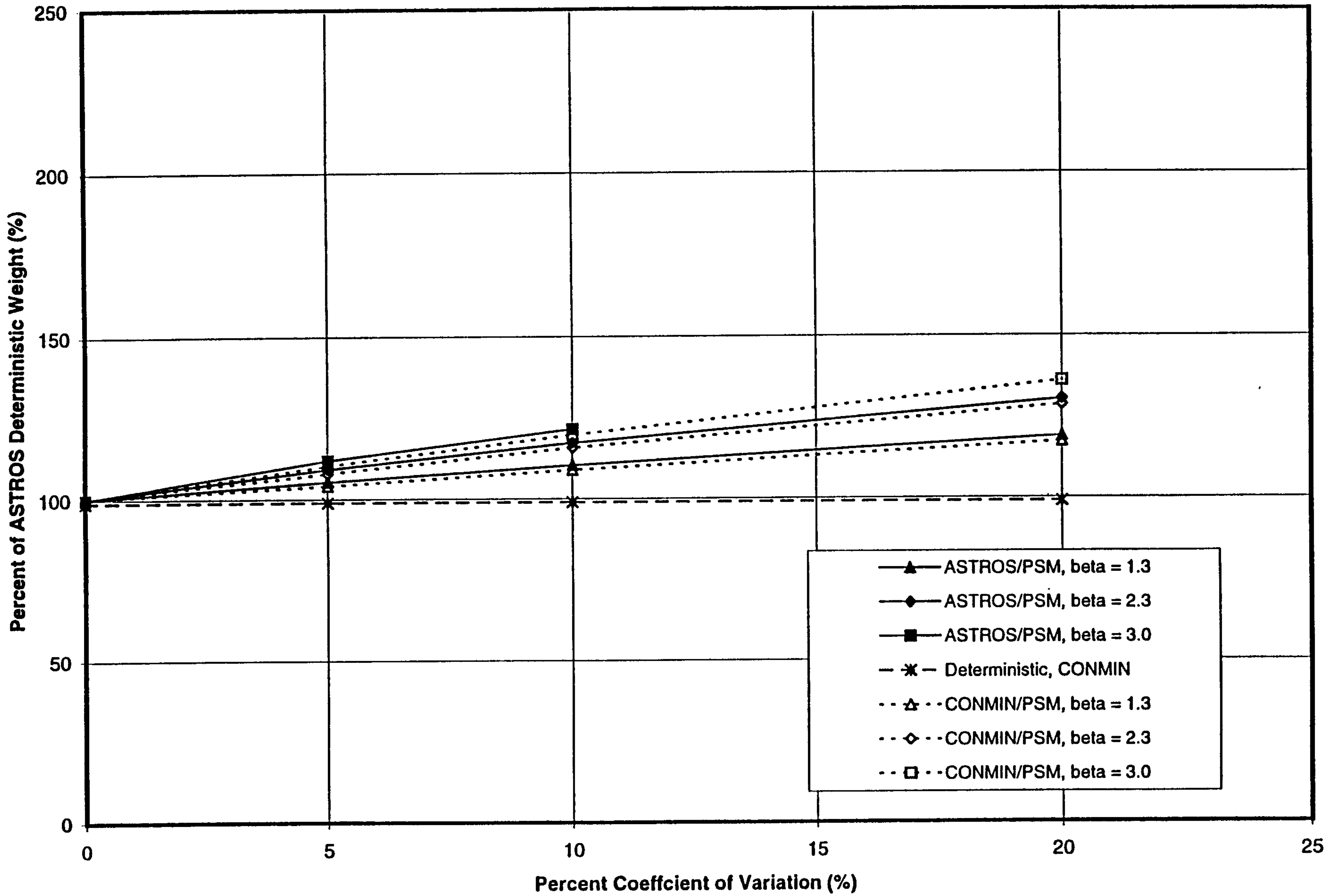

Figure 5-3. Comparison of PSM Optimzation Codes for Cantilever Box Beam, ASTROS vs. CONMIN

5.3 Comparison with Reliability-Based Optimization

Luo and Grandhi recently published results from their implementation of reliability-based optimization (RBO) in ASTROS [4-5]. In order to compare the results of the foregoing probabilistic safety margin (PSM) approach with Luo and Grandhi's RBO approach, the Intermediate Complexity Wing (ICW) example published in [4-5] was run using the modified version of ASTROS described in Section 5.1. A sketch of this model is shown in Figure 5-4.

The structural model of the Intermediate Complexity Wing uses 62 quadrilateral and 2 triangular membrane elements to model the wing skins, 55 shear panels to model the substructure, and 39 rod elements as posts to complete the interconnection of the upper and lower surfaces. The deterministic design problem minimizes the structural weight subject to the wing tip displacement constraint of 12.92 in. under static loads representing subsonic air load. Quadrilateral and triangular membrane elements representing the corresponding upper and lower skins are linked, resulting in 32 global design variables. The shear panels representing each spar and rib are linked, giving 11 global design variables. All rods are linked as one additional variable for a total of 44 global design variables. After 20 redesign cycles, deterministic optimization gives the minimum weight of 66.57 lb.

Luo and Grandhi performed a probabilistic design optimization for the ICW assuming a constant COV of 5%, and a safety or reliability index of 3.0883 corresponding to a 99.9% probability of nonexceedence on the wing tip displacement constraint. This increased the mean weight to 68.95 lb. The PSM approach applied to the same problem increased the mean weight to 69.34, almost the same as the weight obtained by Luo and Grandhi. A comparison of design variable scaling coefficients is shown in Table 5-3, where the scaling is relative to deterministically optimized values. Figure 5-5 plots these values for easier visualization.

Several observations can be made. The first is that the total weights obtained by the two methods reflect less difference than the individual design variables. While the two sets of design variables reflect somewhat the same trends for the skin elements (No.s 1 through 32), the trends for spar, rib and rod elements (No.s 33 through 44) are not similar. The second is that while the trends seem to indicate an overall decrease in weight relative to the deterministic design, the weight actually increases slightly. This is because the change is biased toward the elements that are already thicker, e.g. the third row of skin elements behind the leading edge of the wing.

These results prompted speculation that higher COV's might result in greater differences. Further comparisons were made. Table 5-4 compares the PSM results with those of Luo and Grandhi's RBO method for other levels of modeling uncertainty and reliability. The additional RBO results were graciously provided by Grandhi, when it was discovered that the version of the modified ASTROS code he had provided earlier handled stress constraints but not displacement constraints. These results are plotted in Figures 5-6 and 5-7. Figure 5-7 contains an expanded vertical scale so that the differences are more discernible.

No. of Nodes	No. of Elements	No. of DOF's
88	39 Rods	294 Constrained
	55 Shear Panels	234 Unconstrained
	62 Quadrilateral Membrane	528 Total
	2 Triangular Membrane	
	158 Total	

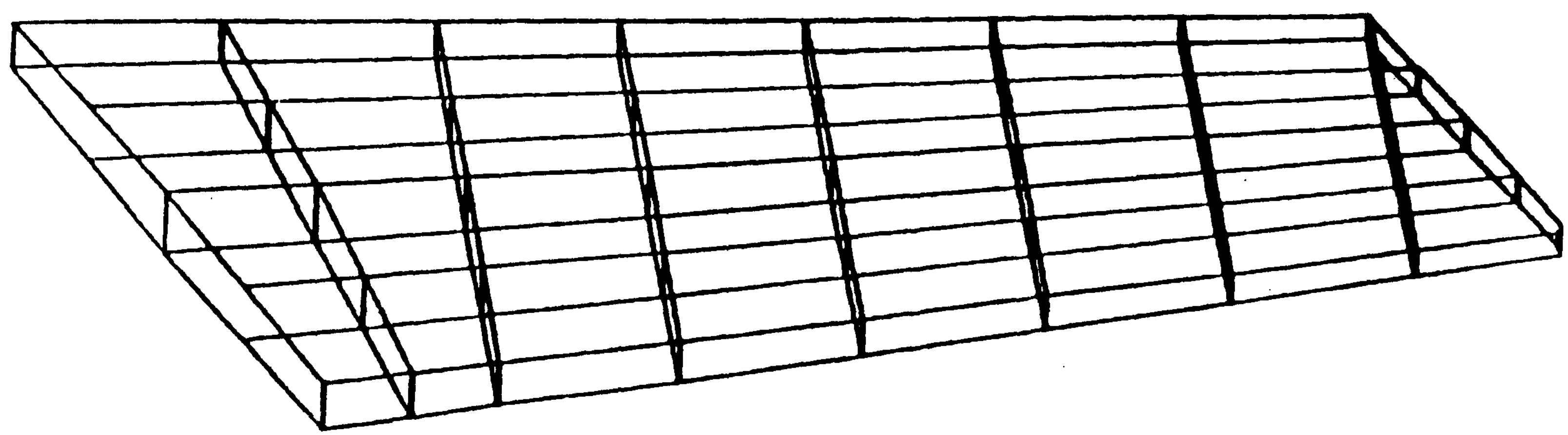

Figure 5-4. Finite Element Model for the Intermediate Complexity Wing (ICW)

Table 5-3. Comparison of Probabilistically Optimized Design Variable Scaling Coefficients, Relative to Deterministically Optimized Design, Obtained by PSM and RBO Methods for Intermediate Complexity Wing, $\beta_o = 3.0883$ (P = 99.9%)

Design Variable: Skin Thickness Ratio				Design Variable: Spar Thickness Ratio			
Location	ID	PSM	RBO*	Location	ID	PSM	RBO*
				Leading Edge	33	1.117	0.587
Wing Tip	1	1.026	1.090				
	2	1.022	0.952		34	1.033	0.999
	3	1.008	1.208				
	4	1.036	0.971	Trailing Edge	35	1.037	0.967
Leading Edge	5	1.021	0.895				
(Typ)	6	0.986	0.816				
	7	1.077	1.201	Design Variable: Rib Thickness Ratio			
Trailing Edge	8	1.036	0.924				
(Typ)				Wing Tip	36	1.008	0.985
	9	1.019	0.889				
	10	0.951	0.816		37	1.021	0.904
	11	1.103	1.155				
	12	1.018	0.897		38	1.036	1.203
	13	1.001	0.882		39	1.040	0.848
	14	0.931	0.818				
Mid Span	15	1.091	1.128		40	1.025	1.277
	16	1.012	0.896				
					41	1.0.31	0.882
	17	0.990	0.818				
	18	0.930	0.831		42	1.029	0.906
	19	1.072	1.102				
	20	1.020	0.930	Wing Root	43	1.057	1.007
	21	0.994	0.774				
	22	0.932	0.832				
	23	1.058	1.068				
	24	1.032	0.989	Design Variable: Post Area Ratio			
	25	1.002	0.876		44	1.039	0.779
	26	0.930	0.794				
	27	1.054	1.058				
	28	1.034	0.985				
Wing Root	29	1.010	1.091				
	30	0.919	0.759				
	31	1.061	1.073				
	32	1.030	0.996				

*Courtesy of Luo and Grandhi for ICW [4-5]

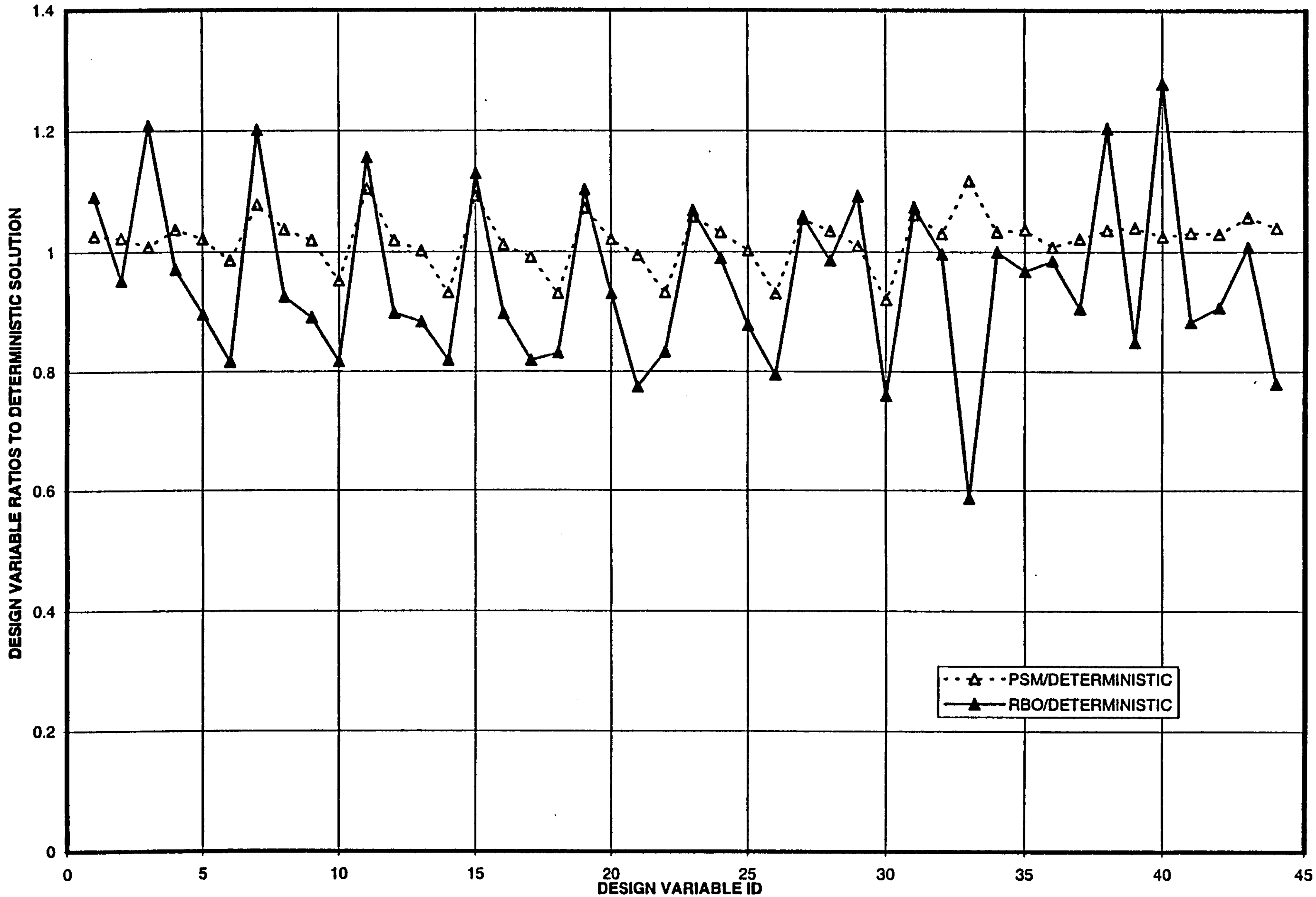

Figure 5-5. Comparison of Probabilistic-to-Deterministic Design Variable Ratios Obtained by the RBO and PSM Methods.

Table 5-4. Comparison of Mean Structural Weights for Probabilistic Design Optimization of the Intermediate Complexity Wing Using PSM and RBO* Methods.

(a) Safety Index $\beta_o = 1.3$ ($P = 90\%$)

Design Weight	Coefficient of Variation		
	5%	10%	20%
W (PSM) lb.	67.92	68.89	71.04
W (RBO) lb.	67.15	68.53	70.85

(b) Safety Index $\beta_o = 3.0$ ($P = 99.9\%$)

Design Weight	Coefficient of Variation		
	5%	10%	20%
W (PSM) lb.	69.10	71.78	76.63
W (RBO) lb.	68.89	71.70	78.25

* Modified-ASTROS Reliability-Based Optimization (RBO) results were provided by Luo and Grandhi for purposes of this project.

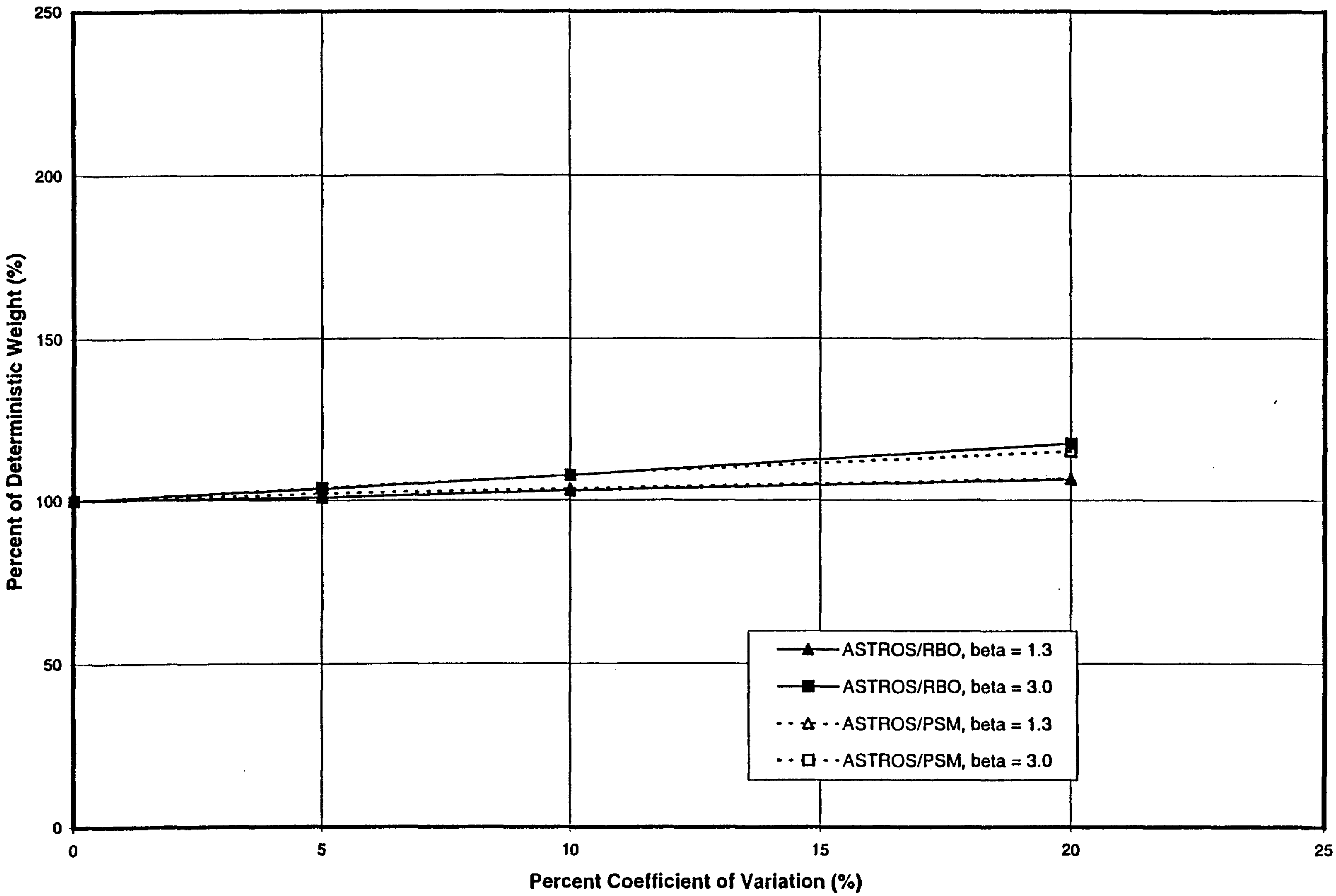

Figure 5-6. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Intermediate Complexity Wing.

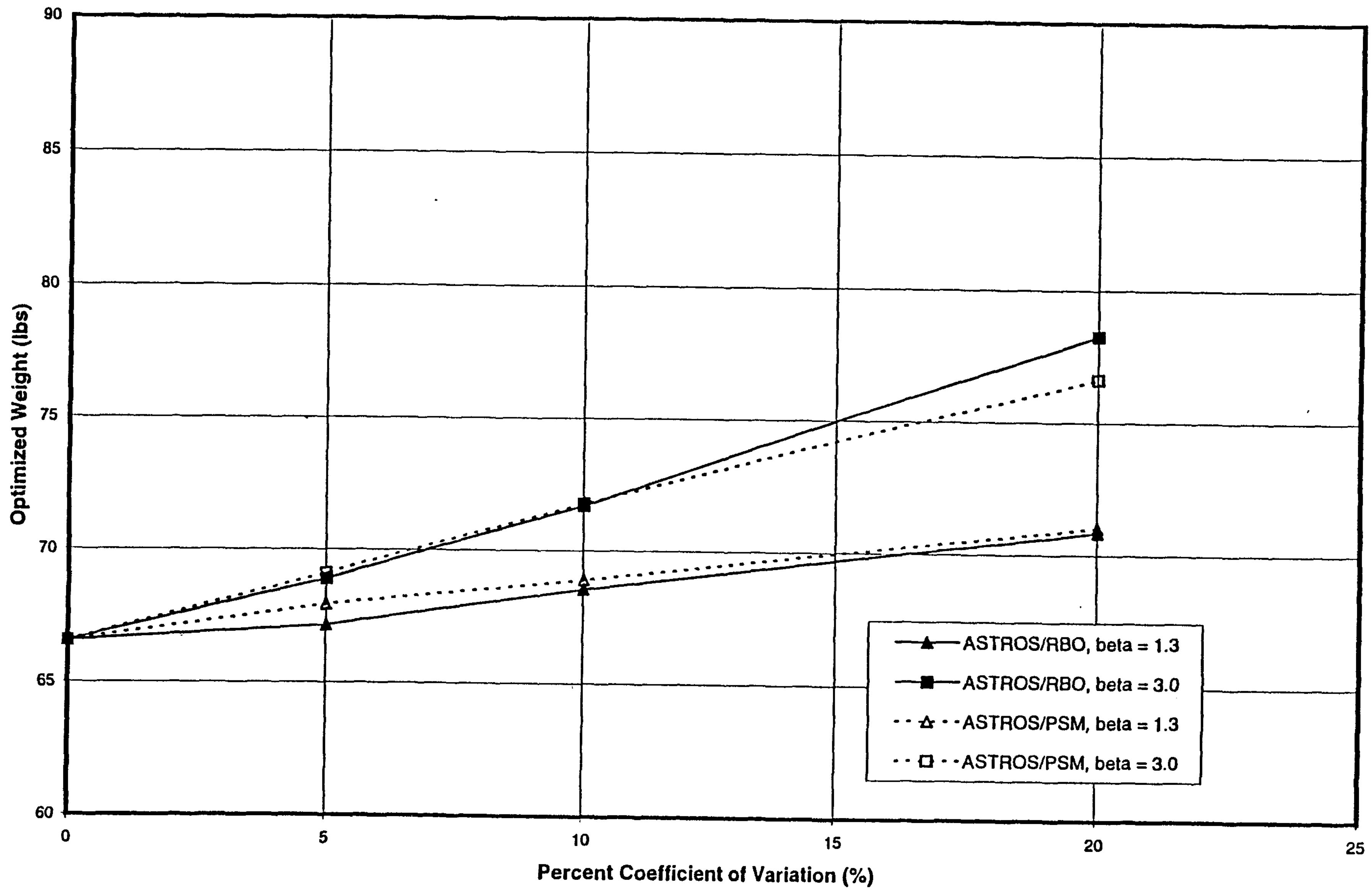

Figure 5-7. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Intermediate Complexity Wing (Expanded Vertical Scale).

There is a danger here that one should be aware of. Regardless of which design optimization method is used, they all depend on derivatives of global response variables, e.g. derivatives of wing tip displacement under static loading with respect to each of the design variables. When the design variables are very localized, as they are in the ICW example, these derivatives tend to be very small. That is, the sensitivity of global response to changes in a very localized parameter will be small. In extreme cases, accuracy will be lost due to roundoff error. In computing the change in global response due to many localized parameter changes, the result involves taking small differences of relatively large numbers, and accuracy suffers accordingly. The solution to this problem is to link design variables over broader regions of the structure so that in effect, the design variables are less localized. It is not apparent whether roundoff error is occurring in the present example. The pattern of skin thickness changes suggests not. However, the apparent randomness of spar and rib thickness changes may suggest otherwise.

In addition to the PSM optimization runs made with the hypothetical coefficients of variation, PSM runs were attempted with the generic uncertainty model, $S_{\bar{r}\bar{r}}$, used in the Cantilever Box Beam example. Several attempts were made with reliability levels ranging from 90% to 99.9%. Only the 90% run converged, and that convergence was achieved with some difficulty, i.e. by starting the optimization at different points in parameter space. The minimum weight design achieved in this example was 73.75 lb., even more than the 71.04 lb. shown for a constant COV of 20% in Table 5-3. Extrapolation of the constant COV results shown in Figure 5-6 indicates an equivalent COV on about 30% for the generic uncertainty model. This value is subject to question for the reasons discussed below.

The convergence difficulties referred to in the foregoing paragraph were traced to problems with rank deficiency and illconditioning of the $S_{\bar{r}\bar{r}}$ matrix. Rank deficiency is due to the fact that an S_{rr} matrix of rank 20 was transformed to a 44×44 S_{xx} matrix, corresponding to the 44 design variables. The illconditioning problem resulted from the frequency scaling used in transforming $S_{\bar{r}\bar{r}}$ to S_{rr} as shown in Equation (5-8). When these obstacles were artificially removed by "fooling" ASTROS, convergence was achieved, albeit with some difficulty. Proper reformulation of the computational procedures will eliminate these problems. The rank deficiency problem will be avoided by transforming the design space to the reduced, orthogonal, normalized space as described in Section 4.2. The illconditioning problem will be solved by transforming $S_{\bar{r}\bar{r}}$ directly to S_{xx}, without the intermediate transformation to S_{rr}.

Beyond these numerical problems, however, there remains a question of how one should define the design variables of a problem in a manner that is consistent with the information contained in $S_{\bar{r}\bar{r}}$. Keeping in mind that this information is derived by comparing global response quantities, one might expect that the structural design variables should be defined in such a way that they individually affect the global response metrics used to define generic modeling uncertainty. For example, in the case of the Intermediate Complexity Wing, it would be reasonable to link the skin thickness parameters over larger regions of the wing surface, not just the top and bottom opposing quadrilateral elements of the finite element model. A similar problem occurs in system identification, (or parameter estimation), when one attempts to estimate very localized parameters using global response data.

6. A NEW METHOD FOR RELIABILITY-BASED OPTIMIZATION

The numerical results compared in Section 5 indicate that the "probabilistic safety margin" (PSM) approach may provide a reasonable approximation to "reliability-based optimization" (RBO) for modest levels of uncertainty and modest levels of design reliability. Modest levels of modeling uncertainty are considered to range up to 10 or 15 percent, and modest levels of design reliability to 90 or 95 percent. When *both* modeling uncertainty and design reliability exceed these levels, the approximation deteriorates. Clearly, there are tradeoffs between the degree of modeling uncertainty and the desired degree of design reliability. An extremely reliable structure cannot be designed when modeling uncertainty is high, without paying a severe weight penalty. This is only common sense. On the other hand, if an exact solution to probabilistic design optimization is impractical due to the computational effort required, then neither approach may be satisfactory. Another method is needed.

This section presents a new method for reliability-based optimization with only a small increase in the computational effort over that of deterministic design optimization. While the method has not yet been implemented in ASTROS, it has been implemented independently and appears to be robust in terms of convergence from arbitrarily selected initial design points to the solutions determined by existing methods. Implementation in ASTROS has been examined and is considered to be feasible.

Following a brief summary of two existing reliability-based optimization methods, the new method is formulated and numerical examples are presented.

6.1 General Problem Statement

A general statement of the deterministic design optimization problem is given as follows:

$$\textit{Minimize}: \quad f(x) \tag{6-1a}$$

$$\textit{Subject to}: \quad g_j(x) \le 0; j=1,m \tag{6-1b}$$

$$\textit{and}: \quad x^L \le x \le x^U \tag{6-1c}$$

where, $f(x)$ is the objective function, x is a vector of design variables, x_i , $g_j(x)$ is a performance constraint, m is the total number of performance constraints, and x^L and x^U are the lower and upper bounds, respectively, on the vector of design variables.

When the design variables are random, Equation (6-1) implies a probabilistic optimization problem. The conventional approach is to convert the probabilistic optimization problem to an equivalent deterministic one. As a first step, the objective function is assumed to be a deterministic function of the mean, μ_x , of the random variable vector, x, which is deterministic.

Only the constraint conditions are expressed as functions of the random design variables, denoted x. The problem of (6-1) is then restated as

$$\textit{Minimize}: \quad f(\mu_x) \tag{6-2a}$$

$$\textit{Subject to}: \quad g_j(x) \geq 0\,;\, j = 1, m \tag{6-2b}$$

$$\textit{and}: \quad \mu_x^L \leq \mu_x \leq \mu_x^U \tag{6-2c}$$

One further modification of the problem statement is required to convert the constraint equations from functions that involve random variables, to alternative functions of deterministic variables. The standard reliability-based design approach is to assume that the random variables, g_j, are normally distributed with mean values, μ_{g_j}, and standard deviations, σ_{g_j}.

$$P_j\left[g_j(x) \geq 0\right] = \Phi\left(\beta_j\right) \tag{6-3}$$

where $\beta_j = \mu_{g_j} / \sigma_{g_j}$ as given in Eqn. (4-28) is the safety index for the jth constraint, defined as the shortest distance from the design point, μ_x, to the limit surface of the jth constraint in the reduced, uncorrelated, normalized design space, y, given by Eqn. (4-21). The object of reliability-based design is to determine a design point, μ_x, such that

$$\beta_j = \frac{\mu_{g_j}}{\sigma_{g_j}} \geq \beta_o \tag{6-4}$$

where β_0 represents the desired level of reliability, and

$$P_j = \Phi\left(\beta_j\right) \geq \Phi\left(\beta_o\right) = P_o \tag{6-5}$$

Finally then, a completely deterministic statement of the design optimization problem with a deterministic objective function and probabilistic constraints is

$$\textit{Minimum}: \quad f(\mu_x) \tag{6-6a}$$

$$\textit{Subject to}: \quad \beta_j \geq \beta_o \tag{6-6b}$$

$$\textit{and}: \quad \mu_x^L \leq \mu_x \leq \mu_x^U \tag{6-6c}$$

where β_j is evaluated for each constraint at $g_j(x) = 0$.

6.2 Existing Methods

Two different methods appear in the literature for solving the reliability-based optimization problem. The first may be called a "double-loop" method, represented by References [4-4, 4-5, 6-1 through 6-3]. It is called a "double-loop" method because it employs nested optimization loops to first locate the maximum probable failure point (MPP) on each of the limit surfaces, from which β_j and $\partial\beta_j / \partial\mu_x$ are determined, and then to optimize the design subject to $\beta_j \geq \beta_0$

The time-consuming part of ASTROS computations lies in the exact analyses which must be performed. ASTROS may execute hundreds of approximate analyses for every exact analysis, but the exact analyses dominate the computational effort. A typical deterministic run may involve tens of exact analyses. In contrast to deterministic design optimization, implementation of the double-loop method in ASTROS might involve hundreds or even thousands of exact analyses as described in [4-5]. Whereas only one exact analysis is required for each major cycle of deterministic analyses, the number of exact analyses required by the double-loop probabilistic method equals one, plus the number of constraints times the number of iterations required in the inner loop to converge on β_j. Luo and Grandhi reported in [4-5] that two or three iterations were required to reach convergence in the inner loop. Thus, a probabilistic problem with 50 constraints might run 100 to 150 times longer than the same problem run deterministically. The double-loop method is not considered viable for practical application.

The second method may be called a "double-design-variable" method, represented by References [4-3, 6-4]. It employs a single loop to optimize the design, but for a problem involving a single constraint, it considers both the mean values of the design variables and the MPP values as *separate* design variables, in effect doubling the number. For a problem with n design variables and m constraints, this method assumes that there are $n(1+m)$ separate design variables!

Thanedar and Kodiyalam in Reference [6-4] report that for simple problems involving only 4 or 5 performance constraints, solution of the probabilistic design optimization problem requires 5 to 10 times the computational effort required to obtain a deterministic solution. These authors also conclude that the method is impractical for realistic applications.

The "double-loop" and "double-design-variable" (or "double-design-vector") methods for reliability-based optimization (RBO) may be identified as DLSV and SLDV methods, respectively, because the first employs a "double-loop-single vector" approach, while the second employs a "single-loop-double-vector" approach. The new method introduced in Section 6.3 is identified as a SLSV method, because it employs a "single-loop-single-vector" approach.

6.3 A New Method

A new method is proposed for probabilistic design optimization that achieves the same results as the foregoing two methods, but at a fraction of the cost. It is a single-loop method that does not increase the number of design variables. Instead of order of magnitude increases over deterministic design optimization, this method is conservatively estimated to increase the cost by less than a factor of two, perhaps significantly less. It is applicable to large practical problems ASTROS environment. Numerical examples have demonstrated the robustness of the method.

The method is derived in a reduced, uncorrelated, normalized parameter space similar to y, as defined in (4-21), *but unshifted.* This parameter space is denoted by z, where

$$z_i = \frac{x_i}{\sigma_{x_i}} \tag{6-7}$$

The mean value of z_i is denoted by μ_{z_i} and the vectors of z_i and μ_{z_i} are denoted by z and μ_z, respectively. The limit surfaces,

$$g_j(x) = g_j(\sigma_x z) = 0 \tag{6-8}$$

unlike those defined in y-space,

$$g_j(x) = g_j(\mu_x + \sigma_x y) = 0$$

are not functions of μ_x provided that σ_x is constant, and therefore are fixed in z-space as the search for an optimum μ_x moves μ_x around. For notational convenience, the constraint expressed in (6-8) will be written in z-space as

$$g_j(\sigma_x z) = G_j(z) \tag{6-9}$$

and the corresponding limit surface as,

$$G_j(z) = 0 \tag{6-10}$$

The distance between a point z and μ_z is expressed as,

$$D = \left[(z-\mu_z)^{\mathrm{T}}(z-\mu_z)\right]^{\frac{1}{2}} \tag{6-11}$$

The point on the limit surface, z^*, giving the minimum distance between z and μ_z is determined by minimizing the distance, D. The problem is stated,

$$\textit{Minimize}: \ D(z) \tag{6-12a}$$

$$\textit{Subject to}: \ G_j(z) = 0 \tag{6-12b}$$

A parallel derivation to that in [4-1], as summarized in Section 4.1.2, leads to the following equation,

$$z^* - \mu_z = \pm \beta \alpha^* \tag{6-13}$$

analogous to (4-31), where α^* is the vector of direction cosines

$$\alpha_i^* = \frac{\left(\frac{\partial g}{\partial z_i}\right)^*}{\left[\sum_i \left(\frac{\partial g}{\partial z_i}\right)^{*2}\right]^{\frac{1}{2}}} = \frac{\sigma_{x_i}\left(\frac{\partial g}{\partial x_i}\right)^*}{\left[\sum_i \sigma_{x_i}^2 \left(\frac{\partial g}{\partial x_i}\right)^{*2}\right]^{\frac{1}{2}}} \tag{6-14}$$

analogous to (4-29). The vector, α^*, is also recognized as a unit vector normal to the limit surface, $G(z)=0$, at the most probable failure point (MPP), z^*. That is,

$$\alpha^* = \nabla_z G(z) / \| \nabla_z G(z) \| \tag{6-15}$$

evaluated at z^*. Eqn. (6-13) implies that the vector, $(z^* - \mu_z)$, is parallel to the vector, α^*, and equal to the distance between $G(z) = 0$ and μ_z, in the direction normal to $G(z) = 0$, at $z = z^*$. This distance is, equal to β and is non negative. Therefore, if α and $(z^* - \mu_z)$ are pointed in the same direction, the sign in Eqn. (6-13) is positive. Otherwise it is negative. If the safe side of $G(z)$ is positive, then the constraint is $G(z) \geq 0$ and $(z^* - \mu_z)$ will be negative. Conversely, if the safe side of $G(z)$ is negative, then the constraint is $G(z) \leq 0$ and $(z^* - \mu_z)$ will be positive.

Up to this point the only difference between the development of Section 4.1.2 in Eqns. (4-21) through (4-31), and that presented here in Eqns. (6-7) through (6-14), is the change of variables from y to z. This change of variables is reflected in the two equations, (4-31) and (6-13). Without loss of generality, one may choose the form of (6-13) corresponding to $G(z) \geq 0$, in which case (6-13) becomes,

$$z^* = \mu_z - \beta\alpha^* \tag{6-16}$$

The key to the new method is to recognize that z^* and μ_z are relate by β, *which is known provided that β is specified as the desired safety factor*, β_0. With this approach, one may visualize a companion surface to $G(z) = 0$, defined by the locus of points

$$\mu_z = z^* + \beta_o\alpha^* \tag{6-17}$$

Thus, there is no need for a second (inner) optimization loop to determine β, because β is specified. And, there is no need to double the number of design variables, because (6-17) determines the relationship between them, i.e. between μ_z and z^*.

With this insight, the optimization problem stated in (6-6) can be restated as follows:

$$Minimum: \quad f(\mu_x) \tag{6-18a}$$

$$Subject\ to: \quad G_j(z) \geq 0 \tag{6-18b}$$

$$and: \quad \mu_x^L \leq \mu_x \leq \mu_x^U \tag{6-18c}$$

$$where: \quad z_j = \mu_z - \beta_o \alpha_j^* \tag{6-18d}$$

Since α_j^* is a function of z_j, (6-18) must be solved iteratively. That is, an iterative solution is obtained, where α_j^* from the previous iteration is used to evaluate z_j in the current iteration. This procedure can be summarized as follows:

$$Minimize: \quad f\left(\mu_x^{(k)}\right) \tag{6-19a}$$

$$Subject\ to: \quad G_j\left(z^{(k)}\right) \geq 0 \tag{6-19b}$$

$$and: \quad \mu_x^L \leq \mu^{(k)} \leq \mu_x^U \tag{6-19c}$$

$$where: \quad z_j^* = \mu_z^{(k)} - \beta_o \alpha_j^{*(k-1)} \tag{6-19d}$$

$$and\ where: \quad \alpha_j^{*(k-1)} = \nabla_z G\left(z^{(k-1)}\right) / \|\nabla_z G\left(z^{(k-1)}\right)\| \tag{6-19e}$$

The new method is efficient because there is no need to calculate a safety index, β_j, for each constraint. This eliminates the entire inner loop of the double-loop method. The method does not require additional derivative calculations, which eliminates the need for additional exact analyses in ASTROS. Therefore, it should converge at approximately the same rate as deterministic design optimization. There is one aspect of the solution that may increase the computational effort slightly. It will be necessary at the outset to evaluate all constraint derivatives to identify potentially active constraints, and obtain an initial value of μ_x to start the iterations. Thereafter it may be necessary to retain a larger number of potentially active constraints compared with those normally retained for deterministic design optimization.

The following procedure is suggested for obtaining an initial value, $\mu_x^{(0)}$, of μ_x. It begins with the selection of a starting point, $x^{(0)}$, in design space. This point is used to evaluate all of the constraint gradients (sensitivities). These gradients are used first to identify the active constraints, and then to determine the initial unit vector, $\alpha^{(0)}$, and an initial set of "mean" design variables, $\mu_x^{(0)}$, to begin the optimization. The initial design point, $\mu_x^{(0)}$, is determined by,

$$\mu_x^{(0)} = \sigma_x \mu_z^{(0)} = \sigma_x\left(z^{(0)} + \beta_0 \alpha^{(0)}\right)$$

$$= x^{(0)} + \beta_0 \sigma_x \alpha^{(0)} \tag{6-20}$$

where σ_x in this case is a diagonal matrix of standard derivations of the elements, x_i, of the vector, x. The vector, $\alpha^{(0)}$, is determined by evaluating the vector, $\alpha_j^{(0)}$, for each active constraint at the design point, $x^{(0)}$. The vector, $\alpha^{(0)}$, is then determined by summing the vectors, $\alpha_j^{(0)}$, to obtain a resultant vector, and then normalizing the resultant vector to unit length. This operation may be written,

$$\alpha^{(0)} = \frac{\sum_j \alpha_j^{(0)}}{\|\sum_j \alpha_j^{(0)}\|} \tag{6-21}$$

A flow chart illustrating implementation of the new method is shown in Figure 6-1. It begins with the input of an arbitrary point in design space, $x^{(0)}$. All m' constraint derivatives are initially evaluated at this point as a basis for selecting a subset, m, of "potentially active" constraints. Then an initial evaluation of normalized constraint gradient vectors, $\alpha_j^{(0)}$ is made for the m constraints. A resultant unit vector, $\alpha^{(0)}$, is then computed for the calculation of $\mu_x^{(0)}$. This vector, $\mu_x^{(0)}$, is input to the optimizer to obtain a new vector, of $\mu_x^{(1)}$, which in turn is used to update the vectors, x_j, giving $x_j^{(1)}$. The previous values of $\alpha_j^{(0)}$ are used for this computation. After obtaining $x_j^{(1)}$, the constraint gradient vectors are recalculated at $x_j^{(1)}$ for input to the next optimization cycle. Meanwhile, α_j^{*} is updated, using the new constraint derivatives, for the next computation of x_j. The vectors μ_x and x_j are alternately updated until the computations converge to a final probabilistic design, μ_x, and a set of final MPP vectors, x_j^{*}, for the active constraints.

Because this method is implemented with only a single optimization loop, and in essence has only a single vector of design variables, μ_x, where all of the x_j^{*} s are related to μ_x through the constraint derivatives from the previous design iteration, it is referred to as a reliability-based optimization "single-loop-single-design-vector" or RBO/SLSV method.

6.4 Numerical Examples

The foregoing method was implemented with a special-purpose code using CONMIN for the optimization engine. The double-design-variable (SLDV) method was also implemented for verification purposes. Both specialized codes were tested with the same numerical examples and found to give virtually identical results. This tends to corroborate both methods.

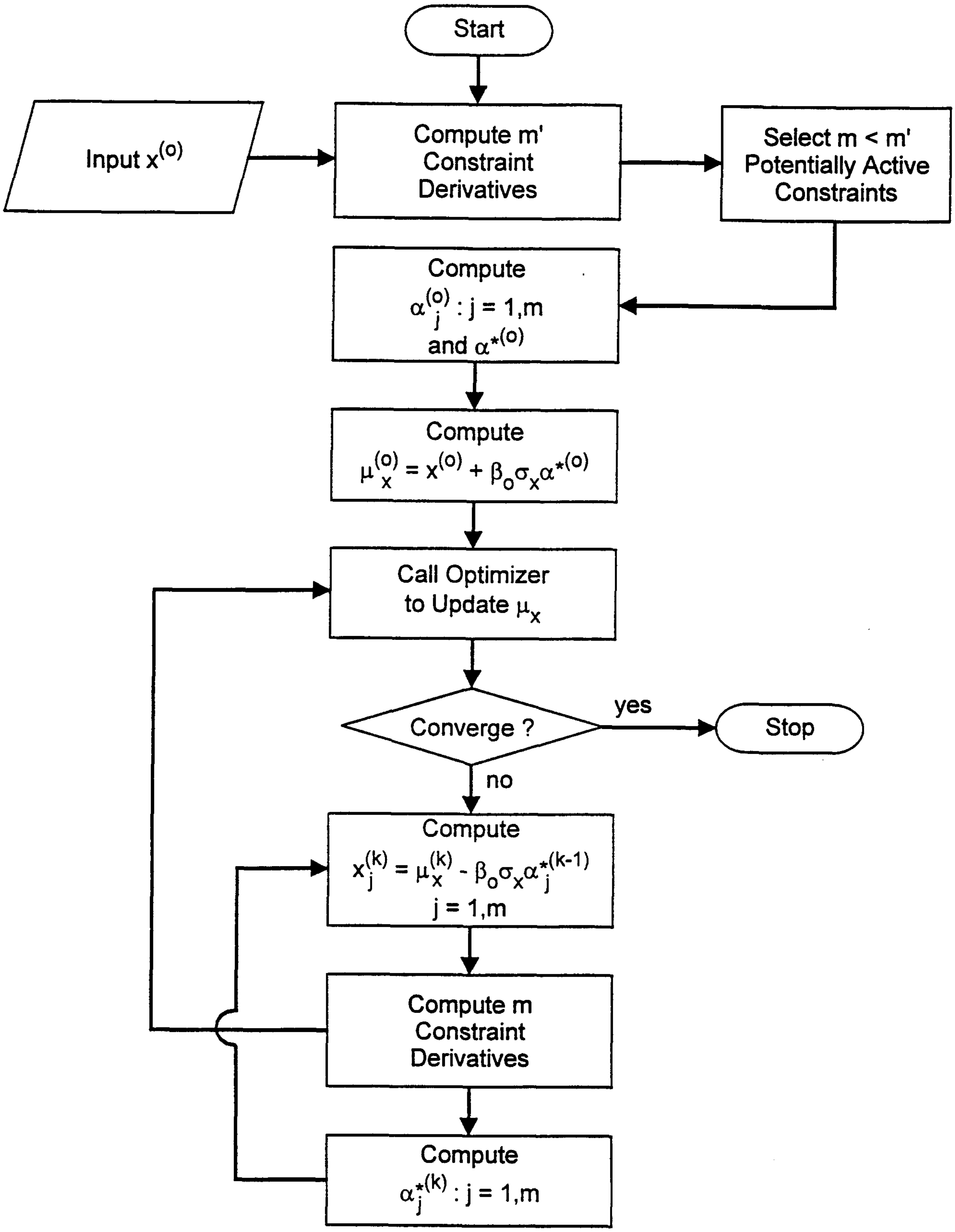

Figure 6-1. Flowchart for Implementation of RBO/SLSV Method

The first example is the Cantilever Box Beam described in Section 5.2. This example was again run with COV's of 5% to 20% and reliability levels of 90%, 99% and 99.9%. The results are summarized in Table 6-1, and illustrated in Figure 6-2. Figure 6-2 again plots the mean weight (i.e. the weight corresponding to the optimized mean design variables) as functions of increasing parameter uncertainty represented by a constant COV for all design variables. The parameter relating the three curves is the safety index or reliability level. The Probabilistic Safety Margin (PSM) results from Figure 5-3 are also plotted (dotted lines) for comparison. Both sets of results reflect a constant COV assumption, i.e. parameter standard derivation is determined by multiplying a variable mean by a constant COV. The last case associated with the RBO/SLSV method did not converge, but the pattern of these results suggests the possibility of an unstable solution when a constant COV is assumed.

What is most striking in Figure 6-2 is the relatively large weight penalty paid for high reliability, even with modest levels of parameter uncertainty. This, fortunately, can be attributed to the oversimplification of the example. Unlike the more realistic ICW example presented in Section 5.3, where many design variables allowed weight increases to be concentrated in the region of maximum strain, i.e. near the root of the wing, the Cantilever Box Beam is uniform along its entire length. Thus, in order to limit tip deflection, the entire beam is stiffened, adding material near the free end where it contributes little to the stiffness.

Aside from this unrealistic aspect of the problem, it is interesting to note, as in the case of the ICW, that the weight penalty increases by disproportionately large amounts as uncertainty and reliability both increase. This effect is believed to be real. The PSM method does not appear to reveal it. The PSM method provides a reasonable approximation only up to about 10% uncertainty and 90% reliability in this case.

The second example is a simplification of the ICW, where a uniform flat box beam was sized to have the same length, average width and depth as the actual ICW, and the same stiffness when acted upon by a uniformly distributed transverse load. This model is illustrated in Figure 6-3. Instead of three design variables, it has only two, the thickness of the top and bottom walls, t_1, and that of the side walls, t_2. The performance constraint is that the tip deflection not exceed u_0 under a uniformly distributed transverse load totaling F lbs. Numerical values of the constant terms are:

F = 43315.8 lb.
u_0 = 12.90 in.
L = 90.0 in.
b = 38.67 in..
h = 3.94 in.
E = $1 \times 10.^7$ lb./in.^{2}
γ = 0.1 lb./in.^{3}

Numerical ranges for the two design variables are:

$x_1 = t_1$ (0.015, 0.30) in.
$x_2 = t_2$ (0.015, 0.30) in.

Table 6-1. Mean Values of ASTROS-Optimized Design/Response Variables for the Cantilever Box Beam Using the RBO/SLSV Method with Constant COV.

(a) Safety Index $\beta_o = 1.3$ ($P = 90\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t in.	0.1	0.1	0.1	0.1001
b in.	6.0	6.0	6.0	6.0
h in.	22.75	24.57	26.67	29.17
W lb.	68.53	72.89	77.93	83.80
u in.	0.169	0.137	0.116	0.089

(b) Safety Index $\beta_o = 2.3$ ($P = 99\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t in.	0.1	0.1	0.1	0.1001
b in.	6.0	6.0	9.89	19.72
h in.	24.17	28.06	30.00	30.00
W lb.	71.95	81.26	95.25	118.86
u in.	0.143	0.097	0.065	0.044

(c) Safety Index $\beta_o = 3.0$ ($P = 99.9\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t in.	0.1	0.1	0.1	did not converge
b in.	6.0	6.98	18.03	
h in.	25.18	30.00	30.00	
W lb.	74.36	88.27	114.78	
u in.	0.128	0.077	0.046	

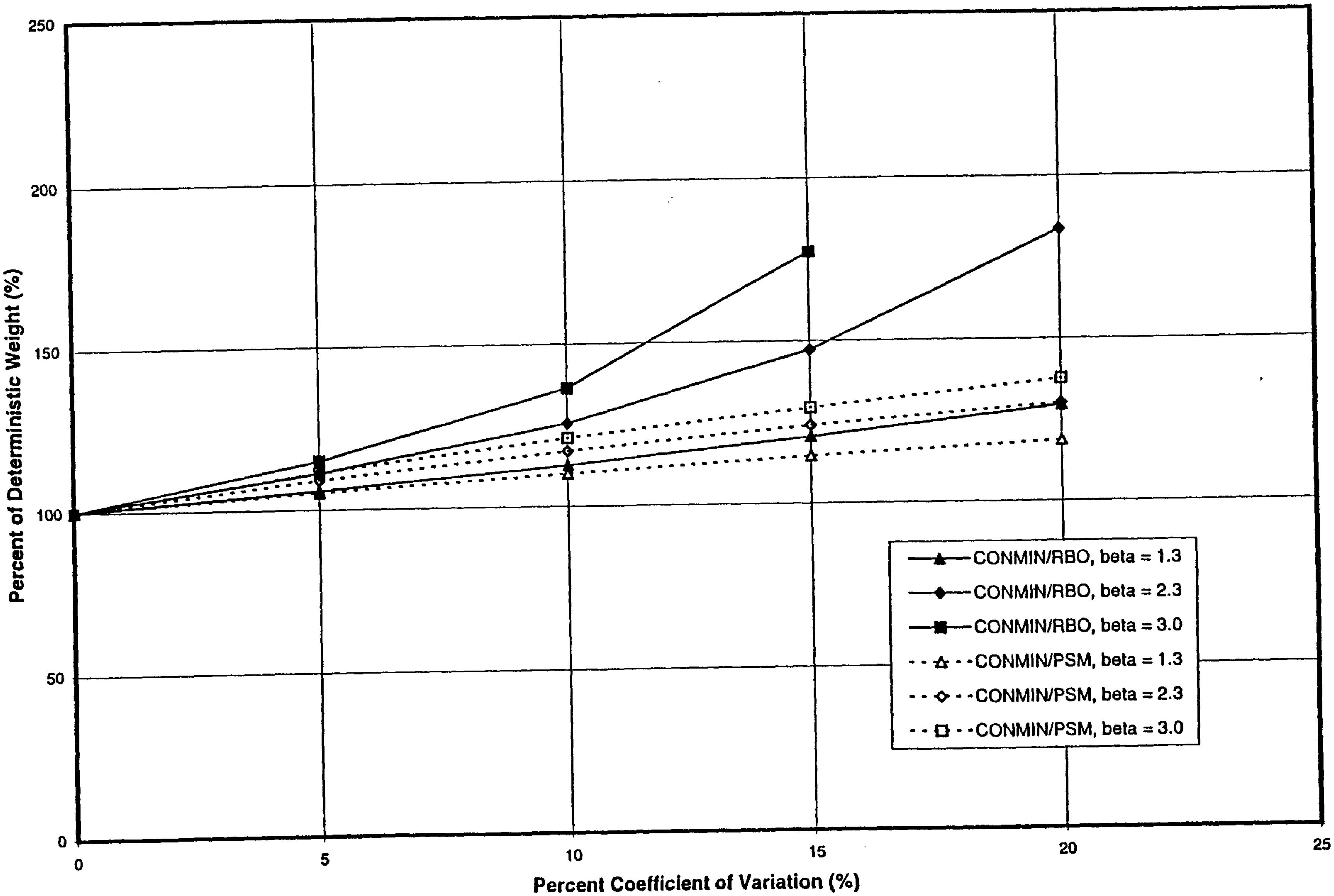

Figure 6-2. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Cantilever Box Beam

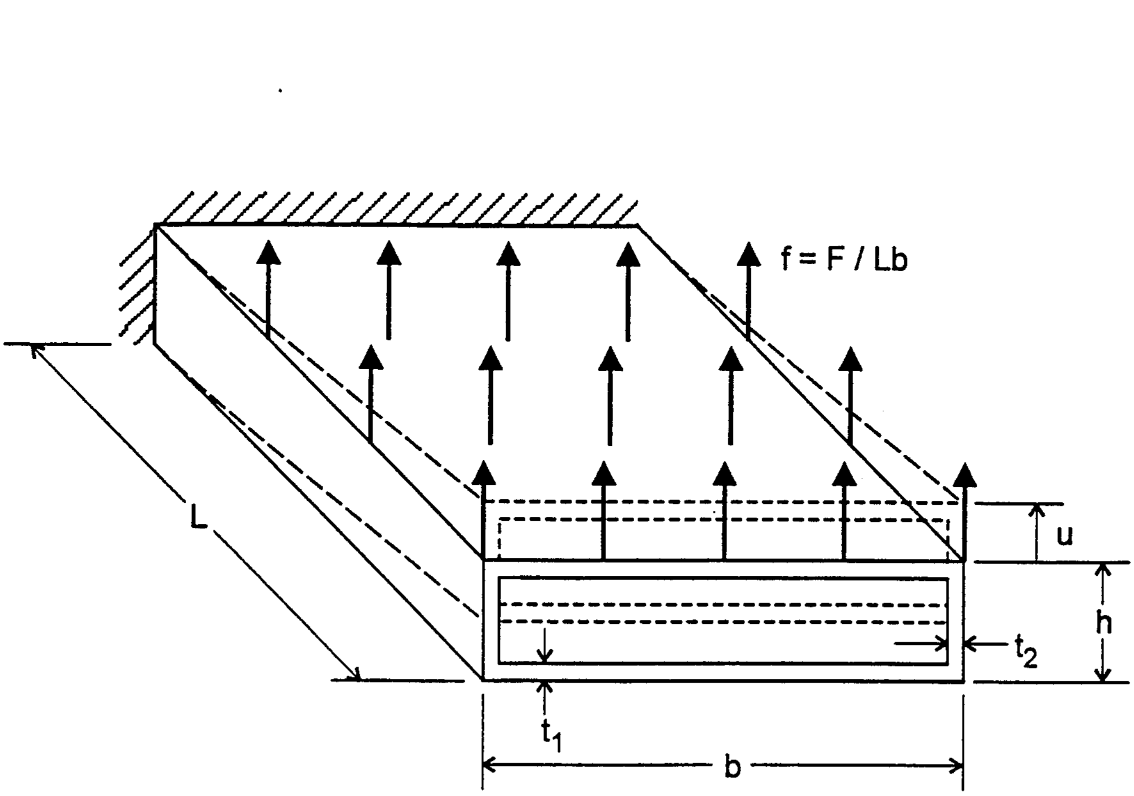

Figure 6-3. Geometry of Simplified ICW.

Three series of runs were made. The first was a single deterministic optimization run to determine the optimium design under conditions of no modeling uncertainty. The results of deterministic optimization are:

t_1 = 0.1018 in.
t_2 = 0.015 in.

W = 71.89 lb.
u = 12.90 in.

In the second and third series of runs, probabilistic design optimization was performed using both PSM and RBO approaches. The SLSV method was used for the latter. Numerical results are summarized in Tables 6-2 and 6-3, respectively, where the mean design values for the two design variables, t_1 and t_2, and corresponding values for the mean structural weight, W, and mean tip deflection, u, under the uniformly distributed static load, F, are presented. Coefficients of variation range from 5% to 20%, for reliability levels of 90% and 99.9%.

These results are plotted in Figure 6-4, where the percentages of the deterministic optimum design weight are plotted as functions of COV, with safety index or reliability as a parameter. As in the case of the Cantilever Box Beam, these results for the Simplified ICW example show that the PSM approach gives a good approximation of the RBO results for modest levels of uncertainty and reliability. However, at higher levels of both, the RBO approach gives dramatically higher weights. Of course, the same observation made in reference to the Cantilever Box Beam example about oversimplification applies here also. Meeting the performance constraint on displacement by uniformly increasing the stiffness of the box beam along its entire

Table 6-2. Mean Values of Optimized Design/Response Variables for the Simplified ICW Using the PSM Method with Constant COV.

(a) Safety Index $\beta_o = 1.3$ ($P = 90\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t_1 in.	0.1085	0.1151	0.1217	0.1283
t_2 in.	0.015	0.015	0.015	0.015
W lb.	76.49	81.10	85.71	90.31
u in.	12.16	11.50	10.91	10.39

(b) Safety Index $\beta_o = 3.0$ ($P = 99.9\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t_1 in.	0.1171	0.1324	0.1477	0.1629
t_2 in.	0.015	0.015	0.015	0.015
W lb.	82.51	93.14	103.77	114.38
u in.	11.31	10.09	9.12	8.34

Table 6-3. Mean Values of Optimized Design/Response Variables for the Simplified ICW Using the RBO/SLSV Method with Constant COV.

(a) Safety Index $\beta_o = 1.3$ ($P = 90\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t_1 in.	0.1089	0.1170	0.1265	0.1376
t_2 in.	0.015	0.015	0.015	0.015
W lb.	76.81	82.47	89.04	96.77
u in.	12.11	11.32	10.53	9.74

(b) Safety Index $\beta_o = 3.0$ ($P = 99.9\%$)

Design/Response Variables	Coefficient of Variation			
	5%	10%	15%	20%
t_1 in.	0.1198	0.1455	0.1851	0.2546
t_2 in.	0.015	0.015	0.015	0.015
W lb.	84.39	102.24	129.83	178.12
u in.	11.08	9.25	7.43	5.61

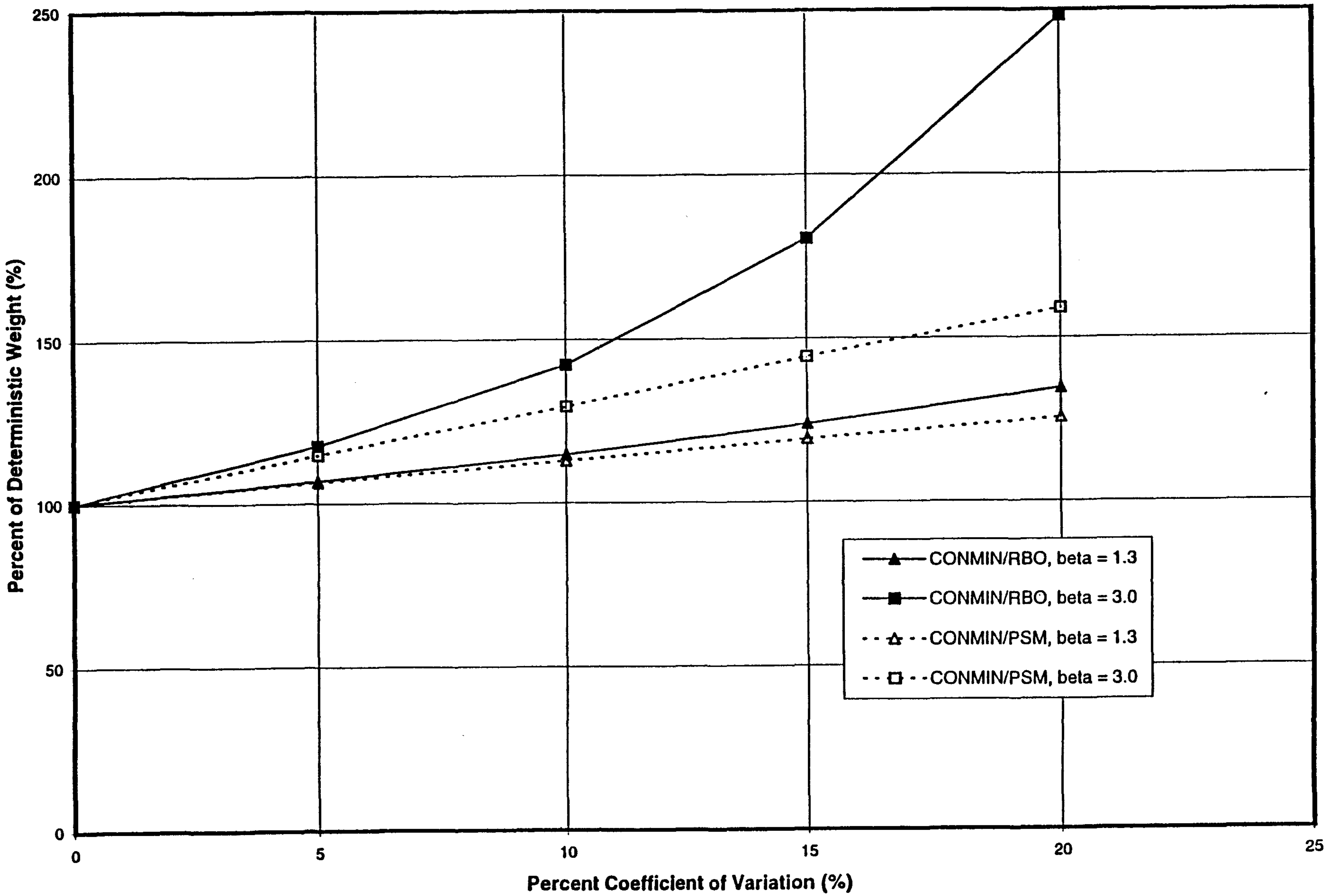

Figure 6-4. Comparison of RBO and PSM Probabilistic Design Optimization Methods for the Simplified ICW

length increased the weight of the beam near the free end where it contributed little to reducing tip deflection.

The purpose of these examples is to demonstrate the new RBO/SLSV method, and compare it with the PSM method originally proposed. The PSM approach was shown in Section 5 to provide a reasonably good approximation to the RBO approach for modest levels of uncertainty and reliability, and clearly offers a cost advantage over existing RBO methods which are estimated to require orders of magnitude more computational effort than deterministic optimum design or probabilistic optimum design using the PSM method. However, the new RBO/SLSV method promises to achieve RBO accuracy with little additional cost over deterministic optimum design or the PSM approach. It is therefore recommended for implementation in ASTROS and further investigation in Phase II.

7. MODELING UNCERTAINTY DATABASE

A major component of the proposed approach to probabilistic design optimization is the development of an experiential database of modeling uncertainty. Modeling uncertainty is this context is defined in terms of the difference between analytically predicted and experimentally measured natural frequencies and mode shapes from ground vibration tests and analytical test support. A brief outline of the basic methodology was given in Section 5.1. Details of the methodology and its successful application to space structures is contained in References [5-1 to 5-3].

A database of modeling uncertainty derived from space structures data was used in this study for purposes of demonstration. The real goal is to derive a similar database for aircraft structures. As presently envisioned, the database would be partitioned into different generic categories, distinguishing between fighter/attack aircraft and transport aircraft, for example. Depending on the availability of data, one might further subdivide the data into component categories, such as wings, tail sections and control surfaces.

Preliminary inquiries have been made of several aircraft manufacturers to determine the availability of the type of data required to compile such a database, and the willingness of manufacturers to provide data for this project. Inquiries so far have been made to both the military and commercial aircraft sides of McDonnell Douglas in Long Beach, CA, Rockwell Aerospace in Seal Beach, CA, and Boeing Commercial Airplane Company in Seattle, WA. Positive responses so far have been received from Rockwell and both sides of McDonnell Douglas. In the case of the C-17, for example, several data sets have been identified as shown in Table 7-1. This is typical of what may be expected for other aircraft.

Much more data are believed to be available from the industry. Table 7-2 contains a list of manufacturers of military aircraft currently in production or recently in production, that will be contacted in Phase II. Those companies that use ASTROS, such as Rockwell Aerospace, are particularly good candidates for data suppliers.

As part of the task of building this database, it will be necessary to investigate what types of design variables can best be optimized with available modeling uncertainty data. For example, the experience discussed in Section 5.3 relative to the use of generic modeling uncertainty for probabilistic design optimization of the Intermediate Complexity Wing, suggests that design variables should span sufficiently large regions of the structure so that they are "observable" from the global response data used to compile the database. This investigation should produce guidelines for the selection of design variables, via design variable linking, that are consistent with the modeling uncertainty data. Other practical considerations will of course be important also, including those pertaining to conventional design practice and manufacturability. Referring again to the ICW example, no one would ever design a wing with the patchwork of different skin thicknesses reflected in this example. When real data are used to quantify modeling uncertainty, the designs must also be realistic.

Table 7-1. Ground Vibration Test/Analysis Data Sets Available for the C-17 Military Transport Aircraft

Test Article	DTIS No.	Test Report No.
Complete C-17, T-1 Aircraft		MDC-J9180, Addendum II
H/S Elevator	L1602-01	MDC-K1954
Aileron	L1602-03	MDC-K1951
Flap	L1602-04	MDC-K1997
Spoiler	L1602-05	MDC-K1955
Landing Gear	L1602-06	MDC-K1988
Rudder	L1602-07	MDC-K1988
Cargo Door	L1602-08	MDC-K1988
J/D Air Defl.	L1602-09	MDC-K1988
Gear Doors	L1602-10	MDC-K1988
Slat	L1602-02	MDC-K1988

Table 7-2. Candidates for Suppliers of Modeling Uncertainty Data*

(a) Fighter/Attack Aircraft

Lockheed Martin/Boeing, Marietta, GA; Seattle, WA	
• F-22	
Lockheed Martin Tactical Aircraft Systems, Ft. Worth, TX	
• F-16 A/B	"Fighting Falcon"
• F-16 C/D	"Fighting Falcon"
• F-16 N	"Fighting Falcon"
McDonnell Douglas, St. Louis, MO	
• F-15 A/B	"Eagle"
• F-15 C/D	"Eagle"
• F-15 E	"Eagle"
• F-18 A/B	"Hornet"
• F-18 C/D	"Hornet"
• F-18 E/F	"Hornet"
• AV-88	"Harrier 2"
Northrop Grumman, Los Angeles, CA	
• F-14 A	"Tomcat"
• F-14 B	"Super Tomcat"
• F-14 C	"Super Tomcat"
Rockwell/Daimler-Benz, Seal Beach, CA	
• X-31	Research Aircraft
• B-1B	(Bomber)

(b) Military Transport Aircraft

Lockheed Martin Aeronautical Systems, Marietta, GA	
• C-130 H	"Hercules"
• C-130 J	"Hercules"
• C-130 T	"Hercules"
McDonnell Douglas, St. Louis, MO; Long Beach, CA	
• C-17 A	
• KC-10A	"Extender"

* Reference: *Aviation Week Aerospace Source Book*, Jan. 8, 1996.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

This report documents the results of an STTR Phase I feasibility study to investigate potential enhancements to the "Automated Structural Optimization System (ASTROS)." ASTROS provides a multidisciplinary analysis and design capability for aerospace structures in general, and aircraft in particular. It includes a specifically designed database and executive system to maximize efficiency, flexibility and maintainability, including the addition of enhancements such as those investigated under this project.

The scope of this feasibility study was initially broad, including (1) the development of a robust design capability through probabilistic design optimization, (2) expanding the multidisciplinary optimization (MDO) capabilities of ASTROS, and (3) linking the three primary design stages, i.e. conceptual, preliminary and detail design. As the project evolved, the effort focused more on the development of methods for probabilistic design optimization, and less on integrating the different design stages. Emphasis on the former was motivated in large part by recent efforts at Wright State University to implement a method for probabilistic design optimization in ASTROS. The latter was de-emphasized when it became evident that critical technology in the area of parametric modeling was not as well developed as originally believed. Part of the MDO expansion effort related to preliminary design was continued, while that part pertaining more to conceptual design was discontinued, after reaching the decision to de-emphasize the integration of preliminary and conceptual design. The following paragraphs briefly summarize the results of investigations conducted during this study.

A major effort was devoted to the investigation and development of methods for probabilistic design optimization. This began with the development of originally proposed Probabilistic Safety Margin methods, i.e. adding probabilistic safety margins to the constraints and the objective function, and using modeling uncertainty to reduce, orthogonalize and scale the probabilistic design variables. The relative importance of these methods was examined through simple numerical examples. These examples suggest that, while the incorporation of modeling uncertainty in the objective function does tend to bias the optimization in favor of design variables with less uncertainty, other things being equal, the primary effect of modeling uncertainty is to move the design away from the active constraints, thereby creating a more conservative design.

Several months after the project began, the project team learned about the work being done at Wright State University. Direct comparisons were made between results obtained from the Probabilistic Safety Margin (PSM) approach, and those published by Grandhi and his colleagues using a Reliability-Based Optimization (RBO) approach. Initial comparisons indicated that the two approaches gave nearly the same results. Further investigation revealed, however, that while the two approaches yielded similar weight penalties for small degrees of modeling uncertainty, the PSM approach tended to underestimate the weight penalties in cases where the modeling uncertainty was greater, especially when a high degree of reliability, e.g. 99% or higher was sought.

The principal difference between the two approaches is that performance derivatives in the PSM case are evaluated at the mean values of the design variables, whereas in the RBO case they are evaluated at the limit surfaces. The latter is reported in the literature to be the more accurate of the two, and to be invariant with respect to the formulation of constraints. The RBO approach was therefore adopted in lieu of the PSM approach for the treatment of probabilistic constraints.

Unfortunately, the RBO method which had been implemented in ASTROS by Luo and Grandhi turned out to be *extremely* inefficient for practical applications involving many design variables and many performance constraints. It involves an iterative solution to achieve the desired safety margin for every active constraint, within each major design cycle of ASTROS, each iteration requiring a separate "exact analysis." This method is referred to as a "double loop" method because of the nested arrangement of optimization loops. Another published method instead doubles the number of design variables for each constraint while employing only a single optimization loop. This method, referred to as a "double-design-vector" method, is likewise unsuitable for practical applications. Both methods require more computational effort than a deterministic optimization solution, by orders of magnitude!

In the process of researching these two RBO methods, a third method was devised. This method involves neither a double-loop nor a double-vector formulation, but is rather a single-loop-single vector (SLSV) method as opposed to the double-loop-single-vector (DLSV) method or the single-loop-double-vector (SLDV) method. It is conservatively estimated to require less than twice the computational effort as deterministic optimization (perhaps significantly less) compared with the other two methods which can require orders of magnitude more. The new SLSV method was implemented and found to yield results identical to those of the SLDV method.

Another investigation compared results using hypothetical modeling uncertainty derived from assumed coefficients of variation (COV) on the design variables, with those using databased modeling uncertainty derived from the differences between modal analysis and test data of generically similar structures. For examples with few design variables (e.g. the Cantilever Box Beam), the results from using the generic database were comparable to those where a 5% to 10% coefficient of variation was assumed for all design variables. For larger problems (e.g. the Intermediate Complexity Wing), the equivalent coefficient of variation was much larger, on the order of 30%. However, difficulties were experienced with convergence and the efficacy of using a globally representative uncertainty model to characterize the uncertainty of very localized finite element parameters was called into question. Convergence problems were traced to rank deficiency and numerical illconditioning, both of which can be dealt with by reformulating solution procedures. The issue regarding the use of global (modal) uncertainty data to represent the uncertainty of very localized design variables appears to be one of an improperly formulated problem. A more realistic formulation of the Intermediate Complexity Wing problem, for example, would be one where the design variables representing skin thickness are linked over larger regions of the wing surface, not just the top and bottom opposing quadralateral elements of the finite element model.

The feasibility of expanding the MDO capabilities of ASTROS by adding a manufacturing detail capability was investigated and confirmed. A framework for incorporating manufacturing detail in the early design process was devised by Professor Ewing at the University of Kansas. The basis of the framework is a hierarchy of input bulk data "cards" which specify manufacturing processes used for bulk parts as well as for joined parts. Manufacturing data include both cost data and detail information which can be used, for example, to apply fatigue constraints on the structure. A method for defining fatigue constraints in terms of stress constraints was outlined. The cost data can be used in two ways. They can be used directly in the optimization process by including cost as part of (or as) the objective function. A secondary objective is to make manufacturing-related data available in the ASTROS database (CADDB) for use in interfacing with conceptual design.

Finally, the feasibility of extending the preliminary design capabilities of ASTROS through improved interfaces with conceptual and detail design stages was investigated. It was originally envisioned that the use of parametric modeling tools might provide a means for using conceptual design information to automate the generation of finite element models for use in preliminary design, as well as a mechanism for feeding information from preliminary design optimization back to the conceptual design level. While this idea has definite merit and excellent long-term potential, it was decided that the current state-of-the-art in parametric modeling would not support the limited effort possible under this project.

One of the more in-depth studies performed by the University of Kansas in this area was the use of discrete optimization, in particular a genetic optimization algorithm (GOA), to optimize the layout and sizing of substructure elements such as bulkheads, frames, longerons and stringers. This is a step that would take the surface geometry determined in conceptual design, and produce an optimum arrangement of framing elements as a basis for subsequent parametric modeling and the generation of a finite element model. Numerical examples were presented to demonstrate the approach, and a FORTRAN code implementing the GOA was delivered to ACTA.

8.2 Recommendations

Recommendations based on the foregoing analysis and conclusions are grouped into three categories: (1) recommendations for the development of a probabilistic design optimization capability for ASTROS, (2) recommendations for the extension of ASTROS' MDO capabilities, and (3) recommendations for improving the interfaces between conceptual, preliminary and detail design. Except as otherwise noted, these recommendations are intended as recommendations for Phase II continuation of the project.

The following recommendations pertain to the development of a probabilistic design optimization capability for ASTROS:

- Implement the RBO/SLSV method for treating probabilistic constraints in ASTROS.

- Perform cost/benefit trade studies to determine whether the additional cost required to implement second derivative computations in ASTROS, for purposes of including modeling uncertainty in the objective function, is justified by anticipated benefits.

- Compile databases of modeling uncertainty based on the difference between analytically predicted and experimentally measured vibration mode shapes and frequencies, from ground vibration tests and analysis of military and commercial aircraft.

- Examine the relationship between covariance matrices which characterize modeling uncertainty in terms of modal mass and stiffness, and the corresponding covariance matrices of selected design variables derived from them, to develop guidelines for design variable linking in probabilistic design optimization.

The following recommendations pertain to the extension of ASTROS' MDO capabilities by incorporating manufacturing detail in the early design process:

- Implement joint strength and fatigue life constraints in ASTROS as outlined in Section 3 and Appendix B of this report.

- Implement cost accounting procedures within ASTROS for purposes of eventual cost-related optimization and life-cycle cost estimation. (This is not a recommendation for Phase II.)

The following recommendations pertain to improving the interfaces between conceptual, preliminary and detail design:

- The idea of using a GOA as a link between conceptual design and parametric modeling in the interface between conceptual and preliminary design should be pursued further. Clearly, the scope of such an effort goes well beyond the simple examples investigated in this study, but the ability to automate the structural framing process, currently performed on an ad hoc basis, appears to be a crucial link in bridging the gap between conceptual and preliminary design. (This is not a recommendation for Phase II.)

- A limited system identification capability, called ASTROS-ID, has been incorporated as a separate run option in ASTROS. This type of capability contributes to an improved interface between preliminary and final design in the sense that data from prototype testing of the final design can be assimilated back into the preliminary design model through the process of system identification. ACTA has developed a more powerful Structural System ID code (SSID) in cooperation with Sandia National Laboratories [8-1,8-2]. It is recommended that ASTROS-ID be upgraded to include the capabilities of SSID, or be replaced by SSID, thereby further enhancing the ability of ASTROS to interface with final design.

- ACTA also has a predictive accuracy code (PDAC) that operates in conjunction with SSID [5-1,5-2,5-3]. PDAC would use the generic modeling uncertainty database assembled for aircraft structures to evaluate the predictive accuracy of preliminary design models for purposes of ASTROS-based analysis. This analysis is used to

determine internal loads for detail design. The incorporation of PDAC in ASTROS would enable these internal loads to be quantified probabilistically to facilitate reliability-based design at the detail design level.

Except as noted otherwise, the foregoing recommendations are intended as recommendations for Phase II continuation of the project. These recommendations have shaped the objectives and overall Phase II work plan outlined in the Phase II proposal submitted earlier. The most significant achievement since submittal of the Phase II proposal is the formulation and numerical testing of the new RBO/SLSV method for probabilistic design optimization. This achievement significantly increases the incremental progress toward meeting project goals. The inherent efficiency of the method suggests that for the first time, probabilistic design optimization can be implemented in a commercial code. The complimentary ability to derive realistic modeling uncertainty data from previous ground vibration tests and analyses on aircraft structures means that the probabilistic designs produced by ASTROS will be fundamentally and traceably grounded in real data.

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APPENDIX A - IMPROVEMENT OF DESIGN INTERFACES

OVERVIEW OF THE AIRCRAFT DESIGN PARADIGM

The modern aircraft design process can be characterized as a generally sequential procedure with three stages:

- Conceptual Design
- Preliminary Design
- Detail Design

While many design iterations occur within each stage, it is rare to iterate across stages; e.g., to update the conceptual design parameters based on preliminary design results. Generally, the design parameters among the stages are considered to be independent and are fixed before transition to the next stage. Revision of an earlier stage design occurs only when preliminary or detail design problems arise that cannot be corrected using the design parameters that are associated with the current stage in the cycle.

During the *Conceptual Design* stage, the designer, using parameters which define the mission requirements of the aircraft, develops a design which will satisfy those requirements. Present methodology is based primarily on heuristics and semi-analytical methods using data developed during the design and manufacture of other aircraft systems. These tools are augmented with simplified rigid vehicle performance analyses.

The design parameters at this stage include gross characteristics of the aircraft such as wing area, taper ratios, thickness-to-chord ratios and so on. This level of design yields the gross characteristics of the aircraft, sometimes including a preliminary outer mold line, or surface geometry, of the plane. More often, a designer then creates a concept geometry, using a CAD system, which obeys the conceptual design parameters.

As a separate step following conceptual design, a structural layout is selected which lies within the proposed geometry and is expected to satisfy the structural requirements of strength and manufacturability. In the current paradigm, other considerations for the structural arrangement are handled in the preliminary or detailed design stages. This step constitutes a transitional step between conceptual and preliminary design.

Once the gross geometry of the aircraft has been designed and the structural arrangement selected, drawings can be made. From these drawings, realistic mathematical idealizations can be created. These include, for example, finite element structural models and CFD models. These models are then used to perform *Preliminary Design*. Unlike the conceptual design which is primarily empirical in nature, the preliminary design step is primarily analytical. Analyses performed using the preliminary design models are intended to validate the Conceptual Design under more realistic operational scenarios.

The design variables at the preliminary design stage are local geometry variables, material systems, structural sizes and control system variables. During this stage, a transition is made to increasingly accurate mathematical idealizations. As the engineering team gains confidence in the concept and arrangement, more accuracy is required to confirm that analytical predictions are physically representative. The end result of the preliminary design process is a small set of mathematical idealizations that are presumed to be valid over the operational envelope of the vehicle.

Finally, when the designers and analysts are satisfied with the preliminary design results, it is necessary to perform some number of *Detail Design* analyses. Such analyses look at the finest details of the airplane such as bolt loads, weldments, and other local responses that might result in system failure. The assumption at this stage is that any modifications required to address the local detail will not impact any of the overall analyses used to validate the preliminary design. This assumption, while valid from a strength and failure point of view, is not valid from a life cycle cost viewpoint.

In the remainder of this appendix, the software tools used in performing each of these steps will be discussed. Most importantly, an understanding of the interrelationship of these tools, today and in the future, will be described.

THE IDEAL DESIGN PROCESS

Ideally, the design process should allow a direct feedback to occur from each design level to the others. This is not the case at the present time. The current research effort has determined that such an integrated approach is beyond the current state-of-the-art. The following sections provide a review of the current technology base, describe the tools available for performing the design process, explain why integration is beyond the scope of this effort, and suggest approaches that could be used to address the complete design cycle in the future.

BACKGROUND

This section briefly describes the software tools for the three levels of aircraft design.

Conceptual Design Tools

There are several software tools for performing conceptual aircraft design. The two most relevant systems are FLOPS, developed by NASA LaRC [2-1], and ACSYNT, developed by NASA ARC [2-2]. These programs consider a broad range of mission requirements and then attempt to develop an optimum design which satisfies them. The classes of data considered are:

- Gross Geometry (including weight, balance, and inertia)
- Detailed data for wings, tails, fins and canards
- Propulsion and engine design
- Mission segment requirements (climb, cruise and descent schedules)
- Noise
- Cost data

These design tools are strongly dominated by overall flight vehicle performance and mission requirements. Thus, all local phenomena and flexibility effects are ignored under the assumption that the structure can be built to satisfy all necessary criteria. This is the domain of the Preliminary Design process.

Preliminary Design Tools

The pre-eminent aircraft design software system in the United States today is the ASTROS program [1-1 to 1-3]. This program was developed between 1983 and 1995 under funding of the United States Air Force Wright Laboratory. The principal developers were the Northrop Corp. and Universal Analytics, Inc. (UAI).

The intent of the ASTROS development was to create a preliminary aircraft design tool that could be used to design the military aircraft systems for the 21st century. As such, the methodologies of the software were targeted to the specific needs of the aircraft industry. These methodologies include:

- Minimum Weight Design
- Composite Material Behavior
- Steady-state Aeroelastic Analysis
- Aeroelastic Stability Analysis

Aircraft systems can then be optimized simultaneously for strength, frequency, and aeroelastic behavior under a wide variety of flight conditions. A minimum weight design results which satisfies all of the design constraints applied to the plane.

In general, a single geometric configuration of the aircraft can be optimized because ASTROS has no provision for geometric design variables that would allow changes to, for example, wing or other surface areas. The only exception to this is a special feature that allows a design to be accomplished for multiple store configurations.

APPENDIX B

Enhanced Aircraft Design Capability for the Automated STRuctural Optimization System (ASTROS)

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ABSTRACT

Aircraft design research was conducted under contract to ACTA, Inc. in the areas of discrete optimization algorithms, methods to include manufacturing details, and the feasibility of incorporating electromagnetic observable (EMO) analyses.

A review of discrete optimization methods has revealed that genetic algorithms are appropriate for application to some aircraft design tasks. A genetic optimization algorithm (GOA) has been shown to be extremely effective for layout and sizing for an aircraft wingbox. The advantage of the GOA approach for design is that no gradient information is necessary, as is the case for other optimization algorithms. The particular GOA used here uses a recently-developed constraint-handling scheme which has been shown to be useful in wingbox design. Suggestions are given for how to expand the use of GOAs into two classes of problems: the problem of overall structural sizing given basic fuselage and wing parameters; and, the broader problem of full aircraft conceptual design.

A framework for incorporating manufacturing detail in the preliminary design process has been devised within the ASTROS environment. The basis for this framework is a hierarchy of input data relations and data items which specify manufacturing processes used for individual parts and for joining (assembly) operations. These data, when fully supplied by the user, would allow cost estimation at the preliminary design level. The data also specifies information necessary to assess fatigue characteristics of the design.

The most effective methods to reduce the electromagnetic observability of an aircraft are directly related to the overall geometry of the aircraft. For this reason the EMO analysis is best suited for the conceptual design phase. An investigation concluded that, presently, there is no inexpensive way to incorporate the EMO analysis into the conceptual design phase due to a lack of analytical design rules for EMO assessment. However, commercial efforts appear to be underway to develop code to make such analyses feasible.

Enhanced Aircraft Design Capability for the Automated STRuctural Optimization System (ASTROS)

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INTRODUCTION

The effort reported here was accomplished under contract to ACTA, Inc. The three tasks addressed are as follows (identified by numeration in the contract statement):

1. Investigate discrete optimization algorithms for use in aircraft design

2a. Develop methods to include manufacturing details in the aircraft design process

2b. Investigate the feasibility of including electromagnetic observables in the aircraft design process

B.1.0 Task 1: Discrete Optimization Techniques for ASTROS

The investigation into discrete optimization techniques for aircraft design, specifically genetic search, has revealed more than just the usefulness of the technique, but also the areas of aircraft design for which it is most well suited. The robustness and ability to handle non-convex design spaces makes it ideally suited for the conceptual design environment. As a result, the application of genetic search methods to conceptual design is the focus of a related Master's Thesis effort. The use of GOAs in preliminary design analyses is felt to be less appropriate. The nature of preliminary design tends not to be one of exploration of options, but rather structural sizing. As a result, genetic search may be more useful in the "gap" between conceptual and preliminary design where preliminary structural layout and sizing is accomplished.

B.1.1 Review of discrete parameter optimization techniques

Most numerical techniques for optimization commonly used today are well grounded in years of experimental application to engineering problems, and their effectiveness is well documented. The majority of these numerical techniques, and certainly the more efficient of the methods, require the use of gradient information. The gradient information is obtained in the derivatives of both the objective function (what is being optimized) and all the constraint functions (the requirements and limitations on the design variables). All of these numerical methods require the derivatives to be at least first-order and many of the more powerful techniques require the use of second-order derivatives to be effective. The evaluation of these derivatives for the objective and constraint

functions at each iteration is computationally intensive, and therefore expensive, and cumbersome for even moderately complex engineering design problems. A further handicap to these traditional numerical methods is their limitation to continuous variables and convex design environments. The gradient methods (hill climbing or slope descending) locate the nearest optimum point to the initial estimate with no guarantee that point is the global optimum if the design space is not convex. It is no wonder then that the amount of experimental research into alternative discrete parameter methods of optimization has increased in recent years with the increased emphasis on process cost minimization.

Discrete parameter optimization algorithms, including genetic search and simulated annealing have been considered for many optimization tasks in engineering. They both appear to be particularly useful for the conceptual design task in aircraft design. Simulated annealing [van Laarhoven and Aarts, 1987] has been used to solve a variety of engineering optimization problems. It has also been used in conjunction with neural networks for aircraft design [Swift and Batill, 1992].

One popular alternative that is presently being explored at major airframe companies [Wilson, 1993] and is being researched in depth at institutions across the world is the genetic optimization algorithm. GOA, or genetic search, research has been around for decades in the social and pure sciences, dating back to the late 50's and early 60's, mainly as a tool to evaluate human problem solving and learning methods and to simulate biologic systems [Goldberg, 1989]. Only within the last decade have genetic algorithms stepped out of the research labs and into the engineering labs as actual problem solving tools as companies begin to recognize their potential. GOA's are simple, adaptable systems for problem solving that are more robust in their application than any numerical method and more appealing because they require no information about the environment, or search space, in which they are working. GOA's remain general and robust by exploiting information available in any search problem. Genetic search techniques have received even greater attention for solving a wide range of engineering problems. They have been shown to be effective in multicriterion design environments [Hajela, 1991], and in particular, for aircraft design [Wilson, 1993].

The design applications just cited, along with all others explored, have handled constraints by imposing a penalty on the objective function for constraint violation. However, a recent extension of the genetic search process [Hajela, 1994] handles constraints by selectively replacing the genetic code of infeasible designs with genetic code of feasible designs. This process is effected by an "expression operator", one which tends to "express" the genetics of feasible designs in place of infeasible designs. The "generic" genetic search algorithm will be described in the next section. In the following section, the genetic search algorithm using an expression operator will be described.

B.1.2 Generic genetic search process

Genetic algorithms utilize the basic biological principles of creation and evolution. The creation takes place in the GOA in the form of a finite number of designs randomly generated to form the initial population. These designs represent a large number of design points in the design space. At this point it is of no consequence to the algorithm whether the designs are feasible or not. Evolution is then applied to the population to produce a new population of, hopefully, better designs. The evolution

of a population occurs according to the biological equivalents of reproduction, and crossover, and mutation. The evolutionary steps are carried out probabilistically on the population according to each individual designs' fitness, or objective function value. The more fit the design, the more likely it's information will survive into the next population. Combining the most favorable design characteristics of the most fit individual designs of a population results in a second generation population of progeny that is better, or more fit than the parent generation.

The basic approach of the genetic algorithm, and a key reason for its superior performance to traditional numerical techniques, is to operate on a representation of the design variables and not the variables themselves. This is accomplished by coding the design individuals in a population into finite length binary strings which represent the variables of the objective function. Each individual is a distinct combination of variable values in the objective function which represents a unique design configuration. Each discrete variable is assigned a unique binary string length. These strings are mapped to real design values.

0000 ⟶ minimum variable value

1111 ⟶ maximum variable value

It should be noted that the variable representation does not have to be a binary string, and indeed, in some different problems would be better represented otherwise. The bit structure of the binary string is analogous to the chromosomal structure of biological genetics. The chromosomes contain the genetic structure of the design. The population is carried to the next generation through the chromosome bits.

Robustness is a central difference of the genetic algorithm to traditional numerical techniques. Traditional numerical methods are known to be limited in their application to specific problems. This could possibly be a reason there are so many numerical methods. To gain this edge in robustness GOA's must differ in fundamental ways. Some of these differences are:

1. GOA's work on a coding of the design set, not the designs themselves.
2. GOA's search from a population of design points, not a single point.
3. GOA's use objective function information to guide the search, not derivatives or any other knowledge of the design space.
4. GOA's operate using transition rules, not deterministic rules.

<u>Reproduction</u>

Reproduction is a process in which individual strings are selected and copied according to their objective function value, or fitness. It is an artificial version of the Darwinian concept of survival of the fittest. The label can be somewhat misleading in that there is no actual addition of an individual to a population as a result of reproduction. Reproduction is simply the selection of a viable and

probable candidate for mating. This selection is biased to choose the more fit members of a population as seen from the objective function evaluations. The probability that a member will be chosen for reproduction is determined by comparing the individuals fitness, f_i, to the overall fitness of the population, $fi / \Sigma fi$. The unfit individuals are excluded from the reproduction operation and their genetic material (design point) is removed from the population. It should be understood, however, that simply because a design, or individual, is not feasible is not reason enough to kill it off. Even infeasible designs can contribute good information to a population. Once the reproduction operation has been applied to each individual in a population a mating pool is formed from which the next generation population, or offspring, is obtained.

Crossover

Crossover is the process by which the next generation is obtained from the mating pool formed by reproduction process. In this process the design information is transferred to the progeny by the parents. The parents themselves are not carried into the next generation however. The strings from the mating pool are "mated" at random. Then, the mated strings undergo a swapping of binary bits, chromosomes, to create the new, and unique individual strings for the next population. The swapping process is applied to bits at locations within the string selected at random. Since this process is random the number of bits swapped is also determined at random so that one bit up to the entire string length less one can be exchanged. An illustration of the crossover process is shown for two 20-bit binary strings.

```
Parent1 = 11001010001110101001
Parent2 = 00101011010010010111

Child1 =  11101011010010011001
Child2 =  00001010001110100111
```

The crossover positions are indicated by an understrike in the parent strings. A probability of crossover, P_c is involved to see if crossover should occur between the individuals. It is apparent that the population size will remain constant across generations. this does not have to be the case. It is the combination of reproduction and crossover that gives genetic algorithms the majority of their processing power.

Mutation

The next operation typically performed in a simple, traditional genetic algorithm is that of mutation. The mutation operator is a low probability random operation. It functions by randomly altering a design by switching an individual chromosome bit in an individual string from a 1 to 0 and vice versa. The main function of mutation is to prevent the overzealous extinction of a potentially useful string by the reproduction and crossover processes. It acts as insurance against premature and irrecoverable loss of important genetic material. This operator, unlike crossover, operates upon a single string position based upon the probability of mutation, P_m. The site on the string selected for mutation is also random. Experimental studies have shown that effective mutation rates are on the order of one mutation per thousand bit transfers. Alternative methods to mutation are available that perform the same function of prevention of overzealous extinction with greater functionality.

Advanced Operators

In addition to the three basic processes mentioned above, it is often advantageous to incorporate advanced operators to handle problems inherent in the search space. Two such operators often used are ***diploidy*** and ***dominance***. These operators serve to protect once successful solutions from overzealous extinction in a hostile environment. Diploidy represents one of the many alternate coding schemes. In this case, each individual string carries pairs of binary bits at each location in the string. Or, each distinct combination of variables is effectively represented by two binary strings. The usefulness of the diploid operator is realized with the dominance operator. Dominance states that one binary bit of the pair in the string takes precedence over the alternate at that position. The concept of dominance has been well researched and documented by geneticists. Diploidy serves as a mechanism for remembering bits and bit combinations that were previously useful and dominance provides an opportunity to shield those useful bits from harmful selection in a currently hostile environment. In this way, multiple solutions can be carried along with one particular solution expressed. This allows old lessons learned not to be lost and, with dominance and dominance changes, still tested occasionally. An extra by-product of using these operators is that mutation should play an even smaller role in the operation of the GOA than normal.

Duplication and ***deletion*** are two operators that can be used to effectively to adaptively control the mutation rate within a GOA search algorithm. Both of these operators are applied to individuals and not across a population, much like the mutation process. Duplication acts on the individual by duplicating a particular bit in the string. Deletion acts by removing a duplicate bit from the string. The result is an "intrachromosomal" dominance that is not unlike that induced using the diploidy operators mentioned previously. Dominance schemes such as these can be used as a method of selection between competing alternatives in a population. However, no such methods have been published.

Two more low-level operators considered to be power boosters for a search GOA are ***segregation*** and ***translocation***. These are tools that are once again applied to the individual strings. Segregation is a selection process used during crossover that will disrupt linkages between bits on related strings. This will effectively prevent poor quality strings from "piggybacking' their way into survival and on into the next population. In conjunction with segregation comes translocation. This operator serves to manage the crossover and segregation of the bits by providing an appropriate map for the shuffling of bits between strings. There has been little experimentation done on these operators, but there is great confidence in their useful application. It is understood, however, that their application would be toward more complex algorithms incorporating "multiple chromosomal" diploid strings that are closer, in structure, to human codings than traditional GOA haploid strings. For example, the human code carries 23 pairs of diploid strings. These two operators are an attempt to closer model and manage the human coding scheme within a GOA.

Summary

The steps described thus far make up the basic, simple genetic algorithm. However, this algorithm is designed to optimize unconstrained objective functions. In most “real-world” applications of optimization there are single, and usually multiple constraints to be considered. For an algorithm to

be of any use it must be able to effectively evaluate the fitness of the population relative to all applicable constraints.

B.1.3 Constraint-handling in genetic search operators

Constraints serve to define the boundaries for acceptable and unacceptable results as well as provide an artificial limit on the range of variable values. Many techniques exist of constraint handling in genetic algorithms. Two very common methods are the use of penalty functions and another termed backtracking [Wilson, 1993]. Another method showing great promise is the use of expression operators [Hajela, 1995].

The incorporation of ***penalty functions*** is far and away the most popular method for handling constraints in genetic algorithms. The penalty method works by degrading an individuals' fitness in accordance to the degree of constraint violation. This has the effect of transforming a constrained optimization problem into an unconstrained problem by incorporating a fitness penalty with all constrain violations. The ease with which the penalty method can be incorporated into a optimization algorithm continues to make it the most widely used method.

Backtracking is an alternative to penalty functions that was developed to attack problems involving search spaces so limited that penalty functions could not handle the limitations. In these problems finding a feasible solution is as difficult as finding an optimum using penalty operators. In backtracking, if an offspring solution violates any constraint, the string backtracks, or de-evolves, toward the genetic material of it's parents until the constraints are met. This method is most effective when used with population adaptivity, or a varying population size.

The method of ***expression operators*** is an advanced method for transforming infeasible individuals into feasible designs. Expression operators involves the use of both an objective function and constraint equations. This method, while more complex than the penalty method or backtracking, is much more robust and powerful in its application. It is, therefore, the constraint handling method used in the GENDES4 genetic optimization algorithm.

B.1.4 Expression operators for constraint handling

This operator begins immediately after the initial population has been created. Each individual in the population is evaluated on both its' objective function fitness and its' constraint violation fitness. Then, all the individuals in the population are rank ordered by their fitness. This ranking is split into two categories, the feasible and infeasible designs. The "best", most fit feasible individual is determined and the rest of the feasible designs ranked beneath it. Next, the infeasible solutions are ranked based upon their degree of violation. It should be noted that this feasibility evaluation has begun before the genetic search process.

Having evaluated each individual and ranked them accordingly, the transformation process from infeasible to "less infeasible" designs begins. The transformation is done on a gene by gene level randomly for each infeasible design. The "best" feasible individual is used as the gene donor for each

of the infeasible designs. For each gene in the infeasible individual a random number between zero and the total number of infeasible designs is selected. If this number is less than the rank of the infeasible design being operated on, then a genetic transfer of material is made from the best feasible design. This random transfer process is done on a gene-by-gene iteration for each infeasible individual.

It is then necessary to check how successful the gene transformation process was in removing infeasible designs from the population. This is done by reevaluating the objective and constraint fitness of the formerly infeasible designs. Again, all remaining infeasible designs are identified and rank ordered.

Now the genetic process of selection, the precursor to reproduction, begins. Since infeasible designs can contribute good genetic material to a population, they are forced into the mating selection process. The mating process for infeasible designs is different than for feasible design parents. First, each infeasible individual is placed into the parent mating pool so that each individual is used only once. Then, a feasible parent is selected to mate with the infeasible parent using the normal random selection process based upon fitness. After all of the infeasible designs have been paired for mating, then the normal selection process is applied to the feasible population. At this point, the stage is set for reproduction, crossover, and mutation to occur normally.

B.1.5 Demonstration of genetic search techniques in wingbox design

In order to demonstrate the usefulness of the new constraint-handling approach, a wingbox design problem has been solved with the new technique and compared with solutions from more traditional algorithms. The problem is to layout *and* size the structural components in a traditional, two spar wingbox cross-section subjected to user-selected shear forces and moments. A set of hierarchical buckling requirements forms the constraint set. In particular, no skin buckling is allowed at the limit load, no stringer buckling is allowed at the ultimate load, and no spar cap buckling is allowed at 120% of the ultimate load. In all cases, as well, no yielding is permitted. Figure B.1 details the wingbox configuration.

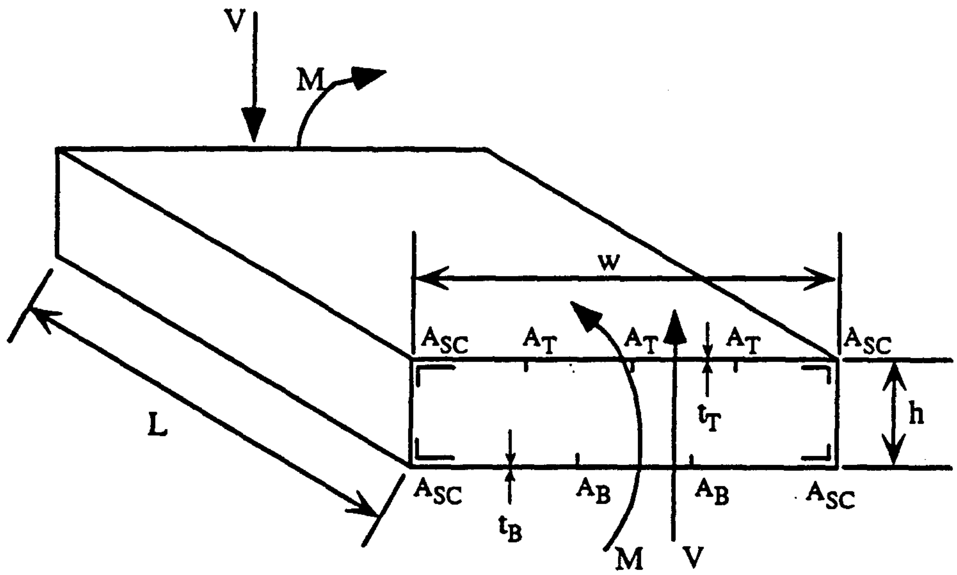

Figure B.1: Wingbox Structural Layout and Loading

The structural component design variables are:

top and bottom skin thicknesses, t_T, t_B
the number of stringers on the top and bottom skin, n_T, n_B
the schedule number of the top and bottom stringers, I_T, I_B
the schedule number of the four spar caps, I_{SC}

In the problem solved here the "schedule number" is the standard equal-length leg right angle extrusion number for a stringer or spar cap. The schedule numbers are directly related to the cross-section of the top and bottom stringers(A_T, A_B) and the spar caps(A_{SC}). Based on these design variables, the objective function can be most simply defined as the cross-sectional area of the wingbox:

$$f(\bar{x}) = (t_T + t_B)\, w + 4\, A_{SC} + n_T A_T + n_B A_B$$

The constraints are based on pure bending stress which is compared to allowable buckling stress or yield. For the purpose of this simplified example, the stiffened panel, stringer and spar cap buckling loads were written as a linear function of schedule number. However, the use of a more complex equation or a look-up table does not increase the complexity of using the GOA.

The wingbox optimization problem has been solved for a single set of applied loads and moments using the following techniques:

NCONF: a quadratic programming algorithm with an augmented Lagrangean objective function using finite difference gradients; devised by Schittkowski [1981], as implemented in the IMSL subroutine library [DEC, 1990];

NCONG: same as NCONF, except with exact gradients;

NEWSUMT: a sequential unconstrained minimization technique with an exterior penalty function for constraint handling using finite difference gradients [Miura, 1979];

NEWSUMTG: same as NEWSUMT, except with exact gradients;

GENDES4: a genetic algorithm based on Hajela's constraint-handling with feasible design gene expression operator;

Table B.1 summarizes the solutions (i.e., the "optimum" solution for the design variables) from the aforementioned solution algorithms. Note that the traditional solutions based on exact gradient calculations perform the best. The genetic algorithm results shown are for the best solution achieved in 5 tries. The results of the 5 genetic searches performed are shown in Table B.2. Note that the genetic search solutions are generally better than the finite-difference-based traditional solutions. This is significant because in many design applications, such as the conceptual design environment discussed in the next section, exact gradients will not be available, and finite difference gradients will be the only ones available. ***This fact seems to favor the use of genetic search techniques for conceptual design. At the very least, GOA algorithms have been established as appropriate for combined layout and sizing optimization.***

Table B.1. Comparison of alternative methods of wingbox design

method	area	n_T	n_B	I_{SC}	I_T	I_B	t_T	t_B
NCONF	22.8	15	15	30	30	30	.24	.05
NEWSUMT	30.6	12	12	26	25	26	.279	.32
NCONG	15.1	15	1	29	8	28	.254	.071
NEWSUMT-G	15.3	15	2	15	8	1	.259	.082
GENDES4	15.9	13	3	16	8	8	.29	.08

Table B.2. Wingbox design using genetic search with an objective function based on weight and constraint violations handled with good gene "expression", after Hajela (with the following parameters: NPOP=100, NGEN=200, NGENESi=6)

run	area	n_T	n_B	I_{SC}	I_T	I_B	t_T	t_B
1	19.1	9	9	8	5	1	.41	.08
2	15.9	13	3	16	8	8	.29	.08
3	16.1	14	10	27	7	1	.29	.06
4	16.1	13	14	16	8	1	.29	.06
5	22.8	5	9	8	3	12	.53	.05

B.1.6 Genetic search techniques for conceptual design

The design process is referred to by Hazelrigg as an iterative process not of problem solving, but decision making [Hazelrigg, 1992]. He outlines three key elements of the decision making process. They are:

- identification of options or choices
- development of expectations for results of choices
- formulate a system to rank the results to obtain the preferred choice

Genetic algorithms incorporate all three of these decision elements into a single analysis tool. This is one important advantage of GOA's to traditional techniques and a reason why there is such interest in their development. If such an artificial system can be made that is robust costly design and re-design iterations could be avoided.

In order to demonstrate the use of genetic search techniques for conceptual design, a novel conceptual design algorithm under development is being "fitted" with GENDES4, the algorithm using feasible design gene expression for constraint-handling. The basis of the novel conceptual design algorithm is designing to bring the greatest capital return to the airframe company. This will be done by favoring a design which captures the greatest share of a perceived user market, and which can be manufactured at a lower cost. In particular, conceptual design variables such as fuselage diameter, number and type of engines, etc., are chosen so as to result in an aircraft which is most capable to capture the largest unserved or underserved traveler market in the future.

The Conceptual Design Module (CDM) being studied in a related Master's Thesis effort represents an important step toward achieving revenue-generating aircraft by considering market opportunities rather than someone's "mission requirements", which are derived from the market opportunities. Conceptual, or configuration, design focuses on the dimensional layout of an aircraft. The CDM, coupled with a non-linear evolutionary optimization method, is a flexible multi-variable design and analysis tool for both commercial and military applications. A cost-effective commercial design is determined through the optimization of the conceptual design for maximum Return On Investment

(ROI) based upon a mission market specification. A cost-effective military design is determined through simultaneous optimization of the conceptual design for minimum Life Cycle Cost and maximum mission success based upon a rank ordered mission specification. The depth of analysis for both is expanded through the consideration of manufacturing costs.

A significant departure from traditional design analysis, the approach toward conceptual analysis taken here is to include as variables only those terms which can be directly affected. This precludes traditional design variables such as range, weight, and field length from being included as it is not possible to affect these items without first changing something else. To accomplish this, relations were created between the weight, dimensional layout variables for the fuselage, empennage, and wing, and the ROI. This is an unusual approach because conceptual design typically begins with, and is guided by, the mission specification which is comprised of various performance parameters. Instead, a mission market specification is required for the CDM. This is simply a collection of the market research used to create the mission specification and contains a description of the target market for the aircraft with listings of city pairs, distances, market volumes and the expected percent of market volumes captured in commercial applications. The military equivalent is a rank ordered list of missions detailing the quantity of specific cargo that must be transported a specific distance. This data represents the input for the CDM and the constraint information for the optimization.

The optimization of the conceptual design is a powerful feature that presently incorporates nearly all components of cost evaluation. Included are the direct and indirect operating costs, manufacturing, and technology costs, as well as an extensive assessment of revenue.

Through the use of evolutionary optimization methods, inherent design value trade studies are performed within each iteration. The optimization algorithm within the CDM can then determine if the market requirements are best met by, for example, a small, low volume aircraft making many flights or a large, high volume aircraft making only a few flights. In military design the mission goals are flexible and weighted according to their rank. For example, a mission specification to carry two helicopters over a distance may be compromised to one if other higher ranked missions are met, and increasing the capacity would increase the cost. This adds the flexibility of intrinsic design comparison without extra excessive coding or performance evaluation. This type of design comparison is not even a consideration in classical design practices following a mission specification.

At the user-input level, the user must specify the number of passengers per day wanting to travel a given distance to a destination city. Such data should be available from airline marketing concerns. The user then selects the appropriate design variables and the number of genes to be used to represent each design variable. Designs are chosen in the random fashion of a genetic search algorithm, then used to determine the return on investment over a design lifetime, based on cash flow generated in the user-specified market. Good designs prosper and poor ones "die out".

The core equations of this algorithm and the user-supplied data requirements have been established. The algorithm is in the process of being coded and tested. The goal is to implement the code within the ASTROS environment.

B.1.7 Genetic search techniques in ASTROS.

Including GENDES into the ASTROS environment is entirely feasible. The bulk data entries necessary to incorporate the algorithm have been devised. For example, a bulk data "card" titled GENETIC allows the user to, for instance, select either "gene expression" (EXPRES) or "cost function augmentation" (COSTAUG) for constraint application. The COSTAUG card allows the user to select either a linear or inverse cost augmentation function..

The associated input data templates and relation entries have been devised (for inclusion into the TEMPLAT.DAT and RELDEF.DAT files required by ASTROS at build-time).

B.1.8 Linking conceptual and preliminary aircraft design

Two ways in which improvements in the way conceptual and preliminary design tasks are linked will now be presented.

B.1.8.1 Improving the ability to devise appropriate finite element models

According to many researchers [Blair, 1995], the key impediment to linking conceptual and preliminary design is the difficulty in devising a finite element model to represent the structure. At the very least, a set of geometric parameters is available from the conceptual design phase. In a better case, various cross-sectional profiles of fuselage and wings are known. However, the finite element analyst needs to make elements of specific sizes "on" the surfaces provided at the conceptual level. Typically, a skin panel element would span between bulkheads or frames in one direction and between longerons or stringers in the other. Without knowing the spacing, the analyst is forced to use an *ad hoc* procedure.

Using the same algorithm described earlier for a wingbox layout and sizing, a fuselage, a vertical stabilizer or any structure made with skin and substructure structural concepts could be laid out and sized. This would form a vital link between a conceptual design and a preliminary design. The enormous benefit is that the preliminary designer then gets a reasonable starting point for bulkhead, frame and rib locations as well as longeron and stringer placements. Using these structural placements, a finite element model to be rather easily made. Also, after preliminary sizing with a traditional sizing algorithm like ASTROS, the structure will be lighter than one based on an *ad hoc* layout.

B.1.8.2 Providing feedback from preliminary design to conceptual design

Many conceptual design algorithms are based on either tabular or response surface representations of the relationships between design parameters and performance. For instance, wing weight can be found in many sources [e.g., Roskam, 1985] as a function of surface area. In other cases, wing weight can be found as a function of multiple parameters, like surface area, aspect ratio, etc. In both cases, the functionality is based on *historical databases*. Such data has a high confidence associated with it. However, as preliminary designs are accomplished--based on user requirements generally

different than those associated with aircraft in the database--it seems appropriate to use the weight and cost data from preliminary designs to update the database, at least until a design has been finalized. In this way, the very rudimentary techniques used for weight and cost estimation in conceptual design will be updated, with some finite level of confidence, to include information from preliminary designs. The accounting for varying levels of confidence as the design converges would also be appropriate, along the lines outlined in the Phase II Proposal [Hasselman, 1995].

B.2.0 Task 2a: Manufacturing Detail Capability for ASTROS

A framework for incorporating manufacturing detail in the early design process has been devised. The basis of the framework is a hierarchy of input bulk data "cards" which specify manufacturing processes used for bulk parts as well as for joined parts. The manufacturing data would include cost data, but also detail information which could be used to apply, for instance, fatigue constraints on the structure. In particular, if a rivet joining process is prescribed, the number and size of rivets needed could easily be determined along with the skin thickness. One of the factors in such a sizing process would be the avoidance of a fatigue life less than that prescribed.

B.2.1 Cost accounting within ASTROS

All manufacturing processes have costs associated with them, and they can be dealt with directly. For bulk parts, the cost is specified, for instance, on a per pound basis. For joining operations, some costs are allocated to specified machines, jigs and clamps. For rivets, for instance, the number and size of the rivets can be automatically calculated.

The key objective for including cost information in ASTROS is to provide cost information to the preliminary design algorithm, especially if cost is part of (or is) the objective function. Currently ASTROS uses weight as the objective function, but this may not always be the case. For instance, if ASTROS is augmented to select rivet sizes and numbers, the cost association allows gradient information to guide the optimizer to structural designs which result in reduced overall costs and failure avoidance associated with rivet selection.

A secondary objective is to provide an opportunity for manufacturing-related data to be available in the ASTROS database (CADDB) for use in a conceptual design algorithm. The conceptual design algorithm being used by a user, would then have an organized, documented database with which to interface. This is discussed briefly in section B.1.8.

B.2.2 Failure modeling associated with manufacturing detail

The manufacturing method used in a design often results in strength and life limitations in the resulting structure. Traditional preliminary design using ASTROS, MSC/NASTRAN or D'Assault/ELFINI is based on strength constraints, that is the avoidance of stresses too high for the structure to withstand, as well as flexibility constraints. ASTROS has some capability to impose

buckling constraints, but to impose fatigue fife or fracture constraints, the user is forced to "fabricate" such constraints in the form of strength constraints.

The goal in this subtask is to implement strength and fatigue life constraints in ASTROS. Such failure modes associated with manufacturing detail need to be included for two distinct reasons. First, their inclusion increases the constraint set to be more representative of the service environment. Secondly, accounting for life-limiting design details allows a better life cycle cost to be computed.

B.2.2.1 Rivet strength

Constraints on rivet shear strength and sheet (skin) bearing strength will first be developed by slight modifications to existing strength constraints. Sensitivities of these constraints will be used during subproblem optimization looping. Formal riveted connection sizing algorithms will be installed in ASTROS for resizing in each iteration. It is well known that differences exist between manufacturers and product classes (e.g., military and civilian) in the fitting and bearing factors used for resizing. However, an effort will be made to accomodate any product- or manufacturer-specific rules in use. The goal will be to establish a general algorithm for strength design of riveted connections.

B.2.2.2 Fatigue at rivet holes

A second area of concern in rivet selection is fatigue failure, typically in the sheet or skin which the rivet is used to secure. The proposal is to use a cumulative damage rule [Miner, 1945] based on user-defined load spectra. Other rules could be used will little change in the difficulty of implementation. Using Miner's rule failure occurs when:

$$\sum \frac{n_i}{N_i} = 1$$

First, the user specifies either a set of representative time histories or a set of "number of occurrence" load spectra for a set of load factor ranges. If a time history of load factor is given, ASTROS will compute a load spectrum. Either time histories or load spectra can be combined by the user to represent the estimated service environment of the aircraft under design. Given the life goal for the aircraft, say in hours, the number of times the "I'" load range will occur in the design life, %. can be calculated. Load spectra sets are tied to specific load cases so that, for instance, a load spectrum representing the load factor variations associated with gust loading can be tied to a load case with symmetric loading on the wings. Each load spectra-load case combination is tied to a set of elements, possibly all of the elements in the model. In this way, the user controls to which parts of the aircraft fatigue constraints are associated. This could save a good deal of processing time if applied carefully.

Using stress range cycles to failure curves ("S-N curves"), the predicted cyclic life at each load range, N_i, can be determined based on the load range "R-ratio", where:

$$R = \frac{\sigma_{min}}{\sigma_{max}}$$

and the notch sensitivity factor for the set of elements under consideration. Note, then, that there is a great deal of data required: An S-N curve must be available for each stress ratio, R, each notch sensitivity ratio and each material under consideration. This information will be sought from the open literature, for instance, the Air Force Materials Laboratory.

Details of the existing rules for design, for instance the proper notch sensitivity factor selection, typically vary only in the numerous design factors used. Therefore, the goal will be to establish a general algorithm for fatigue constraints on riveted connections.

In order to provide ASTROS with the ability to design with fatigue constraints, analytical sensitivities will be devised for "inner loop" resizing. For a constraint of the form:

$$g(\bar{x}) = \sum \frac{n_i}{N_i} - 1$$

the sensitivities with respect to design variables are:

$$\frac{\partial g}{\partial x_j} = \sum \frac{\partial g}{\partial N_j} \frac{\partial N_i}{\partial \sigma_j} \frac{\partial \sigma_i}{\partial x_j}$$

The gradient of g with respect to N_j is easily found, from Miner's rule. The gradient of the log-number of cycles until failure with respect to σ can either be calculated from a table of values or expressed analytically. For instance, if $N(\sigma)$ is assumed to be of the form:

$$N = ae^{-b\sigma}$$

then the desired gradient is:

$$\frac{\partial N}{\partial \sigma} = -abe^{-b\sigma}$$

The gradient of σ with respect to all design variables is already available within ASTROS.

For later versions of ASTROS in which development cost is an admissible objective function, sensitivities of cost as a function of rivet design variables will be derived. Rivet design variables, such as skin thickness and rivet diameter, for various types of rivets and skin preparations (e.g., countersunk holes, polished skin, anodized skin, etc.), then would be selected in the optimization scheme based on overall cost. As with weight minimization design, however, constraints on shear strength, bearing strength and fatigue life would still be appropriate.

B.2.3 Manufacturing detail bulk data items

The basis for finite element property information in ASTROS (and NASTRAN) is the heirarchy of Connectivity, Property and Material. So, for instance, a bar element has connectivity specified with a CBAR card, which references a specific PBAR property card. The PBAR card specifies properties like cross-sectional area, but also references a specific MATi material card. For instance, a MAT1 card specifies the modulus of elasticity and Poisson's ratio. The idea for including manufacturing detail is to reference manufacturing detail information with the ASTROS property cards.

The strategy is two-fold. First, the property cards for all finite elements will have an associated manufacturing process. This could be as simple as an anodizing process or as complicated as a peening operation. Secondly, the process for joining all parts must be specified.

As an example, the following summary of proposed changes and additions to ASTROS bulk data entries is provided. The names of data items and relations were selected to be as evocative as possible.

The following additions to bulk data relations would allow a manufacturing process and a joining process to be added to both bar and shell elements, the most common elements in a preliminary design finite element model:

PBAR

add:	MANIDi	id of the manufacturing method(s)
	JOINID	id of the joining method
	NSMPU	non-structural mass per unit length (e.g., for a leading edge assembly attached to a front wing spar)

PSHELL (specifies properties for a shell element)

add:	MANIDi	
	JOINID	
	NSMPU	non structural mass per unit area (e.g., for interior wall in a fuselage)

The values of the MANID entries would "point" to MANUF bulk data relations. The JOINID entries would point to a PJOIN relation. The NSMPU entries allow mass for non-structural items to be added to the model.

Some of the new bulk data relations introduced above would be as shown below. These relations tie a manufacturing process to a finite element and provide for the need for jigs and special tools to be used in the manufacturing process.

MANUF (manufacturing process)

MANID	
NAME	to include processes like PEEN, PAINT, etc.
COSTPU	cost per unit area or length, based on context
CONSUMi	ID of a consumable item
CNSMPUi	consumption per unit area or length, based on context
MACHIDi	
TMACHi	machine time per unit area or length, based on context
JIGIDi	
NJIG	number of jigs required
TOOLi	
NTOOL	number of tools required

MACHINE (machine specification)

MACHID	
NAME	
COSTPU	cost per hour of operation

JIG

JIGID	
NAME	
COST	cost, if new

TOOL

TOOLID	
NAME	
COST	cost, if new

Other relations, for joining processes are given below. The CJOIN card is actually a new connectivity relation, but has only manufacturing information.

CJOIN (specifies the line along which a joining operation will be used)

CJOINID	
NA,NB	node numbers of endpoints
JOINID	

PJOIN (properties of the joint)

JOINID	
MASSPU	mass per unit length
SIZETH	size parameter, based on context, e.g., rivet diameter or bond line width
SIZETH2	size parameter, based on context, e.g., bond line thickness
MACHIDi	machining or other process operation id
JIGIDi	IDs of the jigs needed for the process
TOOLi	tool IDs

In order to include effects due to fatigue, both the loading spectrum and the stress-cycles to failure data must be provided. The SPECTRM relation includes the spectrum in terms of load factors for each load case considered by the optimizer. Fatigue data is needed in terms of stress ratio, so the stress ratio will be computed from the spectrum data.

SPECTRM (load factor vs time, to be used in fatigue analysis)

LCASEi	load case number
TABLD1i	table with spectrum info for the ith load case

SNCURVE (stress vs cycles fatigue curve)

TYPE	type, either ANALYT or TABL
R	stress ratio
A	a in $N = a \exp(-b\sigma)$
B	b
TABL1ID	ID of TABL1 with stress-cycles table

Note that the stress ratios from the spectra supplied may not exactly match the stress ratios in the stress-cycles to failure data. Therefore, some form of interpolation is necessary.

B.3.0 Task 2b: Electromagnetic Observables Analysis for ASTROS

The electromagnetic observability (EMO) of an aircraft by radar is a key measure of the worth of a military aircraft design. To be sure, there are both active and passive measures which can be taken to decrease the observability of an aircraft. However, the most effective measures are those related to the overall geometry of the aircraft. Decisions on the overall geometry are typically made at the conceptual design (or configuration design) level. Therefore, the best place for EMO analysis is at the conceptual design phase.

Historically, the level of analysis undertaken at the conceptual design phase tends to be based on "rules of thumb" or simplified design equations. For example, when a wing is being selected, an estimate of lift is based on design parameters such as aspect ratio, wing sweep, wing length, etc. An analysis using computational fluid dynamics (CFD) codes is not appropriate for each design iteration.

However, there does not appear to be any readily available set of analytical design rules for EMO assessments. It is well-known that designs with traditional cylindrical surfaces and regular-shaped wings with blunt leading edges are not appropriate. Beyond these general guidelines, it appears that, at present, the only way to assess EMO at the conceptual design level is to conduct a very expensive analysis.

The state of the art in solving the EMO problem, that is, Maxwell's equation, is well-established. The finite difference method is typically used with at spatial mesh with 7-8 differencing cells per wavelength of the highest frequency of interest. For the highest frequency radar systems, on the order of 10 GHz, this means that even a symmetric aircraft analysis (based on a half-model), demands the highest-performance computers or computer webs available. Such a computer or web can be described as one providing "100's" of Gigaflops and "10's" of Gigabytes of memory. [Parala and Walsh, 1995]

At least one software vendor, Electromagnetic Applications, is currently involved in parallel code optimization for use in a distributed computing (computer web) environment to make such analyses feasible. This code is currently being modified to give the user access to definition of a wide range of material properties on the periphery of the transmission field. In particular, the user will have access to the definition of frequency-dependent dielectric constants, conductivities and permeabilities of layers of a generally anisotropic layered medium. From these properties, the overall frequency-dependent reflectivity and conductivity impedances are calculated for the boundary. The software, EMA3D, is most commonly used to determine the electromagnetic emission properties of electronic devices on a component level. No full-aircraft analysis has yet been completed. Another vendor, MacNeal-Schwendler (MSC), offers the EMAS code, which is also typically used for component-level analysis. AGAIN, no full-aircraft analysis has been completed [Jennich, 1995].

B.4.0 Assessment of Design Software State of the Art

A review of conceptual and preliminary design software will now be given. This review was essential to understanding the appropriate role for genetic algorithms in the design process. This section concludes with a recommendation for moving towards an integrated design system bridging the gaps between conceptual, preliminary, and detail design.

B.4.1 Review of conceptual design software available

Three "popular" conceptual design computer programs have been reviewed, AAA, FLOPS and ACSYNT.

B.4.1.1 Advanced Aircraft Analysis (AAA)

AAA [anon, 1985], developed and marketed by DARcorporation under the direction of Jan Roskam, is a design tool intended to be used by a sophisticated designer. That is, the designer must make all trade-offs and decisions, while AAA provides a detailed set of performance analyses. Perhaps most notable are the aircraft stability and control analyses, which are not available in other codes. The analyses available range from simple formulae, to moderately computational techniques. At all stages of the analysis, the designer is afforded gradient information, which is intended to be used to give direction for design trades. The output of the user-aided design is an aircraft geometry based on wing and fuselage profiles. Many cost relationships allow for estimated cost of ownership.

B.4.1.2 FLOPS

FLOPS has been developed under the direction of Arnie McCullers at NASA Langley [McCullers, 1995]. This program is an automated design tool used to size a specified aircraft configuration for a particular mission--based on range, speed and payload weight. The program has the capability to estimate aircraft drag, component weights, noise, performance and cost. The user specifies the type of aircraft--transport or fighter--to determine which database to use in the component weight estimation. The user can select from a number of optimization algorithms which can be used to size the aircraft relative to several objective functions, e.g., minimum gross weight, empty weight, cost, etc. The output of the program is a set of numbers which specify the major geometric dimensions of the aircraft.

In a typical industrial setting, the user provides the program with initial estimates of fuselage size and wetted area required for the payload and mission requirements. The user then provides initial estimates for the wing area, sweep angle, aspect ratio, thickness to chord ratio and taper ratio. The empennage is usually scaled with the wing area based on a tail volume coefficient. The program is then used to optimize the wing configuration and resulting aircraft for a given engine. Successive executions provide the user with optimized aircraft for several engines, giving the designer the information necessary to select the best engine for the mission. [Hagerott, 1995]

B.4.1.3 AirCraft SYNThesis (ACSYNT)

ACSYNT was developed under the direction of Paul Gelhausen at NASA Ames [Gelhausen, 1987]. It is now marketed through Virginia Polytechnic Institute. Like FLOPS, this program is an automated design tool. Unlike FLOPS, ACSYNT has a graphics module which makes output configurations easier to visualize [Moster, 1995]. At this time, little more is known about ACSYNT, except that there are more aircraft types for which the code is suitable, for instance general aviation aircraft.

B.4.1.4 Closure

The conceptual design software reviewed provides the designer with a set of numbers which specify the overall geometry of the aircraft. All of the programs provide sufficient detail to depict the outer surface geometry of the aircraft. None of the programs provides enough structural detail to allow development of a model suitable for finite element analysis.

B.4.2 Review of preliminary design software available

Many finite element codes can do the preliminary design task, i.e., structural sizing based on a given connectivity (geometry) and various performance constraints, e.g., strength. Both MSC/NASTRAN and ASTROS allow imposition of additional aerodynamic performance constraints like lift effectiveness and flutter avoidance.

Other user-defined constraints are possible with both ASTROS and MSC/NASTRAN. In ASTROS the user defines new relations and modules which are added to ASTROS--essentially by recompiling to form a new version of the code. In MSC/NASTRAN, constraints may be defined in the input data as long as they can be formulated in simple equation form in terms of design variables, constants or response quantities calculated by the code. As an example, both ASTROS and MSC/NASTRAN can define localized buckling constraints. One advantage of ASTROS is that more complex constraints may be formulated. Another is that new data types can be created, making the input data process less complicated. The key advantage of MSC/NASTRAN is that new constraints can be added quickly, without recompiling the code.

Perhaps the key output of the preliminary design task is the overall structural weight. However, a designer is also interested in the cost of a structure. So, it would be useful for preliminary design codes to include a manufacturing cost estimate. This is possible in MSC/NASTRAN by defining a response quantity in terms of an equation based on various user-defined constants and the connectivity of the structure. However, ASTROS is much more easily modified to address this need since new data relations and analysis modules are easily devised.

B.4.3 Problem areas for conceptual design codes

The key need for conceptual design codes is to consider more of the details of the design at this level of design. One way to accomplish this is to actually consider more detail! Another is to allow for feedback to conceptual design from a preliminary design which is based on an earlier conceptual design.

One way to increase the level of detail considered at the conceptual design level is to "force" the designer to add numerous "necessities" to the design model. This could include the locations of windows, doors, fixtures, and nonstructural mass to the model. This would provide for a better weight calculation. Another is to provide a way for the basic substructure to be defined. In particular, the bulkhead/ring and rib spacing should be set at the conceptual design level. As discussed later, this would greatly enhance the ease with which a preliminary design model could be developed.

Detail at the conceptual design stage can be provided indirectly by updating weight, cost and performance estimates in the conceptual design algorithm with feedback from the preliminary design stage. When a conceptual design is used to spawn a preliminary design, it is reasonable to expect that the cost, weight and performance calculated in a good preliminary design process could be used to update the rules used at the conceptual design stage to estimate the same quantities. Therefore, if a feedback path is provided from preliminary to conceptual design, it would enhance the overall design process.

B.4.4 Problem areas for preliminary design codes

Three problem areas for preliminary design codes have been identified. The key problem is the difficulty in developing an appropriately detailed finite element model based on the conceptual design. Secondly, there is no code available which can assess the cost of a design at the preliminary design stage. Finally, preliminary design codes need to be able to consider a wider range of strength and stiffness constraints, such as fatigue and localized buckling.

All conceptual design codes provide basic, overall geometry of a design, for instance, in terms of fuselage and wing profiles. From this a preliminary designer can easily construct the outer surface geometry of an aircraft. However, "meshing" this surface with a finite element grid is problematic. In particular, there is typically no data from conceptual design on bulkhead/ring and rib spacing. If this was available, the mesh would be much easier to build. Also, most conceptual design codes do not include windows, doors, fixtures and nonstructural mass. If they did, a better finite element model could be built and a better weight estimate would result. Information on substructure, windows, etc., simply needs to be provided to the geometric modeler for the finite element model from the conceptual design module.

A cost model needs to be added to preliminary design codes because cost is at least as important as weight. Cost is included at the conceptual and detailed design levels, but is missing at the preliminary level. If manufacturing costs are included for all parts in the finite element model, the overall

manufacturing cost can be estimated. If windows, doors, fixtures and non-structural masses are assigned costs, these can be included in the overall cost as well. A framework for cost accounting can be easily developed within the ASTROS environment.

Fatigue and buckling constraints are a natural extension of the generic strength constraints available in all preliminary design codes. Using such constraints makes the structural optimization results more realistic, especially in light of the fact that buckling and fatigue govern a greater portion of the structure than any other failure mechanism. ASTROS can easily be modified to accommodate both fatigue and localized buckling constraints.

B.4.5 Major elements of an integrated design system development

An integrated aircraft design process which encompasses both conceptual and preliminary design must allow for better communication between modules and must include numerous improvements to the individual modules.

In order for conceptual and preliminary design modules to communicate, a process to feed design information from a preliminary design (spawned from a conceptual design) back to the conceptual design module must be developed. This process must include a way to update the rules for cost, weight and performance estimation in the conceptual design module based on cost, weight and performance calculations in the preliminary design module.

In order to improve the process of generating a finite element model for preliminary design, the overall dimensions of aircraft components as well as key substructure details (ring/frame and rib spacing) must be passed easily to a geometric modeler. Ideally, the geometric modeler will be a parametric modeler to allow for ease in changing dimensions and having the finite element model change along with the overall dimensions. The substructure details, as well as locations of doors, windows, fixtures and nonstructural masses must be defined in the conceptual design module and passed to the geometric modeler.

Within the preliminary design module, manufacturing cost must be calculated in order to support an increase in certainty in cost estimates as the design moves forward. More realistic constraints, to include localized buckling and fatigue, must be included in the preliminary design modules.

In order to develop an integrated design system from scratch, enormous resources would be required. However, all of the improvements listed above can be ***demonstrated*** by working with public domain conceptual and preliminary design modules, namely FLOPS and ASTROS. Using the Computer-Aided Design Data Base (CADDB) associated with ASTROS as the overall database makes good sense as well. In the case of both ASTROS and CADDB, adding both analysis modules and data relations is exceptionally easy. In fact, FLOPS could easily be integrated within ASTROS, the most difficult part being the task of setting up the FLOPS relations (both scalar and matrix quantities) within CADDB.

The total task of demonstrating a major improvement in integrated design software is too big to be attacked in a program, like the SBIR Phase II Research Program, with funding in the neighborhood of $250,000. Therefore, it is appropriate to tackle specific elements of the bigger problem.

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