IPPD THROUGH ROBUST DESIGN SIMULATION FOR AN AFFORDABLE SHORT HAUL CIVIL TILTROTOR

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Abstract

Beyond the Bell/Boeing 609, the next step in civil tiltrotor evolution will most likely be a larger capacity vehicle (~ 40 passenger class) similar to NASA's vision of a Short Haul Civil Tiltrotor (SHCT). This vehicle will be designed, built and operated in an era being shaped by today's increased emphasis on affordability. This paper discusses the authors' views on the subject and outlines the steps taken to develop a new methodology which will allow a true assessment of the affordability of such a SHCT. Affordability will not be defined by cost metrics alone. Instead, it will be based on the concept of value and tradeoffs between cost and mission effectiveness; measured by maintainability, reliability, safety, etc. In addition, the motivation for this shift in design philosophy and the resulting need for knowledge to be brought forward in the proposed methodology is reviewed. Furthermore, this shift in knowledge calls for a paradigm shift in the design evolution process based on the realization that decisions made during the early design phases are not deterministic in nature and should therefore be handled probabilistically. The approach taken acknowledges this need and defines a suitable probabilistic design environment. The fundamental building blocks of this method are also outlined and discussed including key concepts, tools, techniques, and the approach taken to implement this process.

Acronyms

IPPD	Integrated Product/Process Development
LCC	Life Cycle Cost
RDS	Robust Design Simulation
RSM	Response Surface Methodology
RSE	Response Surface Equation
DOE	Design of Experiments
CCD	Central Composite Design
OEC	Overall Evaluation Criterion
FPI	Fast Probability Integration
CDF	Cumulative Distribution Function

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Motivation

" In a broad sense, the most important benefit needed today in the helicopter business -- the most exciting man-on-the-moon project -- is dramatically reduced cost, or improved affordability."[1] This excerpt, taken from Dr. David Jenney's 1996 Alexander A. Nikolsky lecture, holds true for the entire helicopter industry and is particularly fitting to the civil tiltrotor concept. For a new concept vehicle (at least in the minds of the airlines and the public) it is imperative that affordability is addressed in all phases of this vehicle's design. The notion, advocated by Dr. Jenney, that affordability must be defined in a "broad sense" is crystallized in the new design methodology presented in this paper. With the Bell/Boeing 609 slated for first delivery in 2001, the next step in civil tiltrotor progress is exemplified by NASA's Short Haul Civil Tiltrotor (SHCT) which will be used as the baseline vehicle (Figure 1). Through this new methodology, the SHCT will benefit from upgrades to the synthesis/sizing code which will provide a better representation of the various contributing disciplines including the economic module. In addition, this vehicle will benefit from the methodology's ability to account for the uncertainty associated with new technologies which are expected and probably required for vehicle success.

Introduction

At its most basic level, Design for Affordability entails comparing the benefits derived from a system versus the costs necessary to achieve these benefits.

Under the cost category, defining acquisition cost as the metric or evaluation criteria for system cost is

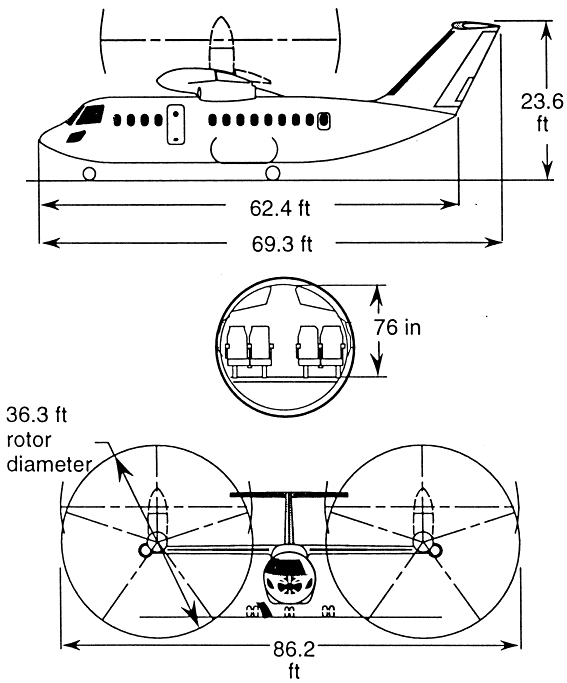

Figure 1: CTR2000 Civil Tiltrotor[2]

inadequate. Thus, the evaluation of a system's cost has shifted from the simple acquisition cost metric to include costs associated with its entire life cycle such as operation and support costs as well as retirement and disposal costs[3].

With this emphasis on life cycle costs (LCC), it is necessary to appreciate the relationship between cost, knowledge, and freedom in the context of system design. Figure 2 shows these relationships for today's design process as well as the desired relationships of the future design process. As Figure 2 illustrates, a large portion of a system's LCC is committed or "locked in" by the decisions that are made in the early design stages of today's design approach. Yet the knowledge of the system is limited during these phases. In addition, freedom to make design changes rapidly vanishes in this approach. Therefore, the early design stages present the only opportunity for the designer to efficiently and inexpensively leverage the cost and design freedom available.

The tools at the disposal of the conceptual designer, however, are not geared toward this end. The primary tool utilized is the synthesis/sizing code which usually is historically based or limited to first order analyses and may include some kind of optimization routine. This process will provide deterministic, evolutionary solutions for a small number of design alternatives which have few links to a truly affordable system. Some of the upgrades

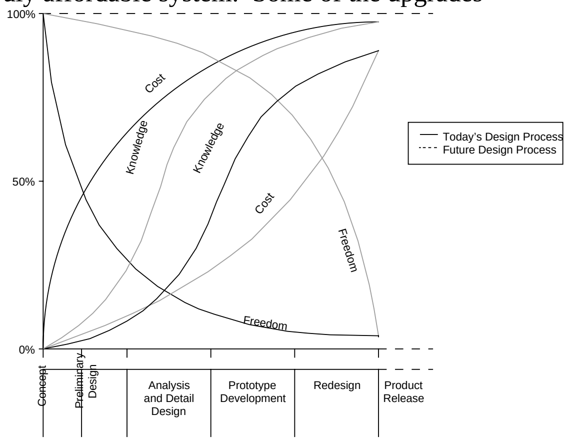

Figure 2: Cost, Knowledge & Freedom Relations (Adapted from Reference 14)

needed by the synthesis/sizing code to allow for a more realistic, representative assessment of system affordability include: 1) linking the code to a cost model that incorporates the needs of the manufacturer and the operator as well as manufacturing processes 2) increasing the fidelity of the discipline level analysis modules within the synthesis code 3) eliminating weight-based cost relationships and moving towards activity or process based cost estimating relationships 4) incorporating risk/readiness assessment for infusion of new technologies 5) addressing issues of code fidelity probabilistically 6) updating the sizing scaling rules inherent to synthesis into more vehicle specific ones 7) bringing life cycle considerations upstream to the conceptual phase where they could be treated as constraints, etc..

By bringing knowledge forward there is a fundamental change in the design process. The deterministic approach is no longer applicable or even desired. The early design phases now become probabilistic in nature. Noise variables in the economic model such as fuel prices and load factors are beyond the control of the designer and must be modeled with probability distributions, if their statistics are known, or with other stochastic methods (i.e. fuzzy logic) if they are unknown. The infusion of technology to enhance affordability, enhance capability or to avoid "show stoppers" must also have an associated uncertainty. This uncertainty is again probabilistic or stochastic in nature since it relies on an assessment of the readiness level of the proposed technology.[4] Even the fidelity of the discipline analyses are fundamentally stochastic in nature since there is always some uncertainty associated with an analysis module. The proposed design methodology presented in this paper acknowledges the need and calls for the development of a probabilistic design environment which ultimately will provide the ability to truly assess the affordability of a complex system.

Affordability

Buried within the design for affordability methodology lies a key observation about the relationship between improvement and affordability. Improvements in the design of complex systems whether on the technical/discipline level or the methodology/process level must be linked to some tangible assessment of a vehicle's affordability. Thus, even the current definition of affordability as the minimization of a system's life cycle cost is still lacking. Design for Affordability represents a paradigm shift where design and evaluation of a system is no longer dictated solely by mission capability or cost in isolation. Instead, it is a robust design that balances mission capability with other system effectiveness attributes while keeping cost under close attention. *This balance between benefit and cost is the main foundation behind design for affordability, and it may be simply measured by the ratio of benefits provided or gained from the product or service to the cost of giving or achieving those benefits.*

In order to identify the disciplines/sciences needed to measure and predict affordability, one must examine what attributes contribute to overall system effectiveness. The approach taken presently is based on the idea that the only way to measure or evaluate total system effectiveness is through the identification and inclusion of all key contributing attributes. An example breakdown appears in Figure 3.

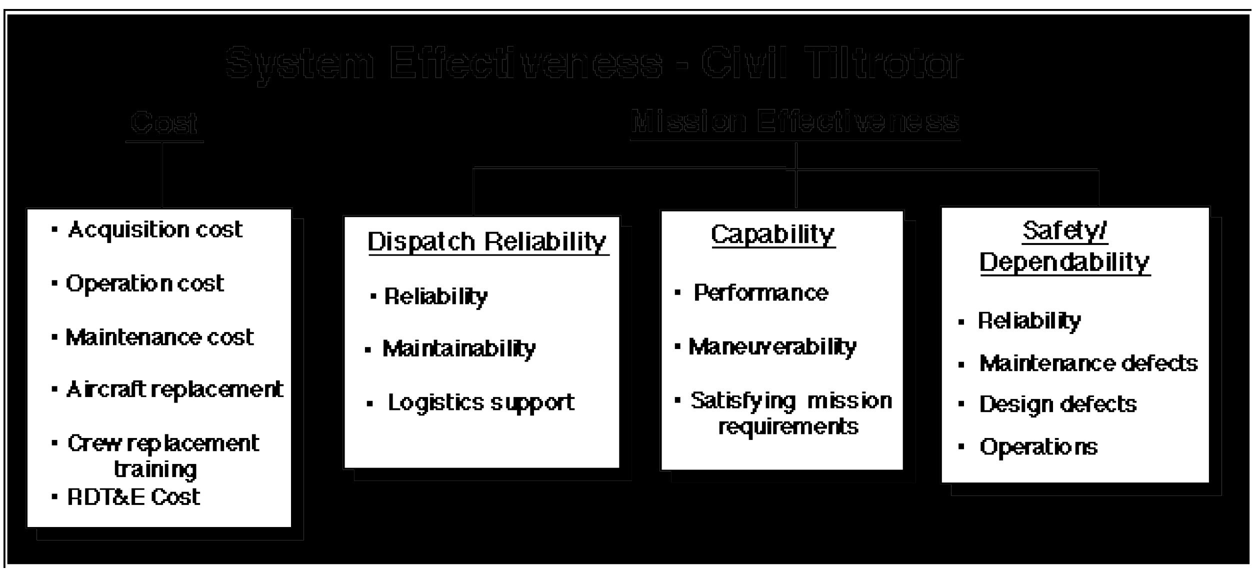

Figure 3: System Effectiveness Chart

With this breakdown in hand, an inclusive metric for affordability can be postulated, and it is defined below as:

$$\text{Affordability} = \frac{\text{Mission Effectiveness}}{\text{Cost of Achieving This Effectiven}} \quad (1)$$

where

$$\textit{Mission Effectiveness} = k_1(\textit{Capability}) + k_2(\textit{Dispatch Reliability}) + k_3(\textit{Safety/Dependability})$$

System Effectiveness can be formally defined by selecting three discipline metrics, each of which represents one of the three key attributes. The metric coefficients, k_i, provide the ability to tailor this effectiveness to specific needs, preferences, or points of view of a customer. These attributes are directly linked to the traditional product and process disciplines such as aerodynamics, structures, propulsion, dynamics, stability and control, manufacturing, and supportability.

Key Elements Needed to Address Affordability

Integrated Product/Process Development

IPPD incorporates a systematic approach to the early integration and concurrent application of all the disciplines that play a part throughout a system's life cycle.[5] The framework for bringing knowledge forward builds on a generic IPPD methodology. The flow of design tradeoffs at different levels with the generic IPPD methodology at the center is illustrated in Figure 4. The time line is from Conceptual Design (top box) to the Manufacturing Process (bottom box) and essentially accounts for the system development process. Illustrated are three levels of parallel design trades (represented as circular iterations): system, component and part. The right half of the circle represents system decomposition (traditional systems engineering approach) and principally includes product design trades, while the left half represents system recomposition (more recent quality engineering approach) and principally includes process design trades. Numerous short design iterations at the system level are sought, with an appropriate reduction in the number of iterations at the component and part levels. The long iteration around the outer loop is definitely to be avoided, for it would indicate that the system had to be redesigned due to design incompatibilities with the manufacturing and/or other downstream processes.

Figure 4: IPPD Flow Diagram

The generic IPPD methodology developed to execute this flow in simulation is illustrated in Figure 5. It consists of an "umbrella" with four key elements identified: *systems engineering* methods, *quality engineering* methods, *a top-down design decision support process,* and a *computer-integrated environment*. Each of these elements by themselves is necessary, but not sufficient, for the conduct of IPPD. Below the "umbrella" are the major activities of each element. Systems engineering was aerospace/military initiated to deal primarily with the performance of large scale complex systems and is predominantly decomposition oriented and product design driven, while quality engineering was predominantly commercially initiated for competitiveness and is predominantly recomposition oriented and process design driven. Since "design tradeoffs" imply a decision-based approach, a top-down design decision support process is placed at the center with a set of generic decision-making steps. The arrows indicate the required interaction and iteration between various methods/tools and the necessity of a computer integrated environment. The primary iteration is between "System Synthesis through Multidisciplinary Design Optimization (MDO)" to generate feasible alternatives which are then addressed for "Robust Design Assessment & Optimization". The evaluated alternatives are then fed back for updated "System Synthesis" to complete the iteration.

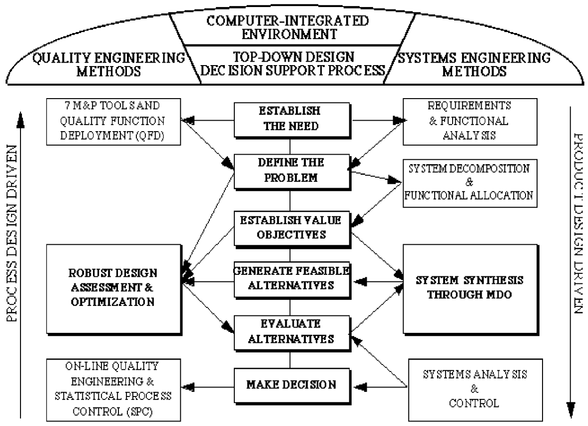

Figure 5: The Georgia Tech IPPD Methodology

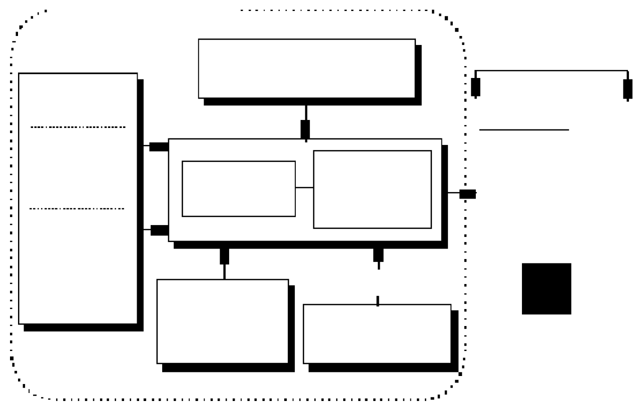

Figure 6: Robust Design Simulation

Robust Design Simulation (RDS)

Robust Design is defined as the systematic approach to finding optimum values of design factors which result in economical designs with low variability.[6] In this case, variability may be due to analytical tool fidelity, operational uncertainty, manufacturing tolerances or due to uncertainty and risk associated with the infusion of new technologies. A Robust Design Simulation approach has been developed which incorporates all elements essential to the success of the design into an IPPD framework. The key elements and objectives of RDS are illustrated in Figure 6. Traditionally, design is comprised of a simulation code (sizing/synthesis with or without economic analysis capability) and an optimization routine which varies the design or economic parameters to yield an “optimum” solution subject to all imposed design constraints. In this approach, a system’s “affordability” was directly linked to a readily attainable performance or weight metric. Typically a historical parametric relation linking cost to some combination of gross weight or empty weight and/or required fuel weight was used to define system affordability.

RDS differs from this approach by accounting for both product and process contributions, to the chosen evaluation criterion, in the presence of risk and uncertainty. Robust Design Simulation may also account for manufacturing issues (i.e. process characteristics) and uncertainty associated with new technologies. These can be measured in terms of confidence and readiness levels. The uncertainty associated with the system is usually provided in the form of a probability distribution when the statistics are known or by a fuzzy set when limited information as to the range and shape of the distribution is available. Thus, RDS does not aim at the traditional optimized point design but provides definition of the design space dictated by the customer requirements, product/process characteristics, and environmental/design constraints in the presence of risk and uncertainty. The design solution sought may not be the optimum solution based on the traditional approach but it will be *an optimal* solution that is affected least by the variables outside the control of the designer.

The success of the RDS approach will hinge on the ability to integrate it into the design process and enhance the decision making capability of the designer and program management. In order to properly represent the product and process characteristics inherent to the RDS approach more physics-based, higher fidelity simulation tools are required to replace the historically based, “artificially regressed” analyses inherent to the sizing and synthesis code. Figure 7

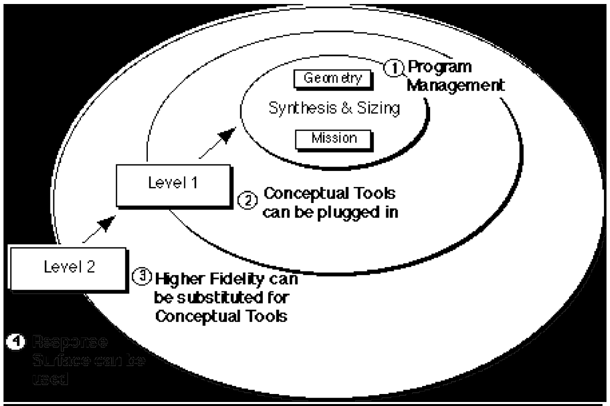

Figure 7: RDS Integration

provides an overview of this process. Direct integration of the various analyses to the synthesis code will undoubtedly lead to a cumbersome and potentially unmanageable situation for the designer. This state is avoided by capturing the essence of the higher fidelity tools by parametrically modeling them with response surface equations (RSE) and incorporating these RSEs into the synthesis/sizing code. This method provides for the smoothest integration of the disciplines into the design process.

<u>Simulation / Probabilistic Tools and Techniques</u>

Response Surface Equations

The method used to create RSEs is a statistical technique which seeks to identify and relate the relative contributions of various design variables or factors to the system responses. Generally, the exact deterministic relationships that govern the behavior of the measured responses to the set of design variables is either too complex or unknown. Therefore an empirical model is constructed which captures the system response as a function of the design variables.

The empirical model used in this methodology is assumed to be second order with *k* number of design variables. This second-degree model is assumed to exist and can be expressed in the following form.

$$RSE = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j}^{k} \sum^{k} b_{ij} x_i x_j \qquad (2)$$

where:
b_i = regression coefficients for linear terms
b_{ii} = coefficients for pure quadratic terms
b_{ij} = coefficients for cross product terms
x_i, x_j = design variables

The RSE is a regression curve (surface) whose coefficients are determined by applying a least squares analysis to the responses generated by a set of experiments or simulations. Although past experience with RSE generation has validated the use of a second order polynomial model the need for a higher order model is possible. In this case, dependent or independent variable transformations may be attempted or the use of neural networks may be employed to model the required responses.

Design of Experiments (DOE)

As mentioned in the previous section, the coefficients of the RSE are determined utilizing a carefully planned design of experiments or simulations. This approach ensures that the resulting RSE will be applicable in a sufficiently large design space without requiring an unrealistic number of simulation runs (or cases) to provide the response data for the regression analysis. The DOE chosen will dictate the number of simulation runs required based on the number of levels considered, the number of interactions modeled and the number of variables prescribed. Table 1 illustrates the number of cases required for different DOEs at three levels. Even for 7 variables at three levels, the full factorial design represents an unrealistic number of design cases. By employing a fractional factorial DOE the required cases are manageable with higher order effects neglected. Fractional factorial designs neglect third or higher order interactions and, in the case of RSE generation, account for only main and quadratic effects and second order interactions (see Equation 2). Table 1 also illustrates the ability to limit the number of cases by limiting the number of variables.

DOE	7 Varia-bles	12 Varia-bles	Equation
3-level, Full Factorial	2,187	531,441	3^n
Central Composite	143	4,121	2^n+2n+1
Box- Behnken	62	2,187	-
D-Optimal Design	36	91	(n+1)(n+2)/2

Table 1: Number of Cases for Different DOEs

Screening Test

In general, the number of design variables which could affect a system response is high. In order to build a first look at the design space, a two level fractional DOE is employed to examine the main effects of the design variables on the response. Since this DOE examines only two levels (i.e. a maximum and a minimum point) it supports a large number of design variables with only a limited number of needed cases especially if only the main effects are to be tested. This screening test allows the identification of the most significant contributors to the response. A graphical representation of this process is presented in a Pareto Chart (Figure 8)

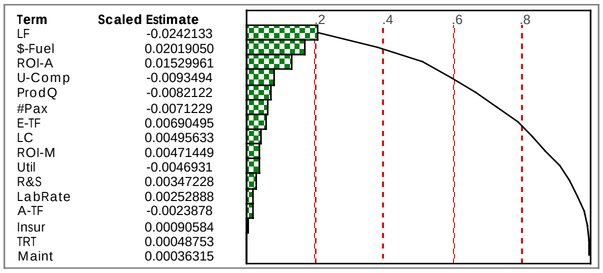

Figure 8: Sample Pareto Chart - Effects of the Design Variables on the Response

Bars indicate the relative contribution of each design variable while the cumulative curve tracks the total response. By setting a desired contribution level, the appropriate design variables are carried on to the RSE construction and all other design variables are set to their optimal value (as determined by expert knowledge or experimental experience) and are lumped together under the intercept term, b_o in Equation 2.

The chosen DOE provides the number of cases and the combinations of levels that need to be considered by a least squares analysis to yield the best possible response surface fit. This methodology utilizes a face-centered Central Composite Design (CCD) to generate the RSEs. This class of DOE breaks down the domain of interest into the *k*-dimensional "cube" part and the "star" or "end-points" part, where each vertex of the "cube" and "star" represent a single design point. Therefore, a "cube" and "star" in *k* dimensions has 2^k and $2k$ vertices, respectively

Since a *k* dimensional cube is impossible to visualize, a simplified version of this concept is shown in Figure 9 for three variables. In three dimensions, the "star" points for this CCD collapse to the faces of the cube and the design is a three level DOE. Along one axis of the cube (i.e. an individual design variable) these three levels would represent the edges of the cube and the center of the cube. Thus, the limits placed on the design variables will ultimately help define the limits of

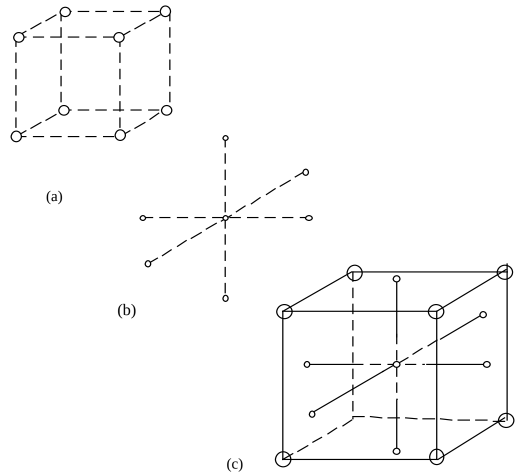

Figure 9: Central Composite Design for Three Variables[7]

the design space and the region of applicability for the RSE generated. The center point provides multiple replications to estimate experimental error. In the case of simulation-based analysis this repetition error is assumed to be non-existent and only one replicate of the center is required.

RDS Implementation

Figure 10 depicts the steps needed for the implementation of the Robust Design Simulation. RDS involves the integration of three elements: Response Surface Methodology, Monte Carlo Simulation and robust techniques. The technique usually referred to in the literature as the Response Surface Methodology is a compilation of the following steps:

- Data gathering/preparation
- DOE matrix generation
- Population of DOE matrix through simulation or experiment
- Analysis of Variance /Regression analysis to create RSEs
- Confirmation test to verify fidelity, accuracy of equations developed

The Response Surface Methodology is used to create the equations needed to parametrically model the discipline analyses as well as provide RSEs for the system metrics. The RSEs are needed by the Monte Carlo Simulation which is employed to allow uncertainty assessment and provide probability distributions. Finally, robust techniques are applied to shrink the variability of these distributions and provide robust design solutions. These elements of RDS are presented in the following sections.

Discipline Integration

On the far right of Figure 10 is a flow chart depicting the execution of the RSM at the discipline level. The first step in this execution is perhaps the most important in the successful implementation of this methodology. Close coordination between the discipline expert and the designer is needed to ensure the design variables selected for a particular response and their associated allowable ranges are appropriate and compatible with both the analysis code and the input variables to the synthesis/sizing code.

A screening test is then performed to reduce the problem dimensionality and to identify the most influential design variables. A Pareto chart is used in this step to determine the variables which will be varied according to the DOE and the variables which will be set at their optimum values. The next step is to choose a suitable fractional factorial DOE. As mentioned earlier, the face-centered CCD is used for this methodology. The empirical model used in this method is a second order polynomial model as defined in Equation 2.

An integral tool for the execution of the next four steps is a statistical software package developed by SAS called JMP®[8]. This package automates the DOE set up by providing the design variable settings needed for each simulation run. The analysis code is then executed for each case stipulated by the DOE with the corresponding design variable settings. Next, the Response Surface Equation is generated by fitting a second order polynomial surface through the case responses. JMP provides the coefficients to the empirical model by performing an Analysis of Variance on the responses. This procedure is also applicable in generating constraint surfaces which are dependent on the design variables.

An accurate regression fit is verified with a whole model test and a residual test.[9] Finally, the RSE is verified by comparing its results against the analysis code for the same settings of design variables. The results must agree within some reasonable error. The RSEs are then inserted into the synthesis/sizing code to replace the discipline modules within the code.

System Level Analysis

The flow diagram shown at the far left of Figure 10 shows the execution of the RSM for the system level responses. At this level the responses are the Mission Effectiveness and the Cost of Achieving This Effectiveness which allow assessment of the Overall Evaluation Criterion (i.e. affordability). Thus by defining the system metrics as a function of design variables and employing, once again, the RSM to the synthesis/sizing code, the designer is able to construct response surface equations for these metrics. The rationale for this approximation is the desire to account

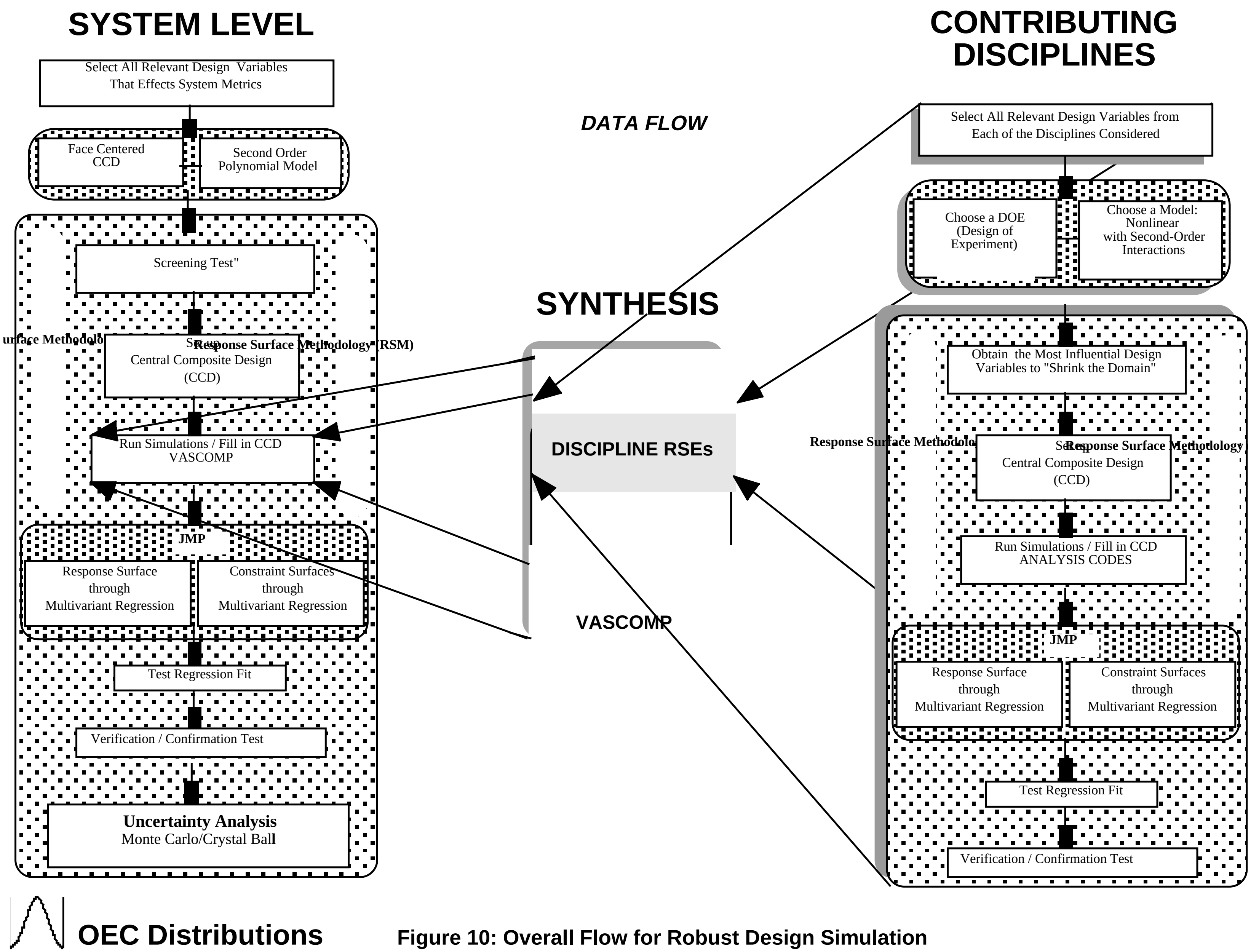

Figure 10: Overall Flow for Robust Design Simulation

for operational uncertainty which is beyond the designer's control. These uncontrollable design variables are called noise variables. To assess the effect of these uncertainties on mission effectiveness and cost, a probabilistic approach is taken where distribution shape functions and ranges for the noise variables are supplied based on statistical data. For given values of the design variables this will yield not a point assessment but a probability distribution. This application of uncertainty to a response is handled using a Monte Carlo simulation and is detailed in the following section.

Current Capabilities

In this section, the uncertainty associated with the cost estimation will be used as an example. Once the RSE is constructed, noise variables along with their distributions are identified. For example the noise variables could be the passenger load factor, fuel prices, the manufacturer's learning curve, aircraft utilization, production quantity, and return on investment for the manufacturer (ROI-M). The distributions for these noise variables may be beta, normal, triangular etc. If little knowledge is available about the shape of the distribution then a triangular distribution shape function may be used. This triangle is centered around the most likely value with range endpoints unlikely to be achieved. The cost RSE and the shape functions are fed to the Monte Carlo Simulation which is nothing more than a random number generator. Crystal Ball[10] is the software package used to implement the Monte Carlo Simulation. It randomly generates settings for each noise variable based on the shaping function and calculates the cost of achieving a mission effectiveness using the RSE provided yielding frequency and cumulative probability distributions for this metric. Typical distributions for a vehicle are shown for illustration in Figures 11 and 12.

Although the cost metric is only one part of affordability as defined in this paper, let us assume for the sake of example that the designer is using cost as his/her definition of affordability. The significance of these distributions is now more readily apparent. Figure 11 provides the designer with a probability distribution for cost which can be compared against some target value. A distinction is now made between a feasible solution and a viable solution. All the cases in Figure 11 represent feasible solutions since the RSE is based on the synthesis/sizing code which provides sized vehicles. A viable solution must not only be a feasible one but it must also provide assurances with high confidence (say 85 %) of meeting the target value. (e.g. ticket price, DOC/trip of a turboprop aircraft). If the cost metric distribution indicates a feasible but non-viable solution, then the distribution must be shifted to the target. This shift is illustrated in Figure 13 along with various ways of effecting this shift. These options

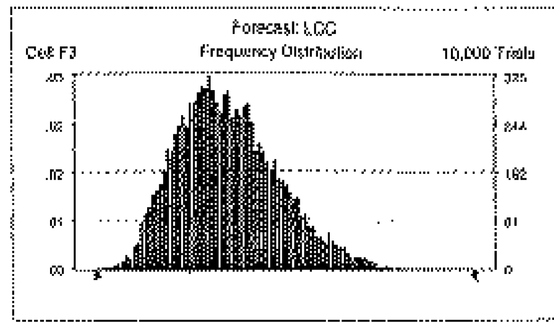

Figure 11: Example Frequency Distribution

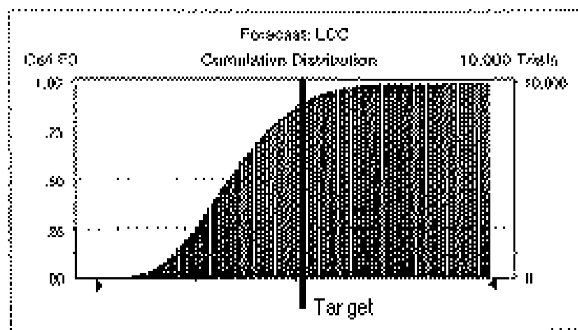

Figure 12: Example Cumulative Distribution

vary from the infusion of new technology to the last resort approach of introducing a fare premium. The ability of this method to support the decision making process is evident in the cumulative distribution provided in Figure 12. By adjusting the target value for cost (the OEC in our example), the designer can clearly assess the probability of producing a viable solution for a specific target.

The power and efficiency of the RSM is seen clearly in this uncertainty assessment. The number of cases run for the Monte Carlo Simulation is on the order of 10,000 cases. The RSE allows calculation of the response via a simple second order polynomial instead of a time consuming synthesis/sizing code. Therefore, changes to the shape functions or changes to the ranges (as long as they lie within the range of applicability of the RSE) of the noise variables can be incorporated in a matter of minutes instead of days or weeks.

Future Directions

Since affordability is defined as the ratio of mission effectiveness and the cost to achieve this effectiveness, it requires the ability to ratio two probability distributions and optimize it subject to a variety of

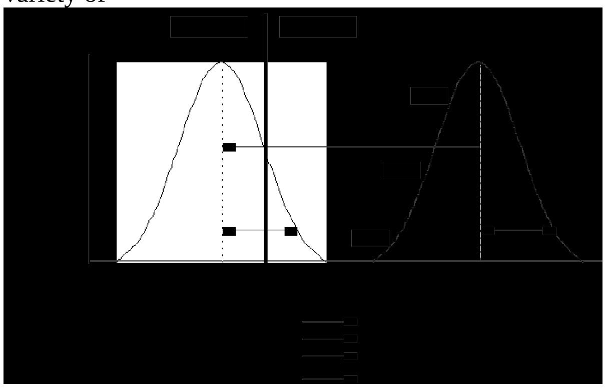

Figure 13: Feasibility vs. Viability

Shifting to Target

constraints that may also be probabilistic. In this case scenario, the RSM approach is clearly not suitable for handling such a complex problem. Thus, research is now being directed towards a numerical technique called Fast Probability Integration (FPI) to solve this dilemma as well as address other concerns such as fidelity issues. FPI is a probabilistic analysis technique which, given random variable statistics and one or more responses, computes the cumulative distribution function of the response and provides sensitivity factors.[11] FPI utilizes a relatively small number of cases (~ 10) to build the cumulative distribution function (CDF) previously generated by Monte Carlo Simulation (using ~10,000 cases). It creates a mathematical expression approximating the CDF which then can be differentiated to provide the frequency distribution. With the creation of a mathematical expression for the system metric distributions, the ability to obtain robust constrained solutions for affordability is realized. The system can now be assessed for feasibility and viability as described in the previous section. A key advantage of this new technique is the ability to eliminate the system level RSEs. Since the technique requires only limited case runs to build the CDF, it uses the synthesis/sizing code directly thus eliminating the need for system RSE approximations.

FPI also provides the ability to manage the fidelity issues associated with the analysis codes and the resulting RSEs. Discipline level RSEs are constructed from analysis codes which inherently have some error (i.e. they get you within say 5-10% of the true solution). Likewise, the RSE has some error associated with the fit of the empirical model. The FPI technique now allows the designer to tag a probability distribution associated with this error on the output of the discipline RSE before it is used by the synthesis/sizing code.

Concluding Remarks

This paper has outlined the steps needed for the implementation of a new design methodology which will enable the affordability assessment of a Short Haul Civil Tiltrotor (SHCT). The methodology is anchored to a comprehensive definition of affordability and builds on the resulting changes to the design process. The IPPD environment for this methodology is implemented through a Robust Design Simulation. A Response Surface Methodology approach and a Design of Experiments technique are employed to assist the designer in creating the probabilistic environment needed to assess affordability. A Monte Carlo Simulation formulation is used to apply uncertainty analysis to the system level responses separately. The Fast Probability Integration method discussed represents a new technique which allows the designer to construct the distributions for affordability in the presence of probabilistic constraints as well as address issues such as analysis code fidelity without resulting to system RSE approximations or Monte Carlo Simulation. Future work will concentrate on linking the system metrics to design variables, researching the potential benefits presented by FPI and exercising the approach on the SHCT.

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