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Non-Deterministic, Non-Traditional Methods (NDNTM)

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Non-Deterministic, Non-Traditional Methods (NDNTM)

Executive Summary

Review Context

The purpose of the study was to identify research opportunities related to the use of non-deterministic, non-traditional methods to support aerospace design. The scope of the study was restricted to structural design rather than other areas such as control system design. Thus, the observations and conclusions are limited by that scope.

The review identified a number of key results. The results include the potential for NASA/AF collaboration in the area of a design environment for advanced space access vehicles. The following key points set the context and delineate the key results.

The Principal Investigator's (PI's) context for this study derived from participation as a Panel Member in the Air Force Scientific Advisory Board (AF/SAB) Summer Study Panel on "Whither Hypersonics?" A key message from the Summer Study effort was a perceived need for a national program for a space access vehicle whose operating characteristics of cost, availability, deployability, and reliability most closely match the NASA 3rd Generation Reusable Launch Vehicle (RLV). The Panel urged the AF to make a significant joint commitment to such a program just as soon as the AF defined specific requirements for space access consistent with the AF Aerospace Vision 2020.

Key Findings:

The point this study brought home is the concurrent need for a national vehicle design environment. Engineering design system technology is at a time point from which a revolution as significant as that brought about by the finite element method is possible - this one focusing on information integration on a scale that far surpasses current design environments. The study therefore fully supported the concept - if not some of the details - of the Intelligent Synthesis Environment (ISE).

It became abundantly clear during this study that the government (AF, NASA) and industry and not moving in the same direction in this regard - in fact each is moving in its own direction.

- NASA/ISE is not yet in an effective leadership position in this regard. However, NASA does have complementary software interoperability efforts that should be a part of any major ISE program. Software standards that assure interoperability of data systems and modeling representations are **enabling** for the proposed research advocated herein and should be a major element in the ISE initiative.
  - The international standard for data interchange is known by the acronym "STEP." The NASA participation and lead for that effort is at the Goddard Space Flight Center.
  - NASA/GRC is leading an effort to define CAD geometry standards through the Object Management Group (OMG).
- To enable the design environment so necessary to the above national vision for a unique space vehicle will require an integrating software environment with interoperability standards that allows the development and widespread deployment of tools and toolsets, rather than traditional "shrink-wrapped" software used by engineers today.

- Someone or some agency has to define that software environment and its standards in order for the US aerospace industry to approach decent levels of interoperability of design tools and design information. NASA has some key efforts in this area.
- Each aerospace company today appears to be developing its own version of an ISE. These are not inter-operable environments.
- The AFRL has its own program called the Common Engineering Environment (CEE).

The AF, NASA and industry could cooperate to develop a true, common design environment in a way that will benefit the nation later on. NASA is the obvious agency to pull this together.

The contracted task of Non-deterministic, Non-traditional Methods (NDNTM) is but a subset task within a design environment.

- A key NDNTM finding is that there is no current need for new probabilistic methods but rather for tools and toolsets to be developed that would support the deployment and use of non-deterministic methods.

Another key finding is that the required accuracy for reliability assessment to support the fleet risk assessments that will underpin the future design environment poses several key issues that must be addressed within NDNTM development.

- We do not have the necessary tools and toolsets to **deploy** today's probabilistic technologies for real systems with flight safety requirements.
- We do not have the needed **error bound** technology base for the various non-deterministic methods.
- We do not have the **design-enabling environment** to support the full deployment of non-deterministic design outside of the research office.
- There is consensus among the industry experts consulted by the PI on these points.

The NDNTM study therefore focused on the issues for enabling this technology base for large-scale aerospace system design. The study concludes by recommending specific programs to support the deployment of non-deterministic design in ways that will be accepted and used by a still-reluctant aerospace design community. The following are the priority-ranked recommendations for NDNTM development.

1. *Probabilistic Data Expert (PDE):* The PDE provides a systematic means for merging disparate forms of "data" into probabilistic design. The data ranges from subjective expert opinions to raw data such as specimen specific fatigue test data.
2. *Probabilistic Updater (PU):* The probabilistic design process for total life cycle design from concept to field deployment for complex systems generally involves reliability growth processes of one form or another. Semi-automated systems to support model updating based on information and data that become available after the initial design are required.
3. *Probabilistic Error Bounder (PEB):* A key and, as yet, not addressed and fundamentally critical need is to be able to compute rational reliability error prediction bounds for the various algorithms likely to be used an advanced aerospace vehicle and propulsion design. Error bounds are needed that span the analysis spectrum from the physics approximations, to the response surface or surrogate models used to represent the physics, to the specific probabilistic algorithms deployed.

4. *Probabilistic Model Helper:* A major limitation in the deployment of probabilistic methods for system design is the current burden that the analyst be a skilled "probabilistic engineer." Non-traditional methods provide a real basis for the development and deployment of intelligent systems to work as probabilistic "robots" or assistants.

5. *Probabilistic Mesomechanics:* Significant progress has been demonstrated in the ability to link material processing simulation software with micromechanical models of material behavior at the mesoscale (grain size, grain orientation, flow stress, dislocation density) to predict statistical distributions of material fatigue strength. Such probabilistic modeling advances lend real credibility to the notion of engineered materials that goes well beyond the simpler notions associated with composite material systems. Probabilistic mesomechanics tools that can support the PDE tool or feed "data" directly into the material data distributions are required.

6. *Response Surface Generator (RSG):* Two methods are currently employed to generate RS's; these are the Taylor series method and the "design of experiments (DOE)" method. RS methods are highly effective over a range of design levels from conceptual to final. A generalized "tool" for effective development and representation of RS's is needed that will interface both to probabilistics and to the closely related field of multidisciplinary optimization (MDO).

7. *System Reliability Interface:* The aerospace system design environment of the future requires the ability to interface multiple models of multiple subsystems in an efficient and accurate manner. Intelligent systems can be developed for linking the information and propagating it to the various "top level" events in order to provide a powerful environment for calculating and managing system level reliability.

8. *Health Management System:* A new Health Management (HM) design strategy should allow inclusion of sensors and diagnostic/prognostic technologies to be incorporated early in the design process to optimize system performance and life cycle costs.

1.0 Detailed Overview of the Effort and Report

The purpose of the study was to identify research opportunities related to the use of non-deterministic, non-traditional methods to support aerospace design. The scope of the study was restricted to structural design rather than other areas such as control system design. Thus, the conclusions are limited by that scope.

Several positive developments characterize the developing aerospace systems design environment based on the observations made during this review. The design environment is undergoing revolutionary changes that are at least as significant as the change from hand analysis to ubiquitous application of finite element methods that began roughly 40 years ago. These changes are associated with web-enabled, distributed computing and with object-oriented programming. Every major aerospace airframe and engine company is actively working on large-scale, integrated design systems with extensive generalized database (what will be referred to as information) linking capabilities.

The fundamental common element in these generalized approaches is information linking where disparate types and forms of information are made easily accessible to the various specialized tools used for design analysis. The enabler for the developing design environment is object-oriented programming, specialized tools for data creation, visualization, and analysis. So-called data wrappers are specialized tools that automatically create links between analysis tools and the required analysis information.

The new software environment is increasingly web-enabled. Web enabling includes the use of Java-based graphical interfaces such that the workgroup on design projects may share information and resources over the Internet. Web-enabled tools mean the programming tasks can be done once and used over a wide range of processors. The tool sets that are being deployed often allow the individual user to tailor their own interface to support specific analysis or interpretation purposes.

These developments are taking place generally outside the context of NASA's Intelligent Synthesis Environment (ISE). The ISE initiative appears to be a result of these developments rather than a leader of these developments. Rather, industry has taken the lead in moving to a new design environment under pressures of product development costs and cycle-times, recognizing that improved information processing is the underlying enabler of true concurrency in design. However, the very fact that each company is developing their own environment guarantees that information sharing required to complete a new vehicle system design for NASA will encounter significant information barriers at the system level.

Finding: NASA has an opportunity under the banner of ISE to provide leadership to the aerospace community by taking leadership in creating high-level information and programming standards that can facilitate advanced space vehicle design requirements. Such an integrated system is seen as a fundamental requirement for the successful execution of the proposed 3rd Generation Reusable Launch Vehicle, for example. Defining such standards would enable tool development and information processing that can be shared between multiple proprietary systems. To date, there is no evidence that the NASA ISE initiative has taken this leadership role.

Finding: NASA has demonstrated leadership in the effective deployment of system integration platforms that enable the aerospace propulsion community to integrate proprietary and NASA-developed codes through the NPSS effort. NASA continues in some areas, however, to pursue multipurpose, stand-alone codes that do not integrate well with other tools or codes.

Recommendation: If NASA were to take the recommended approach to ISE by facilitating an aerospace industry **integrating** design environment, NASA would also have the ability to promote the development of tools that can easily be integrated by the various aerospace firms, contractors, and universities into this design environment. This report **recommends** the development of several key, object-oriented software tools or toolsets that build on non-traditional design methods and facilitate the widespread application of non-deterministic design methods that will be critical to the success of a new space vehicle design program. Such tools will achieve NASA's goal of deploying NASA-logo bearing products to the design workplace if they employ modern, object oriented programming methodology.

A critical design requirement for future space vehicle designs is high system reliability over the full life cycle of the system. Non-deterministic design methods are an intrinsic element in meeting this requirement. A major element in the completed review of NDNTM has been to assess the current state of probabilistic methods for structural design. The information used to make the following finding is based on the following sources:

- The ongoing efforts by the Society of Automotive Engineers (SAE) Committee G-11 Probabilistic Methods (PM) Committee. That committee effort includes assessment of the technical quality and capabilities of various probabilistic methods. The work of this group can be referenced at http://forums.sae.org/access/dispatch.cgi/TEAG11PM_pf.
- Reviews conducted by the USAF as part of the current contract on probabilistic high cycle fatigue (HCF) under the leadership of Stress Technologies, Inc.
- Input from various probabilistics experts including Southwest Research Institute, Unipass Software Systems, ARA Inc., and members of the technical staffs at Boeing, Pratt & Whitney, Rockwell, Honeywell, and GEAE.
- Proceedings of the AIAA Nondeterministic Methods Forum conducted in Atlanta GA on 3 April 2000.
- Recorded comments from the AIAA Nondeterministic Methods Panel in Atlanta GA on 4 April 2000.

Finding: The various algorithms for probabilistic structural analysis are diverse in structure, approach, and capabilities. The algorithms themselves are still the subject of intense scrutiny and debate. However, there is consensus that there are no substantive research opportunities at this time for new or improved probabilistic algorithms, per se.

Finding: The integration of probabilistic structural analysis algorithms into system design is primitive at best. Significant research needs and opportunities have been identified that will move probabilistics from the research application to vehicle system design capability. The needs will draw on technologies developed in the general area of **NDNTM**.

Figure 1 illustrates a nondeterministic design environment based on today's probabilistic design codes, shown at the center. The current study has found widespread interest in and need for powerful "tools" that will provide critical interface capabilities between the designers and the current probabilistic algorithms. The various tools (meant in the broadest sense) include the following items.

Probabilistic Data Expert (PDE): The PDE provides a systematic means for merging disparate forms of "data" into probabilistic design. The data ranges from subjective expert opinions to raw data such as specimen specific fatigue test data. The PDE relies on non-traditional methods for integrating "fuzzy data" based on qualitative information. The major technology needs here are in creating tools for automating the data acquisition and integration processes. A pilot study for probabilistic HCF has been forwarded to NASA under the ISE banner as part of the joint AF/Navy/NASA and Industry program. However, there are additional basic research needs in addition to the proposed pilot study.

Probabilistic Updater (PU): The probabilistic design process for total life cycle design from concept to field deployment for complex systems generally involves reliability growth processes of one form or another. Early in the design process, the reliability characteristics of the subsystems are either not known or crudely known. Testing during development should focus on those results that are most effective either in demonstrating greater reliability or increasing the assurance (reducing the uncertainty) in the reliability prediction. There exists a critical need to provide a generalized tool that will provide intelligent ways to update the current reliability and assurance intervals (akin to statistical confidence intervals) taking into account new information and data. Reference [33] discusses these intervals.

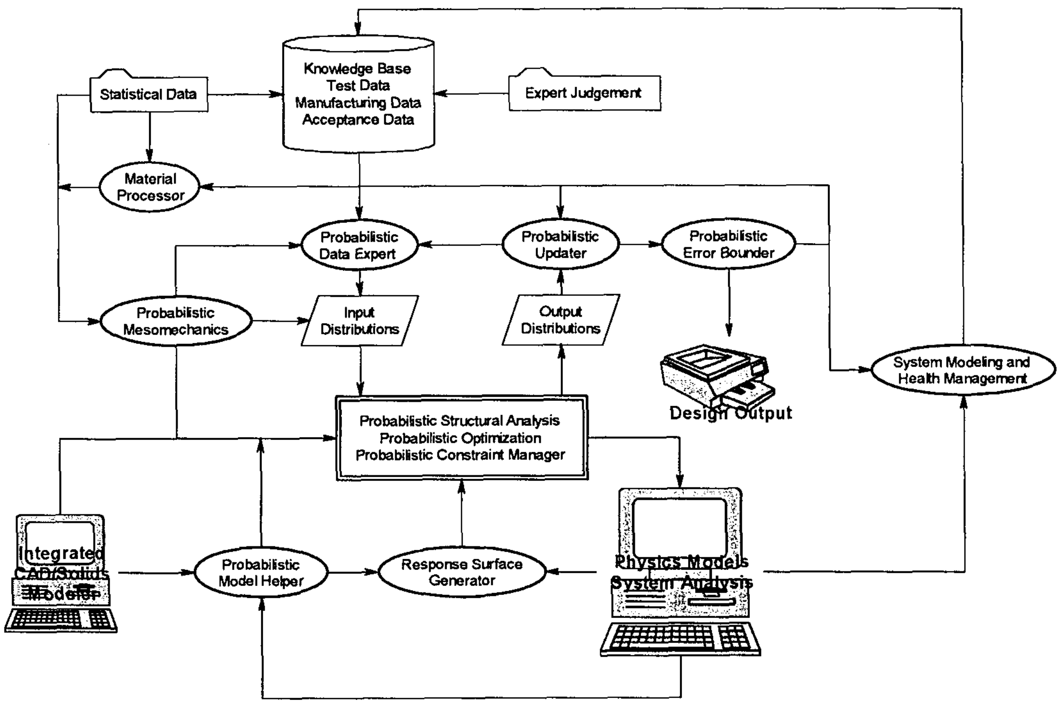


Figure 1: Integrated Nondeterministic Design Environment

Probabilistic Error Bounder (PEB): Many systems design processes have allowed for generalized levels of comfort in product performance – so-called "fuzzy" non-deterministic output. However, both the commercial workplace and the demands of government acquisitions have transformed the aerospace vehicle design requirements from non-analytical reliability bases to specified levels of "demonstrated" reliability that may include both test and analytical bases. A key and, as yet, not addressed and fundamentally critical need is to be able to compute rational reliability error prediction bounds for the various algorithms likely to be used an advanced aerospace vehicle and propulsion design. Error bounds are needed that span the analysis spectrum from the physics approximations, to the response surface or surrogate models used to represent the physics, to the specific probabilistic algorithms deployed. In fact, it is likely that engineers will need to deploy hybrid combinations of the current probabilistic methods (e.g., FPI, Monte Carlo importance sampling) for large, system design problems. Error identification, tracking, accountability, and bounds are required for the full process.

Response Surface Generator (RSG): All current probabilistic algorithms for any but the most trivial problems use a "response surface" or surrogate model to describe the component, sub-system, or system level behavior as a function of the design variables. Thus, it is a surface in the N-dimensional design space of the problem. In fact, it is increasingly likely to be a union of many such hyper-surfaces that can be used for complex system design. An example of a powerful algebraic system for manipulation of RS's that could be easily extended to non-deterministic design is seen at the Rockwell Science Center link: http://www.rsc.rockwell.com/designsheet/.

Two methods are currently employed to generate RS's; these are the Taylor series method and the "design of experiments (DOE)" method. The former are more likely to be employed near a critical design point while the latter are more often used to span a wider range of the design space. Fast probability methods such as the Fast Probability Integrator (FPI) algorithms or importance sampling (a Monte Carlo simulation strategy) are performed using the RS and do not directly use the actual detailed simulation. As such, the RS methods are highly effective over a range of design levels from conceptual to final. A generalized "tool" for effective development and representation of RS's is needed that will interface both to probabilistics and to the closely related field of multidisciplinary optimization (MDO). Further, the *PEB* tool and the *RSG* tool should be able to work together to adaptively build optimal RS strategies that combine computational efficiency with minimizing the probabilistic approximation errors for large system design problems.

Probabilistic Model Helper: A major limitation in the deployment of probabilistic methods for system design is the current burden that the analyst be a skilled "probabilistic engineer." Such individuals at this time are probably numbered in the low dozens and are scattered between software firms, universities, government labs, and industry. The field is not one that has received much attention in academic curricula although the topic is now covered in the most recent undergraduate mechanical design texts. Further, the process of preparing and interpreting a probabilistic design problem involves the inclusion and assessment of many more sources of information and decisions regarding the analysis strategy. Non-traditional methods provide a real basis for the development and deployment of intelligent systems to work as probabilistic "robots" or assistants. The approach will likely require significant use of adaptive networks, software robots, genetic algorithms, expert systems and other non-traditional methods.

Probabilistic Mesomechanics: Significant progress has been achieved since the early attempts at what was called "level 3" probabilistic material modeling as part of the original NASA Probabilistic Structural Analysis Methods (PSAM) contract. Demonstration problems have shown the ability to link material processing simulation software with micromechanical models of material behavior at the mesoscale (grain size, grain orientation, flow stress, dislocation density) to predict statistical distributions of material fatigue strength. Such probabilistic modeling advances lend real credibility to the notion of engineered materials that goes well beyond the simpler notions associated with composite material systems. Probabilistic mesomechanics tools that can support the PDE tool or feed "data" directly into the material data distributions are required. Automated, intelligent systems are envisioned with the capability to forward model material processing to define scatter in properties as well as sensitivity links to the independent process and material primitive variables. Further, the inverse problem of optimizing the processing and design of the material microstructure provides the ultimate in an "engineered materials" design capability.

System Reliability Interface: The aerospace system design environment of the future requires the ability to interface multiple models of multiple subsystems in an efficient and accurate manner. Each failure mode of the system has its own probabilistic model in terms of a response surface or surrogate model representation of the physical problem together with the associated non-deterministic design variable descriptions. Current NASA technology focuses on traditional block-diagram forms for representing system reliability. Each block is typically represented by point estimates of reliability that are not linked to the underlying physics or to the distribution and confidence in the underlying variables. Physics based system modeling provides an information-based opportunity for linking the key design parameters and physics-based models together from the sub-system/component level to the full system level. Intelligent systems can be developed for linking the information and propagating it to the various "top level" events in order to provide a powerful environment for calculating and managing system level reliability.

Health Management System: Health Management is a philosophy that merges component and system level Health Monitoring concepts, consisting of anomaly detection, diagnostic and prognostic technologies, with consideration to the design and maintenance arenas. Traditionally, Health Monitoring design has not been an integral aspect of the design process. This may be partly due to the fact a cost/benefit model of a HM system configuration cannot be fully realized at this stage. Without a doubt, Health Monitoring technology must "buy" its way into an application. Hence, the need exists to extend the utility of traditional system reliability methods to create a virtual environment in which Health Monitoring architectures and design tradeoffs can be evaluated and optimized from a cost/benefit standpoint. This capability should be present both during the design stage and throughout the life of the system. A new HM design strategy should allow inclusion of sensors and diagnostic/prognostic technologies to be generated in order to produce an enhanced realization of component design reliability requirements at a very early stage. Life Cycle Costs can be reduced through implementation of health monitoring technologies, optimal maintenance practices and continuous design improvement. To date, these areas have not been successfully linked with non-deterministic design methods to achieve cost/benefit optimization at the early design stage.

Summary Recommendation: Significant opportunities and critical needs exist in the area of non-traditional methods as applied to the area of non-deterministic modeling to support reliability-based design for advanced, complex aerospace systems. While the ISE initiative has the overall responsibility for the environment, the current NTNDM contract effort clearly establishes an opportunity for NASA/GRC leadership in the development and deployment of interoperable modeling tools that will substantially enable the deployment of non-deterministic capability to the aerospace industry. NASA/GRC is urged to define a long-range plan (5 to 10 years at the current level of funding) to fund the above tool needs.

2.0 Proposed NASA Research Announcement (NRA) Focus Areas

2.1 Probabilistic Data Expert

2.1.1 Background

Probabilistic system analysis capabilities for complex aerospace systems must be effective elements within generalized design environments for integrated vehicle and propulsion systems. The information required to support such integrated design systems will characterize the uncertainties inherent to the type of design data (e.g., loads, materials, etc.) at a level of fidelity consistent with the knowledge available at the particular stage of the design process (e.g., conceptual, preliminary, final, in-service) [1]. Some of the design information will consist of usual forms of materials data such as "A" or "B" allowables and the supporting statistical data base such that probability distributions and confidence levels can be assigned to the data. Some of the design data will involve engineering judgment based on experience [2]. Such data is "fuzzy" data in that there may be significant reliance on subjective measures and estimates. Some of the design data may be in the form of qualification testing at the sub-system or component level.

The inherent range in design data from very subjective to fully characterized statistical models must be included in the probabilistic design analysis cycle. However, subjective data must be mapped into probability distributions to support the design process in ways that most correctly capture the expertise of the individuals submitting the data while removing to the greatest extent possible biases and unrelated judgments of the experts. Such "fuzzy" input data must then be effectively merged with the other types and quality of probabilistic input data so that the usual formalisms of probabilistic design analysis can be deployed.

2.1.2 Statement of Work

A comprehensive "tool set" is to be developed that accepts a full range of input data from domain-expert opinions to crisp statistical data and creates probabilistic data sets that define distributions (closed-form to empirical), uncertainty characteristics for the distributions, truncation levels, etc. such that comprehensive probabilistic design analysis can be performed on the created input data. Further, the tool set will provide linkage such that the resulting probabilistic design analysis distribution and levels of assurance (equivalent to statistical confidence levels) can be related back to the specific information elements for the un-mapped, raw input data. When data is taken from physical test results or from analysis models, the data is to include estimates of experimental error, modeling error, and any biases in these errors. Finally, the provided probabilistic design analysis input distribution data (known as "prior" distributions) are to be accessible through the tool set to a range of updating strategies. The technical elements to be included in the tool set are as follows.

- Tools and strategies that support self-elicitation of expert opinions for the knowledge base for pilot applications.
- Graphical tools specifically tailored to define design system processes and interactions, logic models, event trees, reliability block diagrams, Bayesian networks, FMEA models, etc. with the facility to generate appropriate data structures for subsequent application.

- Knowledge base groupware with extensive capability for segregating proprietary databases, tracking knowledge use to and from the application software to be used on pilot problem.
- Mapping tools for converting knowledge base into prior distributions with traceability.

2.1.3 Software Requirements

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.2 Probabilistic Updater

2.2.1 Background

Probabilistic design analysis for complex aerospace systems is required to support the entire life cycle of the system from conceptual design to service use. Knowledge of system variables and operating characteristics will increase in quality through the life cycle. Development testing is an inherent part of the life cycle of these complex systems and is intended to provide cost-effective means for improving the state of this knowledge. Improved knowledge and the associated development costs must be fully integrated into the probabilistic design analysis process for these complex aerospace systems. The integration must be a proper blend of automation and judgment such that prior distributions are updated for continuing system assessments of performance reliability consistent with sound engineering principles.

Bayes theorem [3] is one but not the only method for updating. When the situation is appropriate for its use, it is often method of choice because of a most desirable result: when the prior distribution and the likelihood reinforce one another (overlap), the posterior distribution from the theorem has a narrower variance. One can overcome some of the major criticisms of the use of Bayes' Theorem as with today's computing we are not limited to using specific distribution forms (e.g., beta) for computational convenience.

By the same reasoning, we are not limited to using Bayes' Theorem when other weighting schemes or conditional probability combining schemes are appropriate. For example, when two sources of information, say two reliability distributions from two experts, greatly differ, one would not blindly just use Bayes' Theorem to combine these. First, as part of the formal elicitation methods (see Probabilistic Data Expert tool above), one would want to try and resolve why the two experts disagreed. Perhaps they had different assumptions or were assuming certain conditions were holding. If such differences cannot be resolved, then the large uncertainty range covered by both distributions reflects the state of knowledge at that time. It then becomes the task of trying to identify how to gather additional information to reduce that large uncertainty. In the mean time, a simple weighting scheme (the default being equal weights) would be a method for combining the two different distributions.

Regardless of the combining method used (Bayes' or other), the recommended approach is to review all combining analysis results with the experts, to make sure that the combination is consistent with the existing state of knowledge. The elements of this process can be implemented in "smart" tools.

2.2.2 Statement of Work

A comprehensive "smart tool set" is to be developed to provide probabilistic updating capabilities to probabilistic design analysis systems. The tool set is to include a knowledge base as well as an adaptive network to support the "intelligent" use of various updating strategies and to advise the user of options or recommendations. The tool set is to operate on predefined networks of the system problem (see 1.1) such that measured results at any node can be used to support an updating of related priors. The tool set is to be configured in such a manner as to permit its application to single node models as well as system models with up to 10^5 degrees of freedom.

2.2.3 Software Requirements

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.3 Probabilistic Error Bounder

2.3.1 Background

The use of probabilistic methods for gas turbine engine design will require efficient and accurate algorithms for low probability of occurrence design conditions. The engineer must have access to automatic algorithms and protocols that provide user-control over accuracy within the constraints of available modeling capacity and time. In order to do this, the various computational algorithms for reliability assessment need to have formal error estimators. Further, given the likelihood that hybrid methods are going to be required, hybrid reliability computation strategies must be developed and qualified.

Fast probability integration (FPI) algorithms include one, two, and three parameter fits to the equivalent normal distributions. Some error studies have been performed. The errors are dependent on the various characteristics of the actual distributions such as uniform and truncated distributions. Some algorithms such as the fast Fourier transform (FFT) are better suited to certain types of distributions. The need is for a systematic study of accuracy and efficiency for various, useful distributions. An analytical estimate of residual errors based on available information regarding the distributions being modeled is required.

The iterative advanced mean value (AMV+) algorithm is taken to be the full iteration process at the estimated and updated design point. The requirements for this methodology are a mathematical demonstration of convergence to the "true" answer and a residual error term for both the first-order reliability method (FORM) and the second-order reliability method (SORM). Since these methods are implicit, the use of nonlinear mapping functions is not to be considered. Computational efficiency vs. accuracy is to be demonstrated.

The response surface method has three areas of error estimations. The first error issue is the error estimates for fitting the response surface. The issues include selection of the fitting points and this should include DOE considerations as well as COV data for each variable. The second concern is the error estimation for the Monte Carlo method itself. Finally, the use of response surfaces for probability levels that are low (or high) focus on accuracy of the response surface near the portion of the design space that is driving that reliability calculation. Thus, local fitting issues rather than global have to be included in the error study and resulting metrics. Accuracy and computational efficiency studies are to be performed.

The "best" solution is likely to involve combinations of algorithms in ways that focus the process of getting to the region of the final design point quickly and resolving the estimated probability for the design point with user-defined accuracy. Residual error estimates are needed. Computational efficiency with specified error levels is to be the selection criterion. New probabilistic sensitivity factors are needed that properly describe the "tail" sensitivities for the response function at the final design point. The method of interval analysis (Section 3.4.4) is seen as an important tool in error bounding by using acceptable intervals to describe the input in a non-probabilistic manner.

2.3.2 Statement of Work

An error-bounding tool set is ultimately required. However, the focus of this effort is first to define good error bounds by analysis for each of the common probabilistic design analysis algorithms in current use for aerospace systems. The error bounds are to provide traceable contributions starting from the physical problem and proceeding through computational simulation, response surface or surrogate model approximations, and then to the final design probability level for any defined critical event.

An industry panel of probabilistic designers is to oversee the development and application of the defined bounds to assure that all relevant probabilistic methods and problem solving strategies are adequately addressed.

Recommended error estimate defaults are to be provided for any required input to the error bound algorithm. Such defaults are to be defined using available statistics or probability theory in a conservative manner. An intelligent interface is to be developed that will both guide and assess the user. Such an interface should have the ability to impose conservative strategies based on an assessment of the user knowledge and expertise. Interval mathematics are to be explored as a complementary, non-probabilistic supplement to the probabilistic error estimation effort.

2.3.3 Software Requirements

The error bound algorithms are to be documented such that any commercial or proprietary probabilistic design system can properly incorporate the algorithms. The intelligent PEB tool is to be developed consistent with the following requirements.

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.4 Response Surface Generator

2.4.1 Background

Response surface methods form the basis of all current NDM if one accepts the fact that FORM and SORM work with fitted polynomials based on the local slope and curvatures of the physical model (which may itself be an approximation of the physics). RS's may be formed from the Taylor series, from a design of experiments (DOE) strategy, or from experimental data. Traditional RS methods derive from the field of statistics and include not only a physical model but information on the statistics of the variables. In the current context we do not include the statistics of the RS but admit that experimental RS's may need to include these measures as part of the "assurance level" associated with the RS.

RS methods may include ties to multidisciplinary design optimization (MDO) where approximations to the objective function may be needed, as in linear programming and in second order methods. The linkage between NDM and MDO is a critical one for future designs of large complex aerospace systems.

The issues of efficiency and accuracy of RS's is critical to NDM of design as well as to MDO where efficiency is most critical. Efficiency in RS approximation may be most important near the mean-value design point and in preliminary or conceptual design. Accuracy will become the critical issue in NDM near the final probabilistic design point.

2.4.2 Statement of Work

A response surface generator tool set is needed. The tool set should provide an open interface to information used to characterize physical phenomena. The tools should include intelligent systems such as agents, knowledge-based rules, or other AI technologies to assist in guiding an efficient computational strategy for both probabilistic design and for MDO. The tools must also provide for user-controlled, variable-fidelity combinations of speed and accuracy in tailoring the RS. The tools must be capable of interaction with the PEB toolset.

The RS tool set is to include a full complement of DOE facilities for multifactor, multilevel "design" variable condition selections. An option to include Taguchi-like DOE strategies focusing on controlled and uncontrolled variables should also be included. All interaction terms are to be included for both Taylor series and DOE strategies.

2.4.3 Software Requirements

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.5 Probabilistic Model Helper

2.5.1 Background

A major limitation in the deployment of probabilistic methods for system design is the current burden that the analyst be a skilled "probabilistic engineer." Such individuals at this time are probably numbered in the low dozens and are scattered between software firms, universities, government labs, and industry. The field is not one that has received much attention in academic curricula although the topic is now covered in the most recent undergraduate mechanical design texts. Further, the process of preparing and interpreting a probabilistic design problem involves the inclusion and assessment of many more sources of information and decisions regarding the analysis strategy.

Considerable work has been done over the past decade to apply probabilistic design methods to component design. A major effort in the field of "six sigma" design has developed a great deal of data on process and property variations for complex mechanical and production systems. Effective linkages to this experience would assure that such knowledge and experience can be accessed by the current NDM system design analyst.

Non-traditional methods provide a real basis for the development and deployment of intelligent systems to work as probabilistic "robots" or assistants. The approach will likely require significant use of adaptive networks, software robots, genetic algorithms, expert systems and other non-traditional methods.

2.5.2 Statement of Work

An adaptive and intelligent PMH toolset is to be developed that will support high quality, high fidelity, and robust non-deterministic design for large, complex aerospace systems. The toolset will monitor, assess, guide, and learn. It will also have the capacity to operate in a tutorial mode based on an assessment of the user skill level. The toolset is to interface to all elements of non-deterministic design of such aerospace systems and include elements appropriate to all design stages from pre-conceptual to deployed systems. The toolset is to operate on at least three levels of user interactions based on a system of expertise evaluation and certification.

2.5.3 Software Requirements

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.6 System Reliability Interface

2.6.1 Background

The aerospace system design environment of the future requires the ability to interface multiple models of multiple subsystems in an efficient and accurate manner. Each failure mode of the system has its own probabilistic model in terms of a response surface or surrogate model representation of the physical problem together with the associated non-deterministic design variable descriptions.

Current NASA technology focuses on traditional block-diagram forms for representing system reliability. Each block is typically represented by point estimates of reliability that are not linked to the underlying physics or to the distribution and confidence in the underlying variables. Typical of this important, but dated, modeling is the NASA QRAS system developed for the current space access system.

Physics based system modeling provides an information-based opportunity for linking the key design parameters and physics-based models together from the sub-system/component level to the full system level. Intelligent systems can be developed for linking the information and propagating it to the various "top level" events in order to provide a powerful environment for calculating and managing system level reliability.

2.6.2 Statement of Work

The System Reliability Interface toolset will define a working environment for managing, linking, and synthesizing system level reliability while providing defined "assurance intervals" for the system based on basic design variable inputs. The system level operation should be capable of linking to the updating tools so that hardware experience, test data, and new information can be used to provide updated system reliability and assurance interval results. The System Reliability Interface toolset shall have adaptive, reliability networks as the basis for recording and calculating system reliability and the marginal distributions for all interactive failure modes at every system level. Furthermore, the toolset shall have an intelligent means for propagating component level failures to the system level while identifying all of the important interactions involved.

2.6.3 Software Requirements

All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

2.7 System Health Management

2.7.1 Background

System Health Management is a philosophy that merges component and system level Health Monitoring concepts, consisting of anomaly detection, diagnostic and prognostic technologies, with consideration to the design and maintenance arenas. Traditionally, Health Monitoring design has not been an integral aspect of the design process. This may be partly due to the fact a cost/benefit model of a HM system configuration cannot be fully realized at this stage. Without a doubt, Health Monitoring technology must "buy" its way into an application. Hence, the need exists to extend the utility of advanced no-deterministic system modeling to serve as the basis for a virtual environment in which Health Monitoring architectures and design tradeoffs can be evaluated and optimized from a cost/benefit standpoint. This capability should be present both during the design stage and throughout the life of the system. A new HM design strategy should allow inclusion of sensors and diagnostic/prognostic technologies to be generated from traditional Failure Mode Effects And Criticality Analysis (FMECA) information producing an enhanced realization of component design reliability requirements at a very early stage.

Life Cycle Costs can be reduced through implementation of health monitoring technologies, optimal maintenance practices and continuous design improvement. To date, these areas have not been successfully linked with non-deterministic design methods to achieve cost/benefit optimization at the early design stage.

2.7.2 Statement of Work

An information environment and the necessary tools will be developed in order to construct a comprehensive non-deterministic-based System Health Management design environment. Design feedback shall be provided by the Probabilistic Updater tools. Linkages shall be provided between the design information, experimental test data as well as on-line health monitoring data and appropriate system models in order to provide continuous design reliability improvements, maintenance management, and life cycle cost reductions. The System Health Management tools and information environment shall also link to traditional system reliability models as derived from FMECA, fault tree, event tree and other appropriate system level representations. A key capability shall be the ability to operate the system by taking advantage of health monitoring to increase overall system performance while maintaining the required system reliability.

2.7.3 Software Requirements

The overall software environment must be designed with specific attention paid to the diversity of data sources needed for System Health Management, from test cell data to fleet operations data to field maintenance data. General purpose tools and communication protocols appropriate to System Health Management will be defined and developed. All software is to be prepared using "C++" or "JAVA" based on the most up-to-date object oriented programming methods. The tool set is defined to mean the collection of all software objects required to provide tailored user interfaces, analysis modules, data interfaces, module linkages, and output tailoring including comprehensive graphics. The tool set is to be provided with non-proprietary "data wrappers" such that the input and output results are able to interact with text, spreadsheet, free-format, and other forms of data records as well as be able to prepare data for commercial analysis codes in the disciplines of structural, heat transfer, CFD, and algebraic interpreters. The underlying analysis software is to be capable of execution on NT workstations and Unix workstations. The interfaces are to be written in Java to be web-enabled and device independent.

3.0 Discussion

3.1 Review of Study Process

The four elements of the study process are shown in Figure 2. The contracted Consultant sought to integrate relevant technologies and requirements by making personal contacts with each of the indicated entities. The study began by a review of efforts relevant to design environments and to non-deterministic, non-traditional design at the NASA Glenn Research Center. The Consultant was briefed on both technology and safety related programs and initiatives including plans for the NPSS environment. The Consultant was given information on the NASA Intelligent Synthesis Environment, which he supplemented, by further study of the literature and reviews with individuals in that program.

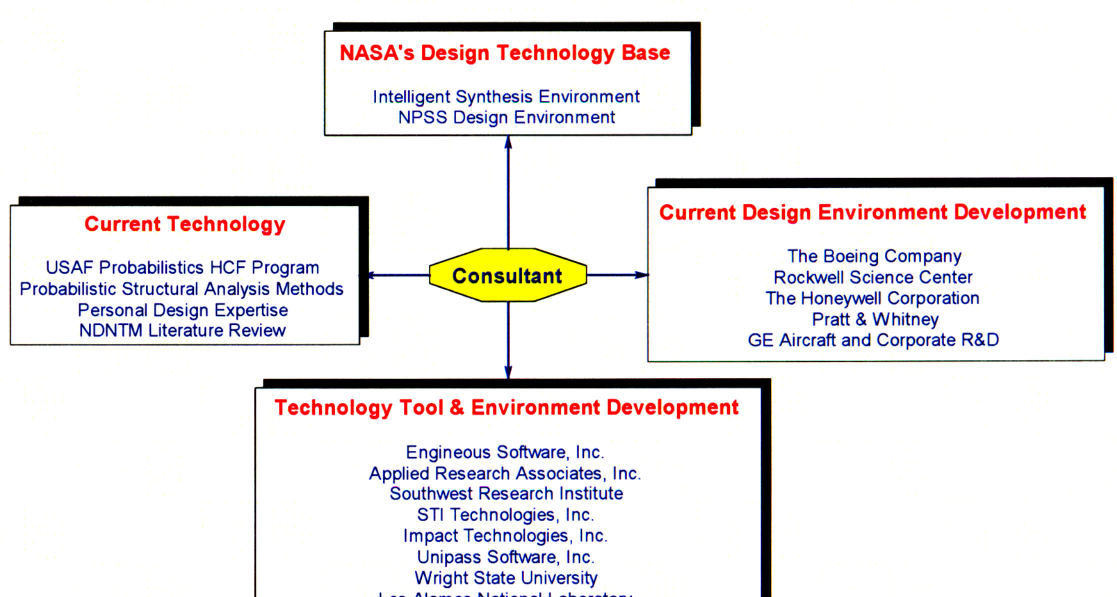


Figure 2: NDNTM Study Process Elements

The Consultant is also very actively involved in the deployment of non-deterministic design methods and requirements for both low cycle fatigue (LCF) and high cycle fatigue (HCF) design of gas turbine engine structures within the Air Force via the Engine Structural Integrity Program (ENSIP) handbook (Mil-Hdbk-1783) in support of the Joint Strike Fighter (JSF) and future Air Force and Navy Aeropropulsion requirements. The Consultant's involvement with the Air Force is as an advisor on probabilistic design and derives from his extensive experience with reliability based design of gas turbines, risk assessment support of large fleets of commercial gas turbine engines, and as the program manager for the NASA-funded Probabilistic Structural Analysis Methods (PSAM) program in the 1983 – 1990 time period. This total experience base has been critical in assessing the elements of a future non-deterministic, non-traditional design environment. It also opened the doors to talking with key organizations and individuals in both the aerospace industry and in technology oriented small businesses.

A literature review of recent publications in various sub-topics within the field of non-deterministic, non-traditional analysis methods has been completed. That review is given in subject areas that were researched included the following topics.

- Fuzzy logic
- Possibilistic analysis
- Interval arithmetic
- Neural networks
- Adaptive and Bayesian networks
- Artificial intelligence (focused applications)
- Genetic algorithms
- Probabilistic methods (only new work)
- Reliability based design (PREDICT)
- Integrated design methods for large system problems
- Chaos and complexity theory
- Health monitoring

The highlights of findings from the literature review will be given in the next section. There were few surprises in that no significant research breakthroughs in non-deterministic methods beyond those already deployed appear to be worth pursuing. However, it is abundantly clear that there are many non-traditional methods that can be brought into the advanced design environment envisioned by the ISE initiative.

The Consultant made a number of visits and teleconferences with key aerospace industries and with critical elements of the small business community that are active in NDNTM development and deployment. In each visit, the Consultant presented a talk on the ISE and discussed how NDNTM are needed to support future design environments. A set of the presentation material from a typical presentation is given in the imbedded PowerPoint presentation in Appendix 4.3. Selection of that page in any electronic form of this report will invoke the Slide presentation.

The discussions held with industry produced a range of input from verbal ideas or priorities for research topics to detailed discussions of new developments related to new design environments that share some of the goals of the ISE but are more coherently defined and being developed. Some highlights follow.

- The Boeing Company

  The meeting was held with representatives of various elements of the Boeing Phantom Works and Rocketdyne Division. The primary focus of the discussion was the Boeing Integrated Vehicle Design System (BIVDS). The Consultant was given proprietary information on this system. The conclusion is that Boeing is making a very serious attempt to define an operating environment that is information based and allows three levels of design complexity from conceptual to detailed design The major outcome of the meeting was a commitment made by Boeing to move strongly to bring non-deterministic methods into BIVDS at the earliest possible time. An action team was initiated to lead this effort.

- Rockwell Science Center

  The Rockwell Science Center has several excellent design system initiatives as well as many concepts for elements of ISE. The most interesting development for NDNTM is their algebraic design environment called Design Sheet™. Design sheet is a constraint manager system for working in very large design environments where designers must balance many requirements off against each other. Examples may be seen at http://www.rsc.rockwell.com/designsheet/. The product calculates constraints and sensitivity equations using the MACSYMA™ algebraic manipulation kernel together with some critical RSC proprietary algorithms.

  One can envision the operation of Design Sheet™ as a linked set of algebraic design rules or response surfaces, linked by common design variables. They have developed an 8,000-degree of freedom model representing the 3rd Generation RLV for NASA. The RSC scientist also pointed to research at the University of Ohio related to large, discontinuous design spaces as an important design environment research project. That site is http:// www.cis.ohio-state.edu/~chandra/aaai-98.pdf.

  A proprietary White Paper was submitted and is included in this report package.

- GE Aircraft Engines and Corporate R&D

  These corporate entities, along with Engineous Software Inc., Stanford, Ohio Aerospace Institute, and others have initiated a major design environment initiative with funding participation from NIST. The project title is "A Federated Intelligent Product Environment." There is much of great value in this effort ranging from effective means for the development and use of CAD information to non-deterministic design [4].

A common theme or element in these efforts is generalized information processing. A number of non-traditional design methods are deployed and all will at some time include a wide range of current non-deterministic design analysis methods. All individuals agreed that a key need for the future is interoperability issues such that tools can be moved between applications. All recognized the need for national initiatives on this issue and agreed that NASA would be a logical agent, with others, for creating such a national effort. And, all agreed that all would benefit.

GE recommends that the ISE initiative consider participation in this effort.

- Both Honeywell and Pratt & Whitney have large scale, proprietary design environment initiatives. They did not provide information on those efforts.

Technology tools and environment research is underway at a number of small businesses. The contract effort involved the ones indicated in Figure 2 where Los Alamos National Lab is included for some of their effort. The sites were selected on the basis of their work in non-traditional system optimization (Engineous) and in non-deterministic design (all others). The key areas of related non-deterministic tool development expertise are highlighted in the following discussion.

- Applied Research Associates, Inc.

  ARA has been very successful in creating a highly capable software interface to various non-deterministic analysis algorithms while using a commercial finite element code for the physics modeling (ANSYS™). ARA has specific capabilities for the Probabilistic Error Bounder as well as response surface technologies.

- Southwest Research Institute

  SwRI is a leader in probabilistic analysis software with the NASA-sponsored NESSUS software product. SwRI identified interval analysis using the new Sun Microsystems Inc. Fortran compiler. SwRI is also highly capable in areas related to design strategy for system reliability.

- STI Technologies, Inc.

  STI has extensive experience in response surface technologies and in random field and random process representations.

- Impact Technologies, Inc.

  Impact Technologies has done excellent work in the area of probabilistic System Health Management through a number of AF and DOE efforts. The SHM tools require extensive use of non-traditional methods for data fusion and for data interpretation.

  A White Paper was submitted and is part of this report package.

- Unipass Software, Inc.

Unipass has also developed a commercial probabilistic design code. They are particularly interested in research areas that are non-traditional applications of probabilistic modeling.

- Wright State University

  Three white papers on Response Surface modeling were submitted and are part of this report package.

- Los Alamos National Lab

  LANL has been very successful in deploying non-deterministic and non-traditional methods to real industrial problems involving total life cycle product design as well as a major industrial processing system. In particular, they have developed with the Delphi Automotive company a design environment called PREDICT. This environment is described by several of their presentations now posted at http://www.frontier.net/~tcruse/predict.

  Several White Papers were submitted and are included in this report.

In visits to each of these entities, a presentation was given. The focus on each of these visits though was in hearing ideas from each on important NDNTM research needs and opportunities. The suggested topics derive from these discussions both in general terms as well as the specifics of white papers that were submitted by some. Each of the submitted white papers is included in this report.

NASA Efforts that Relate to NDNTM

Following a presentation of this work to NASA/GRC, the author was made aware of other NASA programs that have relations to this effort. These include the development of data sharing standards via the international STEP standard led by NASA/Goddard. A description of this effort has been taken from their web site (http://step.nasa.gov) as follows.

> "The information generated about a product during its design, manufacture, use, maintenance, and disposal is used for many purposes during that life cycle. The use may involve many computer systems, including some that may be located in different organizations. In order to support such uses, organizations need to be able to represent their product information in a common computer-interpretable form that is required to remain complete and consistent when exchanged among different computer systems.
>
> STEP (ISO 10303) is an International Standard for the computer-interpretable representation and exchange of product data. The objective is to provide a mechanism that is capable of describing product data throughout the life cycle of a product, independent from any particular system. The nature of this description makes it suitable not only for neutral file exchange, but also as a basis for implementing and sharing product databases and archiving."

NASA Glenn Research Center is supporting another compatible effort focusing on developing CAD geometry standards. That work can be viewed at http://www.grc.nasa.gov/WWW/icad and is a cooperative effort through another international consortium known as the Object Management Group (OMG). More information on OMG is available at the site http://www.omg.org. The following is the mission statement of the OMG:

> "The OMG was formed to create a component-based software marketplace by hastening the introduction of standardized object software. The organization's charter includes the establishment of industry guidelines and detailed object management specifications to provide a common framework for application development. Conformance to these specifications will make it possible to develop a heterogeneous computing environment across all major hardware platforms and operating systems. Implementations of OMG specifications can be found on many operating systems across the world today. OMG's series of specifications detail the necessary standard interfaces for Distributed Object Computing. Its widely popular Internet protocol IIOP (Internet Inter-ORB Protocol) is being used as the infrastructure for technology companies like Netscape, Oracle, Sun, IBM and hundreds of others. These specifications are used worldwide to develop and deploy distributed applications for vertical markets, including Manufacturing, Finance, Telecoms, Electronic Commerce, Real-time systems and Health Care.
>
> OMG defines object management as software development that models the real world through representation of "objects." These objects are the encapsulation of the attributes, relationships and methods of software identifiable program components. A key benefit of an object-oriented system is its ability to expand in functionality by extending existing components and adding new objects to the system. Object management results in faster application development, easier maintenance, enormous scalability and reusable software."

Both the STEP and OMG efforts are enabling software developments complementary to the technology development recommendations included in this report. Clearly, the integration of such interoperability standards in any future software development research initiatives that are a part of the ISE initiative is imperative.

The preliminary findings of this study were also presented to LaRC. Members of the Structures Lab and the ISE program office attended the briefing. The briefing was generally well received and no conflicts were identified. Subsequent efforts to brief this study at NASA/ARC to the Intelligent Software Initiative and the Design for Quality Initiative were unsuccessful.

The NASA/MSFC Structures Laboratory (Dr. Roger Townsend has a number of projects underway in association with Vanderbilt University under the leadership of Prof. S. Mahadevan). The details of those projects are given in the Appendix, Section 4.5.

3.2 Relation of NDNTM to ISE

The operating premise for the current study is that NDNTM are a subset of the future design environment, seen by NASA as the Intelligent Synthesis Environment (ISE). Thus, it was deemed appropriate that the study should include reviews of ISE as well as studies of the various aerospace industry approaches to the design environment of the future. A typical structure for ISE is the simple interaction diagram shown in Figure 3.

Figure 3 is framed around a cultural change in the creativity process. Such a change cannot occur, as is known to the ISE proponents, unless the ability to access, process, and interpret information also undergoes radical change. Non-deterministic design, in and of itself, poses such a radical change in the design environment. Such change is slow in coming but it is coming. NASA should continue to lead in such radical changes as it did in non-deterministic design methods for aerospace systems but the current study suggests that NASA will have to make some cultural changes as well.

The current study mostly focused on the Life Cycle Integration and Validation element with some interaction with rapid design and synthesis. The question posed during the many interactions with others was "what are the unique requirements for the total life cycle design analysis of complex aerospace systems based on reliability-based considerations?" More generally, what are the non-deterministic research needs to allow such a radical change in the design environment for such system design problems?

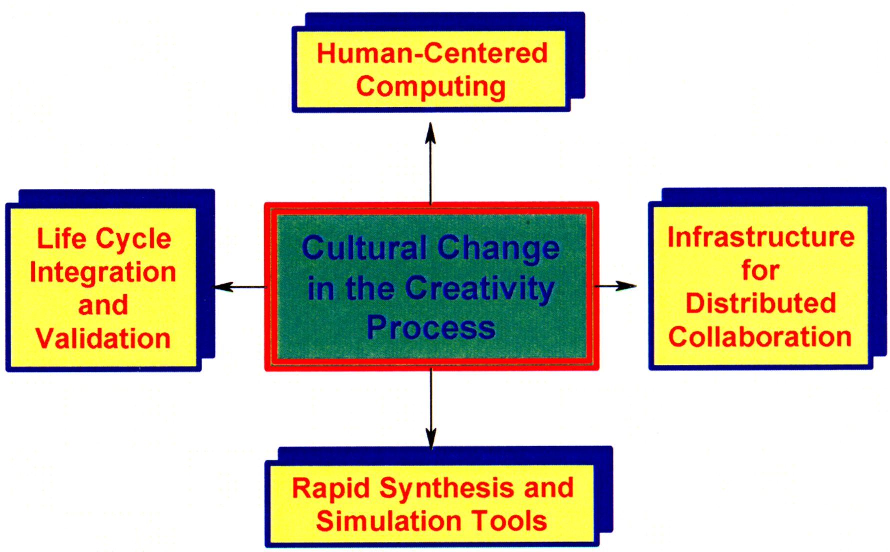


Figure 3: Overview of ISE Initiative

There are many common elements between the Consultant's view of NDNTM and ISE. However, the overwhelmingly common characteristic of both is that both are "information processors" (IP). Such an IP focus is attributed to both as both the non-deterministic design process and the future total system design process will operate on disparate types and forms of data, expert judgment, approximations, and so forth. It is most effective in terms of modern developments in software engineering to see these as information rather than data.

One proposed representation of NDNTM is given in Figure 4. This representation is drawn as a design process. Based on the literature review and other data sources, the most liberal view of NDNTM is shown in a logical arrangement.

- **Information Input**

  In the past, data for probabilistic modeling was in the form of statistic data represented by analytical or empirical distribution functions and their parameters. For the future, input will include a much broader range of information. Such information that is subjective or "fuzzy" is envisioned as a critical element in non-deterministic analysis. The elicitation of such fuzzy input is a critical element in the process such that expert bias and prior assumptions do not overly influence the representation of the information.

- **Information Fusion**

  This critical junction is where one must convert disparate forms of information into a common basis for modeling. A critical element in the technology requirements here is the translation of properly-acquired fuzzy input into sensible probabilistic representations. It is also the place where new information must come in to update prior information.

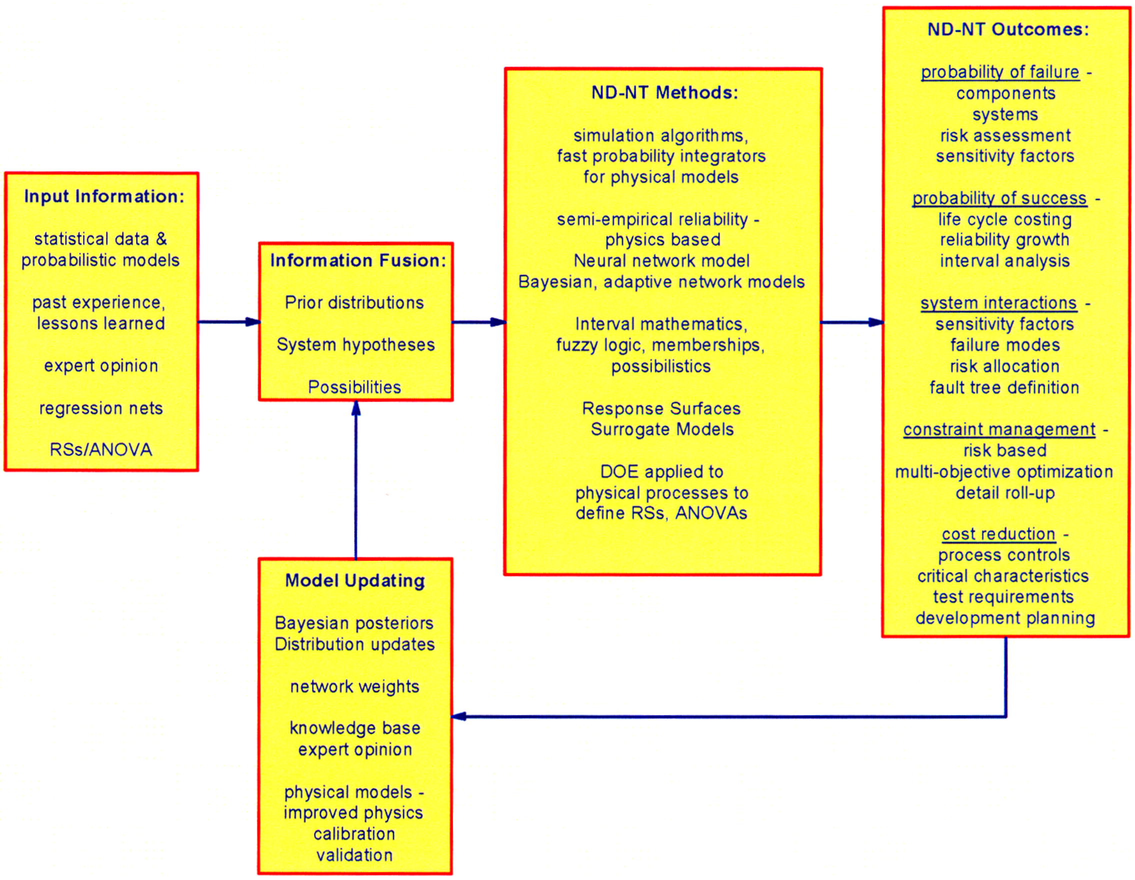


Figure 4: Elements of the ND-NT Design Process

- **ND-NT Methods**

  This element contains all of the possible ND-MT methods of modeling that were considered in the current program. At this point, the collective judgment is that the simulation algorithms and probabilistic methods do not need an infusion of new technology. However, semi-empirical, physics based models of systems based on various networking modeling methods is likely to be important, especially for large systems. Interval mathematics may yet buy its way into design. However, this can happen only if interval mathematics (discussed in Section 3.4.4) is much faster to execute than traditional probabilistic methods, given the relatively low amount of information that is conveyed and that alternative, probabilistic methods can be used for getting the same and more information. Fuzzy logic and its attendant elements of membership functions and possibilistic analysis is NOT seen as playing a role in this stage of the overall design system of the future for aerospace systems.

Response surface modeling or surrogate (simplified physics) models is intrinsic to non-deterministic design. All probabilistic methods use such models in one way or another. DOE approaches or Taylor series approaches are variations on RS methods. The use of DOE to construct such surfaces from empirical data is seen as an alternative to network models, although the technologies may merge.

- **ND-NT Outcomes**

  This is the heart of the design process valuation. A proper ND-NT design environment in the other entities in this diagram will yield much more useful information for making decisions for design stages from conceptual design to detailed design.

- **Model updating**

  A critical element in any design process is updating. Viable design operations have evolved means for capturing past experience for new designs. Viable risk management programs allow for updating the assumed statistics used in the previous modeling. Certainly verification and validation of physics models is a real part of good design practice today.

  However, the future design environment needs rigorous and sensible formalisms for capturing new data as a product is developed and deployed such that the data is fed into the process not only for new designs but also for managing the design and maintenance of current products.

3.3 Interoperability and Software Environment

This Consultant is not an expert in software engineering. Nonetheless, the various discussions as well as a professional awareness of new trends compel one to include a brief set of comments on this topic. Past software development efforts from NASA Glenn Research Center have generally, but not always, had a single, "shrink-wrapped" code as their objective. It has been stated by NASA/GRC management that part of the valuation of leadership from a NASA center is its ability to point to industry use of NASA products. This is a very understandable metric.

However, the design environment of the future is object-oriented software, not modular codes. There are big differences. Object oriented code provides many features but one of them is adaptivity in run-time. Another is the ability to create tools that can be used – again in run time – in various parts of the problem process without requiring recompilation of source code.

If one looks at the recent software engineering initiatives such as the DARPA Robust Design Computational System (RDCS) effort at Rocketdyne

http://www.frontier.net/~tcruse/rdcs/rdcs.htm/

and the Engineous Software called iSight,

http://www.engineous.com/isightv5.html#products

one sees a likely paradigm for the future. The computer screen is the design desktop. Tools are dragged from one part of the analysis process to another. Datasets are dragged and dropped onto an analysis process the designer has just set up on the desktop. Such flexibility in the design analysis process is critical to the productivity goals set by all major firms.

3.4 Non-Deterministic and Non-traditional Methods: Status and Opportunities

The methods selected for review were taken from the AIAA Structures, Dynamics, and Materials Conference held in Atlanta in April 2000. A summary of the panelist input is given in Appendix 4.2. The list of methods is as follows. Following each item is a brief discussion and conclusions for each topic based on the completed literature review and various meetings. The titles and order are those that defined the AIAA Forum on non-deterministic approaches.

3.4.1 Neural Networks

References that were reviewed include [39, 41, 44, 45, 46, and 47].

Neural nets (NN) have the ability to represent physical responses somewhat like a Response Surface used in design. A NN model training process is used to establish nodal weights and biases. In general, NN weights do not conform to specific physical variables. A NN would be used to model a RS only if one had datasets and not a physical model. However, the statistical method for constructing RS's is more robust as far as sorting out noise from model behavior and for giving statistics that can be used in constructing assurance intervals for error analysis when applying the RS. As pointed out in [39], NN's rapidly lose their attractiveness for large numbers of NN nodes.

Reference [41] summarizes various uses of networks for data-mining. Such applications may be valuable when constructing data models for non-deterministic design based on extensive test data. An interesting example of the use of NN's to model a combination of experimental data and varying types of modeling results for airfoil design is given in [44]. These authors use the NN as a effective way to solve the inverse problem for finding a RS from disparate data sources. The also report that their strategy for training results in nodal weights that can be tied to specific design variables.

A Bayesian network is one in which the nodal weights represent conditional event probabilities, as discussed in [45]. Such modeling appears to be useful for large system reliability problems and provides a direct means for simulating the top event and knowing its probabilistic design variable causes. They state that the Bayesian network method is preferable to Monte Carlo for system simulation for the additional information on conditional probabilities that is gained.

Conclusion: The review indicates that an important role for NN's is likely to be found in the proposed Model Helper and Data Expert. The application of NN's with a strategy to tie the nodal weights to physical variables appear to be an effective data mining strategy to support probabilistic input. Bayesian networks and other probabilistic learning networks appear to be useful for system reliability modeling. Finally, NN's have a valid and important role in the data gathering and interpretation role in System Health Management. It does not seem likely that standard NN's will be used in the probabilistic algorithms.

3.4.2 Fuzzy Theory

Fuzzy theory is a "hot" area and is reviewed in References [14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, and 32]. The last of these, [32] compares probabilistic and fuzzy modeling for reliability. Fuzzy set theory and the closely related field of possibilistics are strongly touted as the new field for probabilistic modeling. This review does not support that position.

Fuzzy systems are based on the mathematics of fuzzy set theory. The above references provide an adequate introduction to these fields. Generally speaking, fuzzy systems are used where so-called "crisp" probabilistic models do not exist, such as in linguistic representations. Characteristic mathematical models are assigned to fuzzy functions that are then combined using fuzzy logic. All input variables to the mathematical-physical model are given fuzzy representations and the physical model is written using the "algebra" of "fuzzy logic" to yield "fuzzy output." As in the paper by Rao [5], one finds that fuzzy physics is violated physics. That is, one loses the constraints of the physical model under fuzzy logic formulations. The only advice offered by that author is that one must impose one's physical intuition to properly understand the results. This is not scalable as a problem solving strategy for large problems.

Fuzzy logic has been used successfully in a number of industrial control system designs that are, in fact, in commercial consumer products today. What is the difference? In fuzzy controllers [14, 15, 20, 21 and 25], for example, it is clear that fuzzy logic designed control systems for nonlinear control problems is highly effective. The difference is that these systems take crisp input, operate on the input using fuzzy-logic constructed if-then rules, and output crisp results. The advantage of fuzzy controllers appears to be the power and flexibility of building the knowledge base of if-then rules and in the superior "smoothness" one gets from such a controller.

Reference [22] applies fuzzy logic to classical reliability engineering. The authors contend that this is the right approach to problems where the input is estimated from engineering experience and judgment. They also contend that this is the right way to represent degraded states of operation, given that the word "degraded" is subjective. However, work at the Los Alamos National Lab [1], has shown that one can take fuzzy input such as these authors refer to and convert that input into probabilistic distributions so that one can perform robust probabilistic calculations on these fuzzy-derived distributions. The analysts at LANL concur with the Consultant that one must use robust non-deterministic algorithms rather than fuzzy algorithms if one is to have any confidence and utility from the results. The fact is that the whole motivation of the fuzzy logic reliability design community to address fuzzy input and output can be addressed in the manner so effectively deployed by LANL in their joint PREDICT system work with Delphi Automotive.

In all the literature reviewed for this program only one remark by an author gives on a reason to ponder a bit more about fuzzy logic [16]: The author cites sources that argue both sides of this issue and concludes that "there is some truth to both sides ..." However, he argues effectively that FL "is a tool of enrichment and not replacement ..." Bezdek and Pal [6] are quoted as saying that "fuzzy models belong wherever they can provide collateral or competitively better information about a physical process." Bezdek and Pal give an example case wherein two bottles of water are lying in the desert and are found there by a very thirsty wanderer. The first bottle has a membership in the set of potable waters of 0.91 while the other has a probability of being potable that is 0.91. In the first case the water shares a high degree of characteristics in common with potable water while the second has a 9% chance of being totally non-potable (poison!). Which do you drink?

Conclusion: Fuzzy input is recognized as real based on the Consultant's experience managing risk-based fleet airworthiness programs for commercial aircraft engines and based on the LANL/Delphi joint reliability-based design program. However, probabilistic algorithms offer the only useful processing element for de-fuzzified input data to support complex aerospace system design. Fuzzy logic might be deployed in program management decision and risk prediction tools.

3.4.3 Chaos Theory

A limited review of this subject focused on potential applications to non-deterministic design [57]. None were found. Chaos theory has a very narrow physical interpretation and while chaotic output appears random, it is not. The reference indicated is to a thesis that complexity can lead to chaos.

Conclusion: Chaos theory does not offer critical capabilities to include in any recommended NDNTM effort.

3.4.4 Interval Arithmetic

References that were reviewed are [35, 36, 37, 38].

This topic appears to be much more interesting to non-deterministic design. Interval arithmetic operates under some very precise algebraic rules and does not lead to systems that violate physics. In fact, interval arithmetic was developed as a way of representing floating point arithmetic errors. As cited in [35], interval arithmetic is now released as a new variable type in the Sun Microsystems Fortran compiler.

Elishakoff and his co-workers have applied interval methods to some structural analysis problems. Ref. [7] combines interval analysis with stochastic finite element methods (second-moment method) to structural frames. Elishakoff applied strict interval analysis methods to computing the range of structural natural frequencies in [8].

In a related technology to interval methods, Elishakoff and his co-workers have utilized what they refer to as convex modeling [9] to compute one-sided bounds on structural behaviors such as natural frequencies and buckling loads [10]. The method is based on defining bounds on uncertain parameters as convex sets bounded by ellipsoids. For such cases, convex methods may be used to compute a corresponding convex set of results, or upper bounds.

Conclusion: Interval methods provide a formal mathematical treatment for problems where (1) no input information can be defined beyond upper and lower bounds for design variables and/or where (2) response ranges are desired for preliminary design purposes. Such methods may be worth considering as part of the required error bounds work proposed herein.

Interval arithmetic may offer, especially as a data type, the opportunity to do rapid analysis of the output range for design problems. It appears to be worthwhile to take some research codes and to convert them to the new type of variable to assess how effective this tool would be in defining design output range for interval inputs. The approach appears to be one that could be applied to error analysis in parts of the non-deterministic design analysis process.

3.4.5 Response Surfaces

There appears to be some confusion here over terminology as applied to probabilistic design. Probabilistic designers have used Taylor series expansions of the physical response of systems in terms of the design variables to construct locally linear (first-order) and locally quadratic (second-order) polynomial fits to model results. Such representations are updated as the "design point" moves through the design space (so-called advanced mean value – AMV – algorithm). This approach might best be called the local-RS approach.

A second approach, and one currently favored by GEAE and PWA, derives from classical statistics [11, 12]. These RS methods have been developed as part of experimental statistics wherein the experiment is designed with varying patterns of high-low values for each identified parameter that can be changed. Mathematical methods are used then to define the RS that is most likely that defined by the experiment and the statistics of variance regarding that fit. One also determines the independence or coupling of the variables in the modeled physical response. The use of certain experimental designs leads to first order surfaces (with interactions) or second and higher order surfaces.

While the use of RS's at GEAE and PWA is a fitting to deterministic and not random system responses, both companies define their approach as a RS approach consistent with statistical derivations. The reason they use this terminology is that they use a variety of experimental designs (DOE) to select the points in the design space that are used to evaluate the response and from which the first or second order surface (with all interaction terms) is fitted. Such a RS method might best be called the DOE-RS method.

The key in all cases is that the RS is a representation of what is probably a model of the physical system. The specific fitting algorithm and probability algorithm define the errors in the non-deterministic results. The two RS approaches have different characteristics in terms of accuracy (local and global) and efficiency. In spite of what GEAE and PWA have taken as positions on RS technology theirs is not the last word.

Conclusion: There are critical technical questions to be resolved regarding RS strategies. Most of the questions should be addressed in appropriate technical meetings and symposia. There are some technical issues that are appropriate for the NDNTM effort.

3.4.6 Non-Deterministic Optimization

Articles reviewed for this subject include [31, 43, 47, 48, 49, 50, 51, 52, 53, and 54].

All optimization algorithms can and should be non-deterministically applied. The two references to the new GEAE design environment [53, 54] clearly indicate this combination is the future for GE. Non-probabilistic elements in optimization can be in the objective function or in the constraints. The issues related to the use of non-traditional optimization strategies (non-gradient for example) such as genetic algorithms and simulated annealing have nothing to do with non-deterministic issues. They have a lot to do with the size, complexity, and nature of the design environment [50, 51].

3.4.7 Taguchi

References [13, 24] are cited.

There are two elements to Taguchi methods. One is a set of experimental designs (patterns of high-lows) as applied in standard DOE methods. DOE strategies seek to define a RS by selecting a sub-set of a full factorial design procedure in order to reduce the experimental cost. The actual patterns are particular to Taguchi and to other developers. The second element is the separation of variables into controlled variables and noise or uncontrolled variables. When trying to target manufacturing processes using Taguchi strategies one seeks to minimize process variability caused by noise factors.

Conclusion: The use of Taguchi or other, newer strategies is limited for the current study to defining RS's while separating controlled and uncontrolled variables. There is no significant research need for work here under the NDNTM banner.

3.4.8 Design of Experiments

DOE applicability to NDNTM and RS strategies are discussed in the bullets above.

3.4.9 Dedicated Expert Systems

Conclusion: Expert systems are at the heart of an increasing number of applications including the fuzzy logic control systems, as previously discussed. Dedicated expert systems will be important parts of NDNTM deployed to support future design environments and system health monitoring [59, 60].

3.4.10 Possibilistic

See fuzzy logic and interval arithmetic.

3.4.11 Probabilistics

Conclusion: Any risk critical design application requires probabilistic algorithms for robust and reliable results. The consensus of those interviewed as well as the opinion of the Consultant is that there are no pressing research issues other than error analysis related to the issue of probabilistic algorithms.

3.4.12 Complexity Theory

Reviewed articles or web sites are given in [57, 58].

From the writer's perspective, advanced aerospace systems may not involve complexity in the terms used in [57, 58] even though system modeling is highly complicated. Complexity theory arose in thinking about biological processes where evolution is involved. Genetic algorithms (GA) for optimization appear to use evolution to arrive at an answer – but is that related to complexity? This writer contends that it is not related because biological evolution leads to time-changes of species indicating that today's answer is not tomorrow's answer. Properly run GA's will produce the same global optimum for large, complicated problems.

However, if we view the design process over time from requirements to system operation, we often speak in terms of the "evolving design." We make binary choices of configurations, there is no uniqueness but there is a strong dependence on the path taken. GA's cannot model this process as a whole because they do not have the full set of options generally available to them. A system design problem for which we cannot find a "feasible solution" may not have one – or the process may be lacking in robustness to the extent that "chaos" is occurring.

Is there a link between complexity/chaos and probabilistic modeling? This writer contends the answer is "no." We may find it easier to configure feasible designs if we allow variability for all of the design variables in the sense that the design envelope is fuzzified. We may then find ways to target the random design variables to arrive at real, feasible designs. However, complexity theory appears to say that it is the shear number of options that we are dealing with that is the issue, not the crispness of the parameters used for each of the modular options that might be considered.

Conclusion: The area of complexity theory as applied to the overall design process may yield some interesting work. However, it does not seem an appropriate area for NDNTM effort.

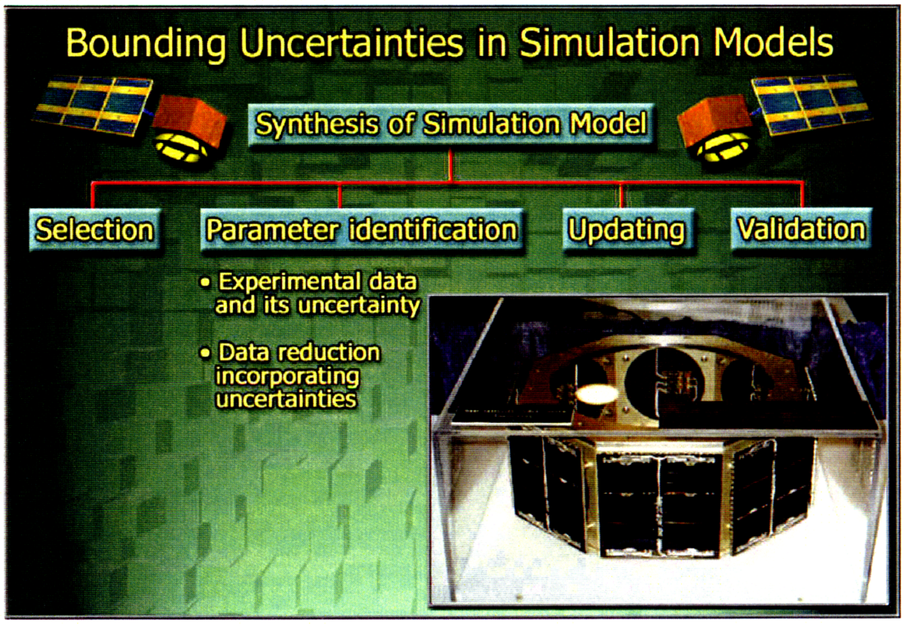
4.0 Appendices

4.1 NDNT Panel Meeting – see CD/ROM files

The following are comments based on a review of the material presented but not on the presentations themselves. Comments will be made on the highlights of the presentation based on the other material reviewed and reported herein. Only some of the presentations are discussed. The selection is based on those presentations that went beyond the use of today's probabilistic methods or made key points related to the purpose of this study.

- **Prof. Ahmad Noor**

A major focus of his review is on the need for non-deterministic methods in the design cycle. The basic rationale is the lack of specificity early in the design



process. The PREDICT program [1] was developed with such a contingency and offers a rational approach to this problem area. An illustration is given in his report for performing interval analysis for a composite shell structure. Again, this problem is properly handled using today's probabilistic methods with simplified inputs based on the range information. The only possible alternative method to consider is interval mathematics. The elements of selection, parameter identification, updating, and validation are fully addressed in today's technology based on probabilistic design. Again, reference is given to a real design process employed in industry [1].

Professor Noor confirmed in private discussions that the use of fuzzy methods for computational algorithms is not recommended due to their inherent limitations. Probabilistic and interval methods are recommended instead. He also makes the strong point that existing deterministic analysis methods should serve as the core of future NDNTM for the detailed modeling. That view is shared by industry and this consultant.

- **Professor Robert Mullin**

  Professor Mullin presents an excellent introduction to interval mathematics for the finite element method. He also addresses the need for probabilistic mesomechanics. The presentation is valuable.

- **Dr. David Robinson**

The conclusion charts from his presentation are valuable to include here.

○Technical Issues (2-5 years)

»new SNL unique algorithms being developed and tested

»SNL Corrosion Initiative - system level impact of microscale evolution of corrosion by-products

»aging analyses

»national power grid vulnerability

»system level reliability vs component reliability

○Educational issues

○Technical Issues (Beyond 5 years)

increased use of NDA methods by engineers

improved communication between software components

time dependent behavior

multiple failure modes

○Educational Issues

Continued lack of support from educational institutions for qualified graduates

The interesting elements contained here that agree with those recommended in this report are improved communication between software elements, multiple failure modes (system analysis), probabilistic mesochanics (as seen in his whole talk) for complex damage modes, and educational issues. The use of probabilistic experts in future software efforts will help here.

- **Professor Efstratios Nikolaidis**

  The presentation is an interesting one favoring fuzzy methods. The earlier review conclusion on fuzzy methods in this report address his conclusions.

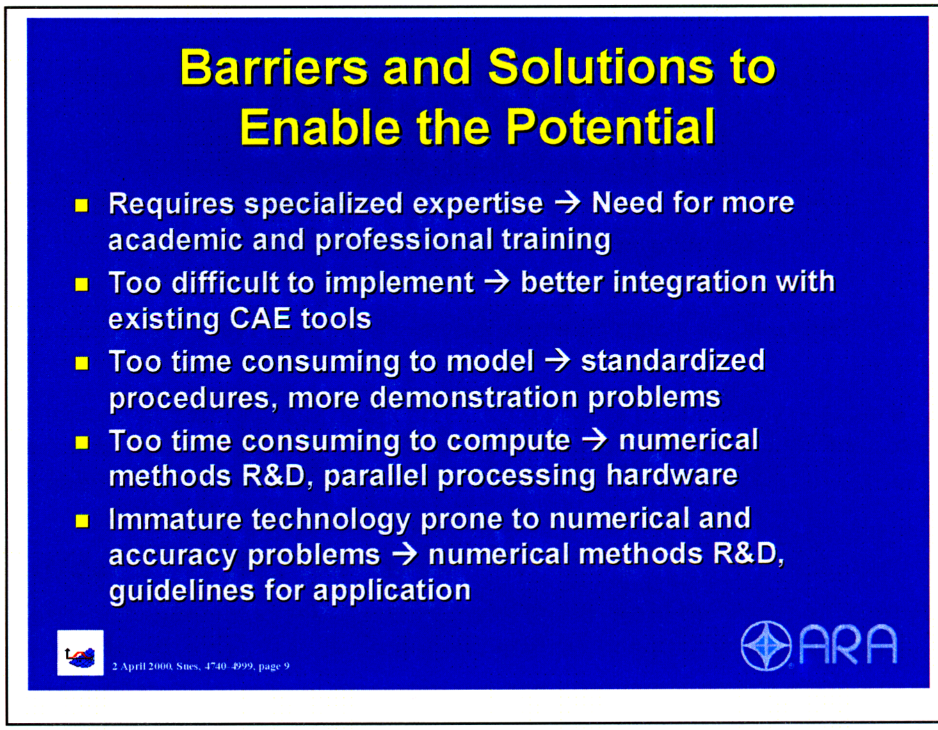
- **Dr. Gene Rogers**

  This is an excellent case for effective probabilistic design analysis of space vehicles.

- **Dr. Norman Kuchar**

  This presentation ties ND methods to GE's six sigma program

- **Dr. Rob Sues**



The above chart is selected from this presentation. The presentation shows effective use of probabilistics, especially in the area of optimization. The above barriers and solutions appear to be consistent with many of the themes in this report.

4.2 Non-Deterministic Approaches Forum

Chairmen: Dr. Chris Chamis and Dr. Surin Singhal

AIAA SDM Conference, April 2000

Panelists: Paul Roth, Bob Kurth, Rob Sues, Eric Fox, Mircea Grigoriu

- Neural Networks:

  (EF) Used with thousands of data points with relatively few outputs. Used where there is no "structural" model of the system. Can be very difficult to interpret the parameters.

  (RS) Used anywhere you can use a response surface. The method is one of generalized curve fitting. Can be used to replace a complex model (many degrees of freedom) with a simple model (few degrees of output freedom).

  (BK) Battelle has made effective use of neural networks in the area of avionics displays in heads-up systems.

  (PR) Cautioned on the improper use of neural networks for extrapolation instead of interpolation.

- Fuzzy Theory:

(RS) Fuzzy theory is for those not comfortable with probabilistic theory. Same goals as probabilistic methods – to bring uncertainty into the design – but not as robust.

(BK) Method is trying to quantify the users lack of knowledge. Battelle does not use fuzzy theory in any applications.

(PR) Have not seen any application of fuzzy theory that could not have been converted to probabilistic theory.

(EF) Fuzzy theory is probabilistic methods using triangular input (for distributions).

(Audience: SS Rao) Fuzzy theory is effective where the input is linguistic and not mathematical.

(Audience: Ahmad Noor) Used where the input data is ambiguous – again a linguistic form of input implied. Believes that there are relationships between probabilistic methods and fuzzy theory but the latter is not a subset of the former.

(Audience: Boeing) Fuzzy theory used to emulate human thinking. Employed in building self-teaching expert systems.

(Audience: Dan Ghiocel) Cannot use fuzzy theory when the inputs are correlated. Cannot quantify risk. Can be used where qualitative output is desired or acceptable.

(Question raised) Is there a rational transition from fuzzy theory to probabilistics?

- Chaos Theory:

  (BK) Battelle has found applications in mixing theory, navigation problems, and – in a probabilistic form – stability problems.

  (PR) Believes that chaos theory will have a significant impact in the future. Two areas of GEAC application are air-fuel mixing in combustion and in engine control.

  (EF) Stock market projections and like problems where there is a lot of noise on top of what is otherwise a moderately well controlled process.

  (Audience: Ghiocel) Chaos theory is a deterministic method where non-periodic and non-closed output occurs with periodic input. Chaos theory cannot handle non-deterministic input. Only the output looks random.

  (Audience: Mullen) Applicable to highly nonlinear problems. The method is far away from design applicability.

  (Leader: Chamis) Chaos theory is probabilistic simulation where the outcomes have equal probability.

- Interval Arithmetic:

  (PR) No one at GEAC is working in the area of interval arithmetic. The method is used to map input bounds into output bounds. Could be used to help the probabilistic designer in this way. MC simulation is more effective here than the formalisms of interval arithmetic.

(EF) If you can use Monte Carlo simulation, you can get all you need from interval arithmetic from probability theory.

(RS) ARA is using the method in developing user manuals to give users expected bounds on output. Have made use of it for various simpler problems. For complex problems, he recommends using design of experiments with 2 to 5 factors per interval over the arithmetic.

(BK) Battelle was very excited about interval arithmetic when first looking at developing a fuzzy finite element analysis system. They stopped development of the system when they could not overcome the zero-divide problem. They were looking for a quantified fuzzy logic system. Some potential for the method.

(MG) Method is not useful for design problems for which failure is caused by extreme events, for example, design for time-dependent loads.

(Audience: SS Rao) Used effectively in tolerance analysis. Automatic operations are fast. Output range is so wide that results can be meaningless. Have to use physical insight to fine-tune the method.

(Audience: Mullen) Have to incorporate physics into the method. He has a working interval arithmetic FEA code. Has overcome cost problems using Monte Carlo. Can reduce large problems to a single FEA run.

- Response Surfaces:

  (MG) RSs are very useful when the system response is undestood. Can give totally wrong results for dynamic problems involving resonance.

  (EF) Response surfaces are best for modestly well-behaved problems. Can test the accuracy of models.

  (RS) Use anywhere you don't have a physical model, i.e., can build an empirical model, same as curve fitting of observed outputs to inputs. Extrapolations with response surfaces can be a problem. Can also be a good surrogate for complex computational models as long as you have a strategy for local accuracy near the final design point.

  (BK) Response surfaces are very successful for complex physical problems that are well behaved.

  (PR) One must pick and choose problems for response surfaces. Rotor mistuning with attendant energy localization is not a good problem. Response surfaces can capture material variability but not nonlinear physics.

  (Audience: Millwater) Response surface methods appear not to work with large numbers of variables, on the order of 20 to 50, that occur in some problems. Above 10 design variables, DOE breaks down as there are too many design points. Can't just throw out design variables using sensitivity measures as they may become important through interactions or at the final design point.

  (Response: RS) Can use multiple response surfaces with system reliability for some of these larger problems.

- Non-deterministic Optimization:

  (EF) Believes that it is important to use a DOE-based approach.

(RS) Believes we should use this method whenever doing optimal design. Conditions for optimal design are always probabilistic. Can get "robust design." Can include cost factors.

(BK) Safety prediction benefits by changing the control limits on the input variables.

(MG) Optimization with reliability constraints is a very promising area for both research and applications. Developments are needed to reduce some shortcomings, for example, the convergence of the solution to local minima.

(Audience: Mahadevan) Stated that reliability estimates themselves are random. Need to combine non-deterministic optimization with robust design methods to minimize output uncertainty.

- Taguchi:

  (RS) Use DOE for process problems. Very similar to probabilistic optimization.

  (BK) Used in optimization problems with DOE.

  (PR) GE no longer talks about Taguchi, which is a subset of DOE.

  (EF) PW does a lot of training in Taguchi/DOE to show how badly the Taguchi designs do in comparison to classical DOE. Non-isomorphic graph designs are better. The original use of Taguchi methods in dealing with uncontrolled variables has been replaced by more recent methods.

  (MG) A version of experimental design.

  (Audience: Mahadevan) They have combined Taguchi with non-deterministic optimization. The method gives qualitative information on which variables to use.

  (Reply: EF) Taguchi array can give <u>bad</u> results. His arrays minimize variable interactions.

- Design of Experiments:

  (BK) This is the most important item on the list. The method is used up front in any multivariate problem. Reliability problems benefit greatly.

  (PR) DOE is a clever way to minimize variance in estimators. Have to be careful though when it comes to interactions.

  (MG) One needs to have some idea of output. Method is useful for variable screening.

  (EF) Fractional factorial is very powerful along with Box-Behnken that is best for nonlinear problems.

  (RS) DOE is used for building surrogates for complex models. For lots of variables, one should probably use Monte Carlo. ARA uses DOE imbedded in their code.

  (Question: Mahadevan) DOE is used for non-repeatable data. The response surface (as used in probabilistic design; also known as the surrogate model) corresponds to repeatable data. Does this change the DOE approach to use?

  (Reply: EF) Box-Behnken or composite designs are best to use if the response surface is nonlinear. Lots of process problems have linearities.

(Reply: RS) Use fractional factorial also. Switch to simpler DOE arrays near the critical region for efficiency.

- Dedicated Expert Systems:

  Panel did not have anything favorable to say here. Professor Rao discussed evidence-based models that translate input into belief functions.

- Possibilistic:

  (MG) Used the example of a coin toss – it is possible for the coin to land on an edge but is there any real probability of that event? Possibilistic methods include results with very low probabilities.

  (RS) ARA has looked at the method as a way to handle fuzzy logic problems. The mathematics are not robust. With the same input one can handle problem with more realistic tools.

- Probabilistics:

  No panel response recorded here except for:

  (EF) Probabilistics can be used with lots or little data or with expert opinions.

  (RS) Use where we have engineered systems and need to do risk assessment, predict product reliability, design for reliability, need sensitivity information, in new design situations where there is no experience base, and to reduce testing.

  (MG) Probability theory is the most efficient and reliable tool for propagating uncertainty through a system. It can be applied when the system and/or the input are uncertain. Recent work on fatigue and fracture mechanics shows probabilistic tools beyond random variables and random vectors need to be considered. For example, random fields are needed to represent the material microstructure. Gaussian and non-Gaussian processes are essential for modeling various actions on aircrafts.

- Complexity Theory:

  The panel had little knowledge of this and invited clarification. Chris indicated that it is in the ISE plan coming out of NASA/Langley.

  (Audience: Noor) Complexity theory deals with problem modeling where there is a large system with a heavy amount of interactions within the system.

  (Audience: Sandia person) Method developed out of work by Los Alamos retirees. They have been working in complexity theory since 1988. Are there equations that describe common elements of the system? “Self organization” can be a part of it. There is a Center for Nonlinear Systems at Los Alamos. Held a workshop on predictability of complex systems. They are involved in the problem of “swarms” where a large group of autonomous robots interact with each other to achieve a defined goal.

4.3 NDNT Viewgraph Presentation - ISE-GERD.ppt

Summarizing the findings and recommendations

Intelligent Synthesis Environment – NASA Initiative

T. A. Cruse
Consultant

4.4 White Papers

White Papers were received in response to the Consultant's invitation. The following pages are cited in terms of the person(s) submitting the White Papers.

4.4.1 Rockwell Science Center

See attached, proprietary file - RSC_white_paper.doc

This file has restrictions on its cover page.

4.4.2 Los Alamos National Lab

4.4.2.1 Information Integration – Dr. Jane Booker

Integrating Information for the Analysis of Simulations

When dealing with the large scale computer simulation codes, it is desirable to gain the most information about the code, its imbedded models, and the affect of inputs on outputs without running all possible combinations of values. Statistical experimental design principles and sensitivity analysis methods can be utilized for this purpose: to learn the most from the fewest number of simulation runs.

When dealing with the analysis of simulation codes, at least two different kinds of uncertainty can arise: uncertainties in inputs resulting in uncertainties in outputs and modeling uncertainty. The former we call sensitivity analysis, the latter is simply "I don't know what my model should be". There are many useful methods (e.g., Latin Hypercube Sampling) that provide solutions for judiciously sampling the input space to learn its effects on the output space. There are also many good experimental design techniques to design the runs for the different values that the inputs can take on, so that fewer runs are required. The modeling uncertainty issue is much less known or studied and is very case/application dependent. It is very difficult to design sampling techniques that search through and study an infinite number of potentially correct models.

While these methods provide ways of minimizing the number of runs, they cannot produce results from only one or two runs. Carefully designed choices of model parameter values and input values can result in understanding how these affect the output in sensitivity analysis. The number of these choices can be far less than the full number required for complete enumeration of all possible combinations. Statistical tools using experimental design and sampling principles provide ways for making judicious choices. This number could be further reduced by taking advantage of other existing knowledge and information about the code, the model, the parameters, and their relationships. The principle of information integration states that uncertainty can be reduced and better estimates obtained by utilizing and combining all available information. A major source of information is the knowledge and experiences of the experts in the subject matter reflected in the code. There could be other sources as well such as results from similar models or codes. We propose to investigate the use of information integration methods in conjunction with sampling and design methods to utilize all knowledge for reducing the number of required runs for sensitivity analysis.

Likewise, all available information about the model could be used to judiciously design code runs for understanding modeling uncertainty. There are many kinds of uncertainty that could contribute to the choice and use of models, and these would be investigated to provide focus for studying this difficult problem.

Model uncertainty is a wide open research area, and we anticipate development and modification of information integration methods to understand modeling uncertainty and to develop tools for analyzing its effects.

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4.4.2.2 Statistical Methods and Experiments – Dr. Michael McKay

Important Research Areas in
Statistical Theory and Methods for Computer Experiments

Many critical scientific predictions come from the integration of experimental data with calculations from numerical simulation models. Valid methods for quantifying uncertainty in scientific predictions require understanding of how uncertainties in data and model predictions combine. Three facets of uncertainty quantification are (1) experimental error, (2) model prediction uncertainty, and (3) combining information. While experimental error is dealt with well by existing statistical methodology, methods for analysis of model prediction uncertainty as well as methods for combining model predictions with experimental data are still in early stages of development. The following paragraphs direct attention to the second point, model prediction uncertainty.

As a setting for model prediction uncertainty, suppose that the prediction y from a model m is determined by a vector of input variables x. The input variables might define initial conditions of a system being modeled as well as parameter values in the rules determining y from the initial conditions. The term *input uncertainty* is associated with a lack of knowledge about appropriate precise input values from which to calculate y. Therefore, x is treated as a random variable with a probability density function which quantifies input uncertainty. The *prediction distribution* is the corresponding probability distribution induced on y by way of the model m, and characterizes *prediction uncertainty*. The objective of uncertainty analysis is to investigate the relationship between the input variables x and the prediction distribution. One part of the investigation is to identify (small) subsets of inputs that are *important* in the sense that they that "drive" prediction uncertainty.

Two common approaches to measuring input importance are differential sensitivity analysis and methods based on (linear) regression and correlation coefficients. Generally, these approaches are only valid in the neighborhood of a "nominal value" or they require that y be approximately linear in x. Furthermore, validity of associated importance measures usually requires that the components of x be statistically independent. Alternatively, variance-based analysis methods provide effective importance indicators (McKay, 1997). The indicators are used to evaluate individual inputs as well as subsets of inputs. However, efficient algorithms for identifying dominant input subsets of size 1, 2, and so forth are needed. Two important research topics follow.

Experimental designs for estimation of variance components. Variance decompositions require efficient experimental designs for estimation of the components of variance for the methods to be feasible. It is proposed to investigate traditional variance component estimation in light of sampling methods for computer experiments, such as, orthogonal array sampling (Owen, 1992) and LHS (McKay, 1979, 1995).

Smart variable selection procedures. When essentially unlimited computer runs are feasible, brute-force sequential selection procedures may be adequate to select dominant input subsets. However, the shear number possible subsets of inputs for models with more than a few inputs can make complete enumeration infeasible. It is proposed that smart variable selection procedures which take advantage of particulars of the variance decomposition and experimental design be developed. It is proposed to try to parallel optimal procedures for subset selection in regression, beginning with Hocking (1967).

Michael D. McKay

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4.4.2.3 Tools for Elicitation – Dr. Mary Meyer

Integrated Tool for Eliciting and Representing Knowledge

One of the most challenging aspects of PREDICT, and indeed any multi-disciplinary enterprise, is representing the knowledge that the technical experts employ in their problem solving. The proposed tool will accelerate this process by guiding the experts, the practitioners, in self eliciting and representing their problem-solving knowledge. The tool is comprised of three integrated parts: 1) a set of questions that walk the practitioners through defining their technical problem and problem-solving processes; 2) a software application that enables them to diagram the structure of their problem-solving processes; and 3) a customized software application that allows them to input this structure as the framework for a prototype knowledge system. We define knowledge systems as web-based electronic repositories that have been customized to their users to bring together their data, knowledge, and methods in structured, quantitative ways to facilitate their problem solving and/or decision making.

The proposed integrated tool is needed for several reasons. First, self elicitation is more efficient than elicitation by another party because it obtains the knowledge from those who possess it and who are most qualified to update it, the practitioners themselves. Yet, the techniques for guiding individuals in extracting their own knowledge are largely undeveloped. Second, practitioners need a graphical tool for representing the structure of their problem solving knowledge that is intuitive, transcends their disciplines, and has the capability of being transformed to mathematically richer diagrams (e.g., conceptual graphs, factor complexes). Third, the rapid pace of R&D demands that practitioners be able to design the organization of their own knowledge systems, ideally in a day, and to upload their files into it structural units.

Work on portions of the integrated tool has begun. For instance, we have made preliminary progress in designing a customizable, self-elicitation process which leverages on the PREDICT elicitation methods (Meyer and Booker, 1991; Meyer, Booker, Bement,1999). This latest work is being done in collaboration with Dr. Ray Paton, University of Liverpool, U.K. (Meyer and Paton, 2000). We have also progressed on the graphical tool for diagramming. Dr. Paton has identified the type of diagram, scratch nets, which will be used for eliciting and representing. Dr. Paton's experience and a body of literature document the ease of use of this diagram—all users need to identify are the parts of a whole (nodes) and how they relate to each other (labeled arcs). In addition, we have successfully pilot tested practitioners' abilities to input the structure for a prototype knowledge base and to upload their files into the created structure.

To continue this work with the aim of creating a prototype integrated tool, we anticipate the next steps as:

1. Develop, test, and refine the set of self-elicitation questions on pilot applications.
2. Develop the graphic tool by adapting off-the-shelf software, such as Visio, to enable users to diagram the nodes and their arcs in scratch net form, edit these diagrams, create a data base of the nodes and arcs, and transform the scratch nets to more specialized types of diagrams, such as hierarchical trees (e.g., factor complexes) and or to intermediate forms from which conceptual graphs could be created,
3. Expand the capability of the knowledge system groupware, such as Lotus Notes Domino, for accepting user's complex representations.

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4.4.2.4 Bayesian Optimal Design – Dr. Jane Booker

Bayesian Optimal Design of Integrated Physical and Computer Experiments

Both high cost and significant time investment are limiting factors in any experimental endeavor. Traditional physical experiments are extremely expensive in today's world of highly complex systems. Computational experiments are also expensive, but mostly due to the time required to develop the computer models upon which they are based.

Research can be made more inexpensive if a combined experiment, using both computational experiments and physical experiments, can be designed. Of necessity is determining the relative worth of each type of experimental result so that resources can be allocated so as to maximize the amount of information gained in an experiment subject to a minimal cost restriction.

Bayesian experimental design is concerned with the problem of maximizing the amount of information gained, taking into account all the uncertainties in unknown quantities. Performing the maximization subject to cost and/or time budgetary constraint can be accomplished using evolutionary programming techniques such as genetic algorithms. This optimization problem is made possible by more powerful hardware and innovative algorithms of today's computing environments.

We have developed Bayesian experimental design calculations for the case where only one source of data is present. Further, we have performed a combined analysis of several different data sources, accounting for possible differences (biases) in the data sources which determine relative worth. We have also developed genetic algorithms to assess process design prior to production, thus eliminating costly mistakes before production begins. Our proposal is to further develop Bayesian experimental design for combined experiments under a cost and/or time budgetary constraint.

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4.4.3 Impact Technologies Inc. – Dr. Michael Roemer

The file is available as a separate document – Impact_white_paper.doc

4.4.4 Wright State University – Dr. Ramana V. Grandhi

The file containing three white papers is available as a separate document – nasa_wp_grandhi.doc

4.4.5 Literature Review for ND/NT Methods

The following summarizes the literature review made as a part of the contract effort.

1. Reference [14]: Third thoughts on fuzzy logic.

   The author is an ardent skeptic of fuzzy logic. The context of the article is control systems. He was invited to assess the use of fuzzy logic (FL) and he finds its applications to be limited. He observes, "when an FL system claims to show great advantages over a conventional system, the advantages arise because the conventional system was badly done, or because it was highly nonlinear. The use of fuzzy logic in controllers is to provide smoother operations, for example. However, Pease argues that the use of proportional, integral, derivative (PID) controllers can do the same thing. He also cites an authoritative (un-referenced) source as saying fuzzy rules grow at a rate of the rules raised to the system dimension.

   The niche in controllers for FL appears to be moderately to highly nonlinear control problems. He cites an example problem of supporting a ping-pong ball on a column of air. There were some problems with the system though and he observed that optimizing an FL system is non-trivial. There is not much supporting data for his comments, which were offered to stimulate discussion.

2. Reference [15] is an introductory statement for a special issue of the IEEE Proceedings entitled Special Issue on FL with Engineering Applications.

   In their introductory sentence, the authors state that "fuzzy logic is a method for representing information in a way that resembles natural human communication, and for manipulating that information in a way that resembles how humans reason with this information." Thus we have two FL issues to consider:

   - Natural language communication of information.
   - Natural reasoning mode for manipulating the information.

   The authors claim that design-to-market processes may be speeded by the use of FL. Application areas have moved beyond controllers to pattern recognition, forecasting, reliability engineering, signal processing, monitoring, and diagnosis.

3. Reference [16] provides a tutorial type of introduction to fuzzy logic systems (FLS).

   An FLS is "able to simultaneously handle numerical data and linguistic knowledge." FL is a nonlinear mapping of input data into scalar output; FL and fuzzy set theory provide the mathematical basis for the nonlinear mapping. The use covered in this paper is for "causal" systems such as found in engineering. This use is a narrow subset of the methodology.

   An FLS is "a linear combination of fuzzy basis functions and is a nonlinear universal function approximator." The author states that this latter property is one that FL shares with feedforward neural networks. The important attribute of the fuzzy basis function is that it can be derived from numerical or linguistic knowledge, cast in the form of "if-then" rules. The author states that FL is, to date, "the only approximation method that is able to incorporate both types of knowledge in a unified mathematical manner."

The author defines two approaches in FL: The first is the model-based approach and the second is the model-free approach. In the former, linguistic statements that are converted to rules, which are then quantified using FL, represent subjective information. In the latter case, the rules are extracted from numerical data and are then combined with linguistic information collected from experts, both using FL. The author considers only the second class of problems as they can be applied to feedforward neural nets (FFNN) and he compares the two methods. The author is concerned about mapping numbers into numbers with front-end fuzzifiers and rear-end de-fuzzifiers.

The Principle of Incompatibility [17] is given by the "founder" of FL: "As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision or significance (or relevance) become almost mutually exclusive characteristics" – or, "The closer one looks at a real world problem, the fuzzier becomes its solution."

A FLS system can be described as taking crisp input and producing crisp output. In between those two is a fuzzifiers of the input data, if-then rules, and a de-fuzzifier output. The rules are derived from experts. The rules are written in terms of linguistic variables. An inference engine is used to process the if-then rules and produces fuzzy output.

The membership function for crisp sets is 0 or 1. For FL, the membership function takes on values of from 0 to 1. The membership function in FL "provides a *measure of the degree of similarity* of an element in U [the set of allowable values] to the fuzzy subset." An example is car manufacturing if one asks the question of whether the car is domestic or foreign made. In crisp logic a rule can fire only if the conditions for the rule are exactly met; in FZ, the rule fires "so long as there is a nonzero degree of similarity between the first premise and the antecedent of the rule." The result of the rule firing "is a consequent that has a non-zero degree of similarity to the rule's consequent."

Fuzzy logic vs. probabilistic models: The author cites sources that argue both sides of this issue and concludes that "there is some truth to both sides ..." However, he argues effectively that FL "is a tool of enrichment and not replacement ..." Bezdek and Pal [18] are quoted as saying that "fuzzy models belong wherever they can provide collateral or competitively better information about a physical process." Bezdek and Pal give an example case wherein two bottles of water are lying in the desert and are found there by a very thirsty wanderer. The first bottle has a membership in the set of potable waters of 0.91 while the other has a probability of being potable that is 0.91. In the first case the water shares a high degree of characteristics in common with potable water while the second has a 9% chance of being totally non-potable (poison!). Which do you drink?

Fuzzy logic systems are universal approximators: The question of how well an FLS approximates an unknown function is an important question in feedforward neural networks. The FFNN is a universal approximator, "which means that a FFNN can uniformly approximate any real continuous nonlinear function to an arbitrary degree of accuracy." The same thing has been proved for FLS if that FLS uses "product inference, product implication, Gaussian membership functions and height fuzzification." Other types of FLSs have been shown to be universal approximators but not all FLSs fall into this class. Such proofs cover existence but they do not say how the FLS is to be constructed. The same is true for FFNNs. The existence theorem for FFNN does not tell how many layers of neurons should be used or how many neurons should be used in each layer or how interconnected the neurons should be. In the case of FLSs the author indicates that one should "design the FLS using *representative* *data* that is collected for a specific application." In fact, one "trains" an FLS in much the same way as a neural net is trained by the data. The author does conclude that 'whatever ... different training algorithm that is used for a neural network can also be used by the FLS. Success of any neural network training algorithm depends on the initial values chosen for the weight. These weights have no physical meaning for the neural network; hence, they usually must be chosen randomly. The parameters of a FLS are associated with membership functions for physically meaningful quantities; hence, it is possible o obtain very good initial values for them." The author concludes further "the fuzzification subsystem within the FLS lets us handle uncertainty in a very natural way, totally within the framework of the FLSs. To date there does not seem to be a comparable way to handle uncertainty in a FFNN."

4. Reference [19] describes the unifying framework of adaptive networks. These are said to have certain advantages over neural networks.

   Emphasis is given to the use of the "back-propagation" learning rule for artificial neural networks. This "universal learning paradigm for any smooth parameterized model" can now not only take crisp data but can take linguistic information. It can also adapt itself using numerical data to achieve better performance. Neural networks are not able to take linguistic information directly.

   Adaptive networks are a "superset of all kinds of neural network paradigms with supervised learning capability." The adaptive network consists of nodes and links arranged in layers. In a feedforward network each layer links to the next layer whereas in a recurrent network, there can be some feedback links. There are no links between nodes in the same layer in a layered adaptive network. There can also be a topological network in which nodes only feed those nodes with higher numbers in the defined sequence.

   "Usually an adaptive network's performance is measured as the discrepancy between the desired output and the network's output under the same input conditions. This discrepancy is called the *error measure* and it can assume different forms for different applications. Generally peaking, a learning rule is derived by applying a specific optimization technique to a given error measure." The backward learning algorithm is based on computing the error using a gradient vector whose components involve the parameter at each node. The basic concept is to pass a form of the derivative information from the output layer to the input layer.

   Special cases of adaptive networks are discussed that have been widely used in the neural network literature: the back-propagating neural network and the radial basis function neural network. The former is widely used in such areas as pattern recognition signal processing, and automatic control while the latter are used to model physiological-like systems where all nodes communicate with all nodes. The adaptive network-based fuzzy inference system (ANFIS) reported in this paper is similar to the radial basis function network. ANFIS is used for nonlinear function modeling, time series prediction, on line parameter identification for control systems, and fuzzy controller design.

   Other learning systems can be used. These include gradient free methods such as genetic algorithms, simulated annealing, downhill Simplex, and random. Applications have favored genetic algorithms. The technology development focus is on "structure determination" wherein the network structure, the fuzzy rule sets, etc. can be defined. Speeding up the learning algorithm is still needed.

5. Reference [20]: Fuzzy logic control.

   This is not reviewed due to its narrow focus. The conclusions indicate that the benefits of FLC over standard control systems are focused on those control system "policies which combine maximization or constraint enforcement with regulation. Many of the control policies implemented are dynamic."

6. Reference [21]: Hardware solutions for fuzzy control.

   The point of this article is that one can implement fuzzy control logic in processors that range from supportive to dedicated. "As a general taxonomy, we can identify four classes among the different implementation alternatives:

   - Software and hardware solutions with general purpose components.
   - General-purpose processors with instructions for specialized computations.
   - Dedicated fuzzy coprocessors.
   - Fuzzy ASICs capable of stand-alone operations.

   The first alternative is the most widely used and software tools to aid in the development of fuzzy controllers have been developed. Special purpose coprocessors have been developed and "usually adopt triangular membership functions, flexible rule format (number of antecedents and consequents), max-min inference method, 8-b precision and centroid defuzzification method. Application specific ASICs have also been developed.

7. Reference [22]: Application of fuzzy logic to reliability engineering.

   The paper makes the usual statement that system design involves uncertainties and that these can be captured using linguistic input. The authors "apply the main concepts of fuzzy logic, fuzzy arithmetic and linguistic variables to the analysis of system structures, fault trees, event trees, the reliability of degradable systems, and the assessment of system criticality based on the severity of a failure and it probability of occurrence."

   One of the features of the design process that the authors seek to address is "the item whose probability of failure is needed often does not exist and it must be "estimated" based on "engineering judgment" or "experience" from "similar" items. The use of fuzzy analysis methods including imprecision and approximations, fuzzy set theory, possibility theory, and their combination referred to as fuzzy logic, the authors seek to "help restore integrity to reliability analyses by allowing uncertainty and not forcing precision where it is not possible."

   The methodology used for system reliability in parallel and series systems is the usual membership function approach with assigned mappings of linguistic characterizations such as remote, likely, etc. to numerical probability ranges. The output is numerical (translated to linguistic) with an assigned "degree of possibility." The resulting output is like getting a probability and a confidence interval in a fuzzy sense. The output needs to be defuzzified.

   An alternative method for computing system reliability for parallel and series systems is that of Misra and Onisawa [23]. There method is consistent with the max-min operations of possibility theory but their results do not provide the correct value when the inputs become crisp.

   The authors address the issue of degraded state in their discussion of fuzzy reliability. They state that fuzzy sets provides a natural way to represent systems with degradation in that there may be many states between fully working and fully not-working. This is achieved by defining the memberships in both the working state and the failed state sets. In general, one set is the complement of the other. They further state that one can interpret the membership functions in "possibilistic" terms as "given that the system is working, the possibility that i components are working is" defined mathematically. They draw a weak tie to the Taguchi

Loss Function [24] in that the membership function for linear degradation is quadratic. The Loss Function evaluates costs associated with component deviations from their nominal values as a quadratic function.

The authors state, "Fuzzy logic provides a more flexible and meaningful way of assessing risk. The analysis uses linguistic variables to describe the severity and frequency of occurrence of the failure. These parameters are 'fuzzified' to determine their degree of membership in each input class using membership functions" they provide. "The resulting 'fuzzy inputs' are evaluated using a linguistic rule base and fuzzy logic operations to yield a classification of the 'riskiness' of the failure and an associated degree of membership in each risk class. This 'fuzzy conclusion' is then 'defuzzified' to give a single risk priority for the failure."

8. Reference [25]: Industrial applications at GE.

   Fuzzy logic control (FLC) is the principal area of applications. The authors state that FLC "has drastically reduced the development time and deployment cost for the synthesis of nonlinear controllers for dynamics systems." FLC has been deployed at GE to turboshaft aircraft engine control, steam turbine startup, steam turbine cycling optimization, resonant converter power supply control, and data-induced modeling of the nonlinear relationship between process variables in a rolling mill stand." The keys for GE is that they have been able to drastically reduce "the development time and deployment cost for the synthesis of nonlinear controllers for dynamic systems."

   The basis for FLC application is the difficulty in synthesizing nonlinear controllers. FLCs are "knowledge-based controllers usually derived from a knowledge acquisition process or automatically synthesized from self-organizing control architectures [26]. The FLC represents the nonlinear control surface with a knowledge base that is executed by an interpreter or is compiled. GE has reduced the design cycle time during the development phase "by using an interactive computing environment based on a high level language with it local semantics, interpreter, and compiler."

   "A hierarchical control scheme permits the decomposition of complex problems into a series of smaller and simpler ones. As these simpler problems are solved, typically be using low level controllers, the can be recombined to address the larger problem This recombination is governed by a fuzzy logic supervisory controller that performs soft switching between different modes of operation." Software maintenance is simplified by being able to switch rule bases for different applications, such as changing from a combat environment to a training environment.

   The paper goes into some detail on the range of their deployed applications. One of these is a neuro-fuzzy system for a critical part of a steel rolling process that cannot be analytically modeled. The problem is worked in the forward direction by acquiring operational data, each one of which is very expensive. The neuro part of the system is deployed to learn what rules govern the data, a reverse engineering problem. The fuzzy part of the system is based on generalizing the rules so that table-lookup is not used. This results in a much simpler system. The rules can be refined with additional knowledge extracted from the system.

   The major research focus at GE is "aimed at extending adaptation techniques developed in other fields to provide automatic tuning of FLCs." The adaptation techniques they review include reinforcement learning, supervised learning, steepest descent, genetic algorithms, and reverse engineering/rule clustering. They believe that including other emerging technologies such as neural network and genetic algorithms will improve the cost/benefit ratio of FLCs when applied to a wide range of complex control problems.

9. Reference [27]: Joint Delphi/LANL project on reliability in product and process design assurance.

   The report summarizes a joint effort between Delphi Automotive and the Los Alamos National Laboratory to develop a software-based mechanical product design system that predicts product reliability from conceptual design to product use in the field. Thus, the developed "PREDICT" product is a life cycle reliability prediction system that captures quantitative and qualitative information about the product during the full design cycle. The PREDICT system also computes an uncertainty range on the product reliability, ties the reliability and its uncertainty to each of the sub-assemblies, and guides the process for reliability improvement.

   A key element of the PREDICT system is the systematic use of expert opinions while stripping out bias to the extent possible. A second key element is the use of Bayesian or other suitable updating methods for updating the product reliability and its uncertainty based on acquired data and usage experience. While specifically designed for use in Delphi products, the PREDICT system defines a generic methodology for product design and development based on a rational (i.e., not experiential) reliability growth process.

   The PREDICT system makes use of fuzzy input data. Domain experts are used to make point estimates of component, subsystem, and system performance in terms familiar to each. Each expert is also asked for a brief summary of their rational for selecting their estimates. They were also asked to provide ranges on their estimates. Such expert input is then transformed into distributional values for the analysis.

10. Reference [28]: Soft Computing and Fuzzy Logic

    The author states that the elements of soft computing include fuzzy logic, neurocomputing, and probabilistic reasoning. "The dominant aim of soft computing is to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Probabilistic reasoning subsumes genetic algorithms, belief networks, chaotic systems, and parts of learning theory. Neuro-computing concerns learning and curve fitting. The concepts within fuzzy logic are the use of linguistic variables and the use of fuzzy *if-then* rules that use linguistic variables. Fuzzy logic is logic with fuzzy set theory.

    A central problem in fuzzy logic is how to infer rules from observations. Recent work has made important advances toward partial solutions of the problem by applying neural net methods with learning based on dynamic [29] and gradient programming [30]. By representing a fuzzy system in a defined multilayered structure and some learning network with backward iteration, one converges on the weights and thereby induces the rules from observations.

11. Reference [31]: Using fuzzy logic to drive optimization algorithm

    If one examines optimization algorithms one finds that the algorithms behave as closed-loop control algorithms. Rao seeks to use the same benefits of fuzzy logic to build non-linear optimizers, in this case the SLP algorithm.

12. Reference [32]: Probabilistic vs. fuzzy set methods for designing under uncertainty

    The basic hypothesis is that the design data is not well known and therefore we do not have perfect "assurance" in the use of probabilistic methods. The desire is to have a conservative estimate of the output reliability. The authors state that "if there is sufficient information to build accurate probabilistic models of uncertainties, probabilistic methods are better than fuzzy set methods." They go on to assert that fuzzy set methods are better "if little information is available." The authors use the terms "fuzzy set methods" and "possibility-based methods interchangeably."

The authors draw several observations and comparisons of fuzzy set and probabilistic theories for large parallel and series systems with crisp failure scenarios. They draw two conclusions based on these observations. In the first, "a fuzzy set method is likely to underestimate the chance of failure of a system with a large number of independent failure modes. On the other hand, it can be too conservative in systems for which the failure region is small compared to the range of uncertain variables." They liken the first to the case of having a lot of information on independent failure modes where probabilistic methods are favored. The second is likened to the case of having limited information on the distributions of the independent failure modes. They then draw the next conclusion that "it is easier to determine the most conservative fuzzy set model than it is to determine the most conservative probabilistic model that is consistent with given information about a problem."

Frankly, I find the logic to this discussion pretty shaky. For example, while I agree that it is easier to define the most conservative possibilistic model, by their own statement it is clear that this result may not be more conservative than a probabilistic model of the system! They seem to be hanging the justification of the fuzzy set model solely on the non-rigorous contention of "lacking data." Further, the approach they use is tied to optimizing a design using probabilistic or possibilistic input. They contend that the first optimal design may be non-conservative – which it certainly could be if optimized to a required safety level and the distributions are not absolutely correct.

The authors "define" uncertainty in the distributions in a soft way by testing the sensitivity of the result to changes in the assumed distribution parameters. They further state, "probabilistic design ... cannot estimate the sensitivities of the probability of failure with respect to the design variables." This is patently wrong. The simulations used by the authors in their demonstrations makes use of a MC loop outside the reliability loop. This is the same way others have modeled assurance intervals [33].

The results of their simulations show that both methods can give unsafe estimates. On average, they get more conservative results for the simulations using designs optimized to fuzzy set models. However, in neither case do they get any level of assurance nor do they tie the results to the most important variable controlling assurance.

13. Reference [34]: Convex modeling.

    This is a very short note and acts now as a place-holder. The contention is that interval arithmetic is a form of convex modeling.

14. Reference [35]: Interval arithmetic.

    The idea for interval math arose out of error analysis. "Error analyses of large scientific, engineering, and commercial algorithms are sufficiently complex and labor intensive that they are often not conducted. The result is that machine computing with floating-point arithmetic is not tightly linked to mathematics, science, commerce or engineering."

    The interval paradigm is said to have the following characteristics that are considered to be valuable.

    - Fallible data can be represented using intervals
    - Any arithmetic computation can be performed using interval arithmetic to obtain guaranteed bounds on the set of all possible results.
    - Interval arithmetic can be used to provide bounds on errors from all sources...

- A valuable link is http://cs.utep.edu/interval-comp/main.html. The interval arithmetic journal is called Reliable Computing, an International Journal devoted to reliable mathematical computations based on finite representations and guaranteed accuracy; since 1997, published by Kluwer Academic Publishers.
- There is also a Journal of Convex Analysis (JCA); intervals are special case of convex bodies (compact convex sets); there is a strong interrelation between interval analysis and convex analysis.
- Set-Valued Analysis; interval analyis is an important particular case of set-valued analysis.
- Bulletin of ACM SIGSAM (Special Interest Group on Symbolic and Alegbraic Manipulations)
- A Special Issue of "Fuzzy Sets and Systems": Interfaces Between Fuzzy Sets and Interval Analysis
- Special Issue of "Journal of Symbolic Computations"
- International Journal of Uncertainty, Fuzziness, and Knowledge-Based Reasoning (IJUFKS). This journal:
    - regularly publishes a special section with abstracts of recent papers on applications of interval methods in knowledge representation, and
    - published a special issue on interval methods in representing and processing uncertainty.

The following quote is taken from the "Special Issue ..." cited above. "Fuzzy set theory when restricted to sets of real numbers can be approached via intervals and interval analysis. The intimate relationship between interval analysis and fuzzy set theory is especially apparent in fuzzy arithmetic, fuzzy optimization and some areas of fuzzy mathematical analysis. A unimodal fuzzy membership function can be formed from a continuum of intervals corresponding to alpha-levels or a continuum of disconnected intervals for multi-modal fuzzy membership functions. Intervals are one type of fuzzy set possessing a rectangular membership function. This being the case, the issues and mathematical analysis associated with fuzzy set theory and interval analysis are mutually relevant."

It should be noted that the latest version of the Sun Microsystems Fortran compiler includes interval variables.

15. Reference [36]: Interval arithmetic.

    The article gives a short introduction to interval analysis and its possible applications. It also gives an overview of existing programming languages for interval arithmetic. The authors state, "the XSC (extended scientific computation) library provides powerful tools necessary for achieving high accuracy and reliability. It provides a large number of predefined numerical data types and operations to deal with uncertain data."

16. Reference [37]: Interval arithmetic (IA) for floating-point computations.

    "Interval analysis concerns the discovery of interval algorithms to produce bounds on the accuracy of numerical results that are guaranteed to be both valid and sharp." The author states that IA has been used to develop entirely new algorithms to solve fundamental problems that appear to have no other solution. Principal among these are: solving nonlinear systems of equations; and nonlinear global optimization (both constrained and unconstrained)." [38]

While interval analysis has a reduced computational speed, the author says that the algorithms are very susceptible to parallel computing.

17. Reference [39]: Artificial neural networks

    The paper is concerned with the solution of ill-posed problems using neural nets to model experimental systems. Size is a big issue as well as noise in the experimental data. "The increased interest in these models is motivated mainly by their enormous potential for the parallel data processing of multidimensional problems…" The approach taken herein for the network is a feedforward multilayer neural network with nonlinear processing elements in the network hidden and output layers. A backpropagation supervised learning algorithm is used to determine the network's connection weights and neuron biases. This is supposed to be robust and accurate in dealing with noise. The problem is that the number of learning sets "increases sharply with the number of cells in the computation grid." A method like simulated annealing is used to determine the weights.

18. Reference [40]: Integration of reliability and testing

    The approach here is probabilistic design that accounts for uncertainties in the analytical model and in the distributions used for the physical variables. Integration of modeling and testing is seen as the way to define a "confidence" interval – or what we are not trying to call an "assurance interval." Unfortunately, here the authors are using statistical confidences based on the amount of testing. Physical uncertainty, model uncertainty, and statistic parameter uncertainties are included. A Bayesian methodology is used for updating with the acquisition of failure test data. Both reliability and assurance interval updates are derived.

19. Reference [41]: Data mining and neural networks

    This is an overview of some strategies used for data mining in five main types of analyses: classification, prediction, clustering, association and sequence analyses. Classification, prediction, and clustering are closely related while association and sequencing are related. Each has different methods for different situations including Bayesian modeling, self-organizing maps, decision trees, multivariate linear regression, neural nets, and genetic algorithms.

20. Reference [42]: Accurate tail probability prediction

    The paper presents an efficient method for estimating tails as used in Bayesian networks when very large confidence intervals are required as in reliability or risk assessment. A comparison is made to a fast probability method, which the authors state is the only competing method.

21. Reference [43]: Genetic algorithm search

    The main point made in this paper is that with the use of a GA search with probabilistic transition rules such that local minima are avoided. GA works directly with the objective function and not with derivatives of it. The authors do point out the enormous computational power required to use GAs, a problem only intensified for large systems.

22. Reference [44]: Combined use of neural networks and response surfaces for airfoil design

    The paper reports on the aerodynamic design of an airfoil using multiple simple response surfaces and neural networks to obtain the "advantages of both." The authors begin with a review of the growing literature reporting uses of neural nets for various aerodynamic design and modeling applications. A principal concept behind some of the important work is to represent the design space using a neural network. This can be seen as a "training derived" response surface in design space. Such response surfaces are seen by the various authors as having great utility in multidisciplinary design optimization (MDO), but it is also obvious such surfaces may have utility in reliability-based design.

The authors state "because most design problems in aerodynamics involve a multitude of parameters and datasets that often lack structure, neural nets provide a level of flexibility not attainable by other methods." They also state that design rules can be incorporated along with high fidelity CFD solutions. A feed-forward, gradient-based learning algorithm is used along with perturbation data about the starting design point to train the neural network.

In the current paper, the authors build a "parameter-based partitioning of the design space" using neural nets to link variables of interest to key design parameters and simple polynomials for the remainder of the design parameters. This approach significantly reduces the factorial design space problem, according to the authors. There is no mention of a more efficient DOE approach.

The authors also address the problem of a final design that is a large distance from the initial design point. They do this by constructing a series of response surfaces in the design space. The neural net advantage would appear to be in providing an efficient means for solving the inverse problem of a response surface definition (as opposed to a matrix inversion requiring a square system) for large data sets. Their methodology would also appear to provide weights that are physically based so that the response surface can be linked directly to the design variables for the reliability problems.

23. Reference [45]: Feature saliency in neural networks

    The authors develop a formal means for assessing the importance of design features in trained neural nets in terms both of the physical sensitivity and the error sensitivities. It would be interesting to contrast this with the DOE and ANOVA methods.

24. Reference [46]: Bayesian network in a reliability problem

    In the words of the authors "A Bayesian network is a directed acyclic graph in which nodes represent random variables and links represent direct probabilistic influences. The variables depicted in the BN represent key parameters characterizing the system being modeled." The network links define conditional probability relations between causes and effects based on the network topology. The total network then represents the system reliability in a direct, physical manner. The topology of the BN is constructed using intermediate variables so that the conditional probabilities are kept simple, using only two parent nodes for each child node.

    As in standard reliability modeling, the number of independent variables is kept small by neglecting those with small likelihoods. The BN provides an easy mechanism to perform "what-if" analyses on the system. Conditional sensitivities are obtained. The what-if analysis can involve changing the prior distributions to see the effect of individual element changes on the posterior distribution.

    The paper gives an example for a power system and shows that the constructed BN gives the same answer as "other methods" which I take to be a simulation based method. However, the authors state that the ability to have a direct computation of the posterior distribution is unique to the BN method. BNs also provide a direct evaluation of conditional probabilities. Commercial software was used to propagate the conditional distributions through to the top event.

25. Reference [47]: Globally convergent optimization with neural nets

    The authors have devised a particular way of constructing NNs such that the constructed net is guaranteed to be globally convergent to solutions of problems with bounded or unbounded solution sets. The authors review the literature on the use of NNs for gradient and non-gradient optimization algorithms that are widely used. The computational advantage to NNs is their inherent parallel structure. The proposed algorithm includes all proposed gradient and non-gradient methods as special cases.

Unfortunately, the authors make the statement that the derived NN is NOT unique for the same optimization problem. How then have we found a global optimal design? Apparently we have not done so. All that is assured is that the algorithm is convergent to A solution, not the solution. There does not appear to be a special capability here for use in reliability problems.

26. Reference [48]: Conceptual design using genetic algorithm for trade selection

    The principal hypothesis behind the paper is that preliminary design for complex systems is often focused on feasibility rather than optimality, given the problem size and methods used. This certainly corresponds to my own design experience on the PW2037 engine where the preliminary design did not consider the downstream impact of early decisions on non-optimality at the sub-system level. As a result, the high-pressure turbine was very non-optimal, but it is flying today. To resolve the problem from the authors' perspective, they address the issue of generating a wide range of alternatives at the conceptual design step.

    The focus in this paper is on combinatorial design where many discrete configurations are to be considered. Classical, continuous variable methods do not work for such design optimization problems. The general field espoused in this article is that of *meta-heuristics* and includes genetic algorithms, neural nets, simulated annealing, tabu search, and hybrids of these. Genetic algorithms work with a population of possible designs rather than evaluating an ordered sequence of designs and are therefore highly parallel in structure.

    The key element in this paper is the use of a spreadsheet environment to represent each of the subsystems as performance models. The GA then is able to select from the multiple design concepts by accessing the spreadsheet.

    My question is whether or not one can be effective for reliability-based design using a GA and a system integration model.

27. Reference [49]: Optimizing to fuzzy, possibilistic constraints

    Instead of usual reliability-based optimization where the reliability constraints are crisp, this application is one in which the constraints are treated as possibilistic ranges. Is there an application for us?

28. Reference [50]: Nonstandard methods for optimization

    This paper gives a reasoned discussion of the limits of standard, gradient-based methods vs. the non-traditional methods such as simulated annealing, genetic algorithms, Tabu search, and rule-based expert systems. For the many variants of random methods, the author says "the computational requirements associated with the use of these methods in problems with increasing dimensionality continues to be excessive, necessitating their use in conjunction with function approximations. The author reviews the combination of algorithmic and rule-based system used by iSIGHT (Engineous Software).

29. Reference [51]: Exploring large design spaces

    A critical element in the ISE picture for the future is the intrinsic element of large scale design problems. This paper reports on an innovative and certainly non-traditional method for exploring these large design spaces. The goal is not optimization, but exploration of multiple configurations (non-continuous design space) with some hope that good designs will not be overlooked. A key question to me is whether or not and/or how to bring reliability into this process. Traditional design optimization is performed in the design parameter space. In his case all design variants are continuously coupled. Conceptual design may include both parameter space design and configuration changes through analogy brainstorming. Such a design process is discontinuous.

Furthermore, the authors state "hill climbing [traditional optimization] techniques, by requiring that a single evaluation function be defined, preclude explicit, local reasoning about tradeoffs among multiple performance criteria. The essential element of the approach is the use of a device library with characteristics for each device, a set of domain critics that assess the devices as they are selected, a design-seeker algorithm, and constraints. The library has extensive performance modeling, the critics are expert systems, and the seeker is a high level filtering process. Much of the paper is concerned with the filtering algorithm but all elements are addressed and demonstrated on an example conceptual design study.

It would appear that a "telescoping" design simulation method is required to assure the systems interfaces of the elements taken from the device library as well as the physical plausibility of the devices. Reliability attributes need to be developed and linked through this process.

30. Reference [52]: Review of computational intelligence

    The article is the editorial overview of a special edition and touches on fuzzy, neural, and evolutionary computation, and on hybrid computational intelligence systems that combine some of these. Useful set of references is provided.

31. Reference [53]: Integrated design systems

32. Reference [54]: More integrated design systems

    These two closely couple reports concern the effort at GE to develop a highly integrated design system for gas turbine engine design. The basis of that system is what they call the Intelligent Master Model (IMM) environment and it supports highly concurrent engine design. Optimality, robustness, and quality are key objectives for the design environment attributes.

    Elements in IMM include the following:

    - CAD systems based on features
    - High- and low-fidelity analysis modules
    - Multidisciplinary design optimization (MDO)
    - Robust design
    - Reliability prediction

    The IMM is "a fusion of knowledge-based engineering with top-down product control, conventional master modeling, and the linked product model environment." "The IMM can contain part dependencies, geometric and non-geometric attributes, manufacturing producibility, and cost constraints, as well as access to external databases, and be integrated with proprietary codes, through the linked model environment."

    The Master Model (MM), at the lowest geometric level, consists of basic features used in solid modeling – holes, fillets, etc. that can be extruded and combined with the usual Boolean operations. The software is highly modular with interoperable tools with data-wrappers providing interfaces. Knowledge-based engineering provides the ability to define, develop and use design rules at any level.

The system supports both the inclusion of quality metrics derived from the GE six-sigma effort as well as probabilistic modeling using Monte Carlo, response surfaces from design of experiments (DOE), and fast probability integration. Robustness seeks to reduce the sensitivity of the design to uncontrolled variables, in a Tuguchi-like sense.

A highly developed part of the environment is the geometric modeling using "feature-based" design tools. The features can then be linked according to rules and design practices captured in simple spreadsheet models. The system integrates CFD, heat transfer, and structural modeling modules.

The written material demonstrates a close affinity with the goals set for the ISE. Non-traditional and non-deterministic elements are significant parts of the developing product.

33. Reference [55]: Possibilistic reliability

    The authors have created an algorithm that derives from fuzzy logic but closely mimics probabilistic reliability methods. By converting all variables into standard normal form and treating possibilistic input with Gaussian participation functions, the authors are able to find a most possible point by a simple and rapid algebraic operation. Cumulative possibility plots and possibility density plots are derived.

    The authors cite speed as a great advantage for their algorithm.

34. Reference [56]: Bayesian updates

    The paper reviews the various Bayesian approaches that might be used in structural reliability analysis when performing quantitative risk assessments. It is a reasonable review of Bayesian methodology. They conclude that "it is often difficult to use the classical Bayesian approach in decision-making as the resulting uncertainty intervals are so large." However, they further say that "if the fully Bayesian approach is adopted, the output results are expressing the analysis group's total uncertainty related to observable quantities, and it possible to present a clear message." The fully Bayesian approach "will provide the probabilities of the uncertain events that are relevant in the specific situation of decision-making. The probabilities are total in the sense that they incorporate all types of uncertainty."

35. Reference [57]: War and Chaos

    This article was read to gain insight into the area of complexity. In the words of this author complexity theory "allows scientists to make mathematical models of events in which the inputs do not necessarily have a direct, or linear, relation to the outcome." He further equates unpredictability with chaos. The author, a physicist, hoped to use complexity theory to predict the point of instability – in the social context of chaos leading to war.

    "Complexity may be defined as the set of deterministic theories that do not necessarily lead to long-term prediction. Such theories are still mathematical and deterministic. ... but the structure of the mathematics is such that we cannot obtain the future values implied by the theory just as a result of a compact, well-defined manipulation of the present values. The calculation requires the *actual* computational stepping through all the intermediate values of the system variables between 'now' and 'then.' Complexity theories thus depend on the complete 'path' taken by the system between its beginning and end points. As such, they are sensitive to all perturbations that may have an impact on the system as it evolves in time."

    To support this, I further quote from the author. The example he is citing concerns planetary motions. The universe might be thought of as having a complicated structure. "The solution of the differential equations [of planetary motion] in closed form gives the structural variables – position and velocity – at any time, in terms of well-determined trigonometric functions. Plug in the time you want, and out come the desired structural variables. *There is no need to* *compute them at intermediate times*. Modify the initial conditions slightly and the output variables come out slightly differently. Thus the entire future of the system, to any specified accuracy, is completely contained in, and obtainable from, the initial parameters and the theory via finite explicitly specified numerical procedures. The closed continuous mathematical form of the solutions to the theory's equations means that output is continuously related to input – there can be no surprises, no disorder and no complexity."

36. Reference [58]: A web site on complexity theory

    The author of this web site defines "Complexity is the property of a real world system that is manifest in the inability of any one formalism being adequate to capture all its properties. It requires that we find distinctly different ways of interacting with systems. Distinctly different in the sense that when we make successful models, the formal systems needed to describe each distinct aspect are NOT derivable from each other."

37. Reference [59]: Gas turbine health monitoring, diagnosis, and prognostics

    This PWA paper reports on a comprehensive system based on statistical inference, artificial neural networks (ANNs), Bayesian updating, and expert systems. The system does not use probabilistics to set ranges on variables but instead uses exponential averaging of engine data. ANNs are built on a sub-system basis to enforce physical behavior to the nodes and training processes rather than the usual ANN condition where the nodal weights have no physical interpretation. This approach aids in fault root-cause identification. "A Bayesian type [of] statistical evidence approach is used to reflect the uncertainties in the rule based system." The knowledge based expert system provides the interpreter for making prognostic inferences based on the information derived from the ANN.

38. Reference [60]: Advanced diagnostics and prognostics for risk assessment

    The elements of the approach are "Statistical-based anomaly detection algorithms, fault pattern recognition techniques and advanced probabilistic models for diagnosing structural, performance and vibration related faults and degradation." The prognostic modules use probabilistic, physics-based models of system behavior to get the expected range of failure lives for risk-based decisions. The probabilistic physics-based models can also be used in making probabilistic anomaly decisions. Fuzzy logic is used to perform real-time sensor validity analysis.

4.5 Application Projects for NDM sponsored at Vanderbilt University by the NASA/MSFC (cf. Prof. S. Mahadevan)

The on-going probabilistic methods research at Vanderbilt University is sponsored by NASA Marshall Space Flight Center through two GSRP (Graduate Student Research Program) fellowships (Joshua Hall and Andrew Stoebner). The two GSRP fellowships fit into the overall objective of the MSFC Structural Dynamics Laboratory (technical lead: Dr. John Townsend) to familiarize its engineers with probabilistic analysis and design methods and to develop demonstration problems of interest to MSFC engineers. Three tasks accomplished under this funding are described below. In addition to these three tasks, MSFC organized two three-day short courses on probabilistic methods, taught by Prof. Mahadevan. The first course covered basic probabilistic techniques -- first-order reliability methods, Monte Carlo simulation, response surface methods, and system reliability analysis. The second course covered advanced techniques in probabilistic finite element analysis, space and time variability problems, advanced Monte Carlo methods, and detailed demonstration problems. The three tasks are as follows:

1. Probabilistic Response Surface Analysis of Solid Rocket Booster Aft-Skirt

NASA engineers at Marshall Space Flight Center (MSFC) have applied probabilistic methods to assess the reliability of the aft-skirt of the Solid Rocket Booster (SRB). The objective of the response surface analysis in this task is to develop a closed form solution for the stresses in the aft-skirt. This solution can then be used as a performance function for further component level reliability analyses on the aft-skirt, or as a simplified model of the skirt to be used in a system level analysis of the entire Space Shuttle. The response surface model is validated with the previous solutions obtained by the engineers at MSFC.

The aft-skirt structure is the mechanism by which the SRB's, and the rest of the Space Shuttle assembly are attached to the Mobile Launch Platform (MLP). The skirt is constructed of 2219-T87 aluminum. Each skirt has four hold-down post forgings, which are butt-welded onto the skin panels. The failure of the skirt is known to occur at a point at the bottom of the weld region between the forged post and the skin of the skirt. The primary contributor to the failure of the skirt is the bending load caused by the Space Shuttle Main Engines (SSME) at start-up. Just prior to launch the SSME's are test fired. This thrust load is eccentric with respect to the aft-skirt, and thus induces a forward sway of the Space Shuttle Assembly. The maximum load to the skirt occurs at the maximum point of deflection due to the SSME thrust.

The engineers at MSFC used a NASTRAN finite element model of the aft-skirt assembly to calculate the state of stress at the critical weld region. An improved design using brackets was also investigated. A large amount of strain gauge data was gathered from the shuttle flights following the Challenger accident. This data was used to characterize the statistics of the loading variables to be used in the probabilistic analysis. The NESSUS/NASTRAN interface was utilized to perform the probabilistic analysis. The results of the prior analyses are compared with those obtained using the proposed response surface methodology, and it is shown that the response surface method provides excellent savings in computational effort for this problem.

2. Probabilistic Analysis of Solar Concentrator

This task presents the consideration of uncertainties and the application of probabilistic computational methods to the dynamic analysis of polyimide inflatable cylinders used in solar thermal propulsion. The basic concept behind solar thermal propulsion is to utilize solar energy as a means of heating a propellant to provide thrust at increased specific impulse. Thrust is produced by expanding the heated propellant through a nozzle. No combustion occurs, and the thrust level is low. For this reason, solar thermal propulsion systems are mainly applicable for orbital transfer vehicles.

A prototype inflatable solar concentrator consists of a torus/lens assembly supported by three struts. This concentrator is constructed of Kapton polyimide film, with epoxy as the primary adhesive for joints. The Fresnel lens of such a concentrator assembly would focus sunlight into a collector near the fixed ends of the struts. Solar energy stored in the collector could be utilized to heat the propellant.

The inflatable cylindrical struts are critical components of this assembly. Therefore, their dynamic and static behavior has been investigated both experimentally and analytically by engineers at NASA Marshall Space Flight Center. The polyimide film material used for construction of the struts is highly nonlinear. Its elastic modulus varies as a function of frequency, temperature, and the level of excitation. It has been already observed that the elastic modulus decreases with increasing frequency, in free-free as well as cantilevered configurations.

The purpose of this task is to apply probabilistic computational methods to this problem. There are several types of uncertainties in these structures, such as material properties, boundary conditions, loading conditions, ambient temperature, damping etc. This task develops statistical information about these uncertain variables using the test data already compiled at Marshall Space Flight Center, and demonstrates the use of this information in the dynamic analysis of the inflatable struts. Two types of NASTRAN finite element models are used, with (1) beam elements that incorporate the frequency dependent nature of the elastic modulus, and (2) shell elements. Two types of probabilistic analyses are performed. The first one is to compute the statistics of the natural frequencies and the load response. The second one is to compute the reliability of the structure under various performance criteria such as strengh, stability, stiffness etc.

3. Reliability-Based Robust Design

This task combines two major concepts of reliability-based design and robust design. Reliability-based design attempts to maximize the reliability of a system. Robust design tries to minimize the performance variation when the operating conditions change. An ideal design will be robust and reliable. The method proposed in this study investigates reliability design and robust design methods and combines both types of techniques into a single objective function. In this study, robustness is defined as variation in the reliability estimate. This technique will allow the designer to satisfy reliability and robustness requirements with one function, rather than looking at them separately. Also, it is shown how to measure each factor's influence on the reliability and robustness of the system.

Three types of design are used to demonstrate the proposed method. Parameter design uses the mean values of the random variables in the design. Tolerance design uses the standard deviations of the variables in the design. Combined design uses both means and standard deviations in the design. These three designs are applied to four demonstration problems: truss design, automotive leaf spring design, weld design, and throttle design.

4.6 Original Statement of Work

Purpose of the Study: To prepare a report to NASA on Non-Deterministic (i.e., non-traditional) Methods for Design. The report will include a review of the methods in terms of basic methodology, an identification of who is doing the work or making applications of the methodology, and how the methodology is being used. The report will also identify application opportunities for NDM in advanced aerospace applications and will define future development needs. The report is to include an executive summary, review of methodologies, applications, future needs and opportunities, bibliography, and an Appendix with site visit interview summaries.

Proposed Statement of Work: The proposed effort will begin by developing a list of sites and/or persons that spans a wide range of the leading work and topics. An initial proposed list is appended to this proposed statement of work. The PI will then contact each site or person to define for them the nature of the NASA-directed study. The PI will obtain written versions of the work being pursued in terms of papers and reports for early review of the methodology and/or applications. Following this review the PI will call each selected site or person to arrange on-site visit with key investigators and/or application engineers. The PI will develop interview notes that summarize the work being done by the methodology developers and application engineers.

The written material and the interviews will form the basis for a written final report to NASA. The work will begin as soon as authorized. The proposed schedule for the interviews and the final report is as follows:

Project initiation: Review final proposed list of contacts and visits.

Phase I:	Make contacts and solicit participation in the study; request relevant written material. [2 weeks]
Phase II:	Review written material and develop regional travel plans; notify NASA Program Manager of each planned trip and proposed contacts. [Estimated schedule based on 2 weeks to prepare for and complete each regional visit: 10 weeks]
Phase III:	Prepare final report draft for NASA approval [2 weeks]

Initial proposed regional travel: Potential travel sites that are initially proposed are given below. The proposed effort is to make five multisite visits to maximize the information return per trip. The PI will arrange the schedule for each multisite visit to maximize the number of specific/individual company/lab/university sites per trip. The proposed travel also includes up to two trips to Cleveland to add to the knowledge base for the report and to present an oral review of the report. An overview of the study is to be used as the basis for a keynote lecture to be given to the AIAA SDM conference in Atlanta GA during the first week in April.

<u>Visit to the Northeast via NYC:</u>

- GE Corporate R&D in Schenectady NY: fuzzy control, uncertainty modeling and analysis.
- Impact-Technology (Dr. Mike Roemer) in Rochester NY; fuzzy neural nets for system health monitoring and prognostication.
- STI (Dr. Dan Ghiocel) in Rochester NY; probabilistic fields and response surface technology.
- UTRC in East Hartford CT (Dr. Wally Orisamolu): fuzzy systems, applications of reliability-based design to non-aerospace systems.
- Cornell in Ithaca NY (Prof. Grigoriu): advanced probabilistic methods.

<u>Visit to central US via Cincinnati:</u>

- UDRI in Dayton OH (Drs. Pete Hovey and Al Berens); random processes; probabilistics for applied NDE.
- Wright State University in Dayton (Dr. Ramana Grandhi); fast probability methods.
- AFRL/PR (Ted Fecke); AF applications and development plans for non-deterministic design.
- GEAC, Cincinnati OH (Drs. Paul Roth and Dennis Corbly): probabilistic design methods for gas turbine engines.
- VPISU, Blacksburg VA (Prof. E. Nikolaidis): fuzzy sets; potentialistic methods.
- ANSYS, Pittsburgh PA (Dr. Stefan Reh): non-deterministic design via CAE.

<u>Visit to Florida:</u>

- PWA (Eric Fox and Chuck Annis): probabilistic design methods for gas turbine and rocket engines.
- U. So. Florida (Prof. S. Rao): fuzzy sets, interval math.
- Florida Atlantic University (Prof. I. Elishakoff): Convex methods.

Visit to Los Angeles:

- Unipass Inc. in LA (Dr. M. Khalessi): probabilistic design technology
- Boeing/Rocketdyne in Canoga Park (Drs. S. Mehta, and Rajagopal, and others): non-deterministic design methodology for engineering systems; DARPA program review
- AlphaStar Inc.: Probabilistic design methods for advanced composites
- UC Berkeley (Prof. Der Kiureghian); advanced probabilistic methods in CE

Visits to Southwest and South-central:

- Honeywell Systems (Dr. Michael Gorelik): applications of probabilistic methods in certified gas turbine engine design; advanced methods.
- Sandia Natl. Lab in Albuquerque: advanced non-deterministic design methods.
- Southwest Research Institute (Dr. Justin Wu): advanced probabilistic design methods and applications.

If a particular site visit is not possible, the PI will follow up with extended phone calls to answer specific technology questions for the report.

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13. ABSTRACT *(Maximum 200 words)*

The review effort identified research opportunities related to the use of nondeterministic, nontraditional methods to support aerospace design. The scope of the study was restricted to structural design rather than other areas such as control system design. Thus, the observations and conclusions are limited by that scope. The review identified a number of key results. The results include the potential for NASA/AF collaboration in the area of a design environment for advanced space access vehicles. The following key points set the context and delineate the key results. The Principal Investigator's (PI's) context for this study derived from participation as a Panel Member in the Air Force Scientific Advisory Board (AF/SAB) Summer Study Panel on "Whither Hypersonics?" A key message from the Summer Study effort was a perceived need for a national program for a space access vehicle whose operating characteristics of cost, availability, deployability, and reliability most closely match the NASA 3rd Generation Reusable Launch Vehicle (RLV). The Panel urged the AF to make a significant joint commitment to such a program just as soon as the AF defined specific requirements for space access consistent with the AF Aerospace Vision 2020. The review brought home a concurrent need for a national vehicle design environment. Engineering design system technology is at a time point from which a revolution as significant as that brought about by the finite element method is possible—this one focusing on information integration on a scale that far surpasses current design environments. The study therefore fully supported the concept—if not some of the details—of the Intelligent Synthesis Environment (ISE). It became abundantly clear during this study that the government (AF, NASA) and industry are not moving in the same direction in this regard—in fact each is moving in its own direction. NASA/ISE is not yet in an effective leadership position in this regard. However, NASA does have complementary software interoperability efforts that should be a part of any major ISE program. Software standards that assure interoperability of data systems and modeling representations are enabling for the proposed research advocated herein and should be a major element in the ISE initiative. The international standard for data interchange is known by the acronym "STEP." The NASA participation and lead for that effort is at the Goddard Space Flight Center. NASA/GRC is leading an effort to define CAD geometry standards through the Object Management Group (OMG). To enable the design environment so necessary to the above national vision for a unique space vehicle will require an integrating software environment with interoperability standards that allow the development and widespread deployment of tools and toolsets, rather than traditional "shrink-wrapped" software used by engineers today.

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