Development of a Methodology for the Determination of Technical Feasibility and Viability of Affordable Rotorcraft Systems*

Dimitri N. Mavris   Andrew P. Baker   Daniel P. Schrage

Aerospace Systems Design Laboratory (ASDL)
School of Aerospace Engineering
Georgia Institute of Technology
Atlanta, GA

Abstract

This paper describes a probabilistic design approach which has been formulated from an affordability viewpoint for the assessment of rotorcraft systems. This method places emphasis on the ability to rapidly examine the design space, identify constraint violations and provides insight as to how the feasible design space could be enlarged through the infusion of new technologies. The paper also provides a rationale as to why a probabilistic design approach is needed to properly examine and facilitate these assessments. The steps required to assess and provide for a technically feasible and viable design space are also outlined. Furthermore, thoughts as to how this technique could be used to investigate and account for tool fidelity modeling, technology readiness impact and benefit/risk/cost tradeoffs are also presented. Descriptions of candidate statistical and probabilistic techniques such as the Response Surface Method, Robust Design Simulation and Fast Probability Integration are provided as needed. Finally, the steps needed for the implementation of this methodology are presented for the design of a notional Civil Tiltrotor Transport.

Definitions

Since many of the topics discussed in this paper represent concepts with which the reader may not be familiar, a few key definitions are offered for clarity:

Ambiguity: The un-described and vague (linguistically) portion of a design [1]. Ambiguity occupies the space complement to knowledge.

Decision Maker: Someone (a professional), or a team of professionals, who has authority to allocate resources and has responsibility for the output decision.

Decision Making: An intelligent activity aimed at allocating resources in order to develop a system to meet the customer's expectations and requirements.

Fast Probability Integration (FPI) [2, 3, 4]: A family of probabilistic analysis techniques characterized by better efficiency and transparency rather than "brute force" probabilistic techniques such as the Monte Carlo (MC) Simulation.

Feasible Alternative: A design alternative which satisfies all imposed constraints (i.e. it is physically realizable).

Metamodel: An approximation of a complex analysis model. Typical metamodels include regression models of complex computer programs based on experimental designs (e.g., the Response Surface Method), artificial neural networks, fuzzy sets, or other metamodel building methods [5, 6].

Metric: A Figure of Merit that characterizes a discipline or function or their related technologies (e.g., L/D for aerodynamics or SFC for propulsion).

Probabilistic Analysis: Analysis which allows for the examination of systems with imprecise or incomplete information (i.e., uncertainty and ambiguity). In other words, a means of forming relationships between input and output variables, including the variability of the inputs.

Risk: Risk can be defined as the probability or chance of achieving an unfavorable outcome.

Robust Design: A design which is least sensitive to influence of uncontrollable factors. A solution that optimizes affordability while reducing associated variability.

Stochastic Process: Uncertain history of response over the range of time values.

Uncertainty: An estimate of the difference between models and reality. Uncertainty is manifested when quantities associated with the product can not be determined exactly, and is a term describing the imprecision in establishing the value of a variable.

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Viable Alternative: A design alternative which is feasible and meets or exceeds the customer objective(s) (i.e., it is physically realizable and affordable).

Introduction

The concepts of feasibility and viability and the methodology to assess and enlarge their design spaces, as presented in this paper, come with the implicit assumption that the design environment in which the decision maker is working is probabilistic or stochastic in nature. The elements of this uncertainty, ambiguity and risk are key factors in formulation of a "modern design theory" which also embraces the paradigm shift present in industry and government today, to shift emphasis from design for performance at all costs to design for affordability. This new paradigm has prompted a re-evaluation of the design process itself and a corresponding shift in the way complex systems will be designed in the future. Forecasting, with a high probability of success, the economic viability of the system in the early design phases appears to be now the key driving indicator of success. Due to the life-cycle implications to this approach a need exists for a formulation which accurately designs in a virtual manner, tests, certifies, manufactures, and operates the system, while accounting for design ambiguity, uncertainty and risk.

It is thus evident that these requirements cannot be handled by a deterministic top-down design approach. Instead, a probabilistic approach is needed where ranges and shapes for all contributing inputs are chosen either objectively, when the statistics are known or subjectively, "fuzzy probabilistic", when data is unavailable and ranges are determined based on expert opinion. Furthermore, through the realization that uncertainty varies with time, as knowledge increases about the design, it becomes evident that a time varying probabilistic problem needs a stochastic treatment. An appropriate comprehensive formulation referred to as the Virtual Stochastic Life Cycle Design (VSLCD) environment has been created by the authors and the reader is referred to References 7,8,9, for a more in depth treatise of this subject.

Traditional design methodologies and techniques are limited in several crucial areas:

- *Feasibility is not established upfront but it is assumed.* The existence and reliance on well documented and correlated historical databases as well as the incremental improvement/variation mindset which dominates the industry makes feasibility an unimportant part of the design process. However, the jump to revolutionary designs or to new technologies which lack the historical databases or even appropriate analysis capabilities mandate the thorough establishment of a feasible design space. A feasible space must exist before viability can be addressed.

- *They are unable to effectively handle the variability associated with economic uncertainty, operational uncertainty, tools fidelity, requirements ambiguity, etc.* The infusion of new technologies, in particular, requires new analysis capability not appreciated by other design methods. In this case, no available analysis tools linking elementary design variables to system responses exist. Thus, this new approach calls for and provides a means to link discipline metrics to system responses to enable opening of the feasible design space, assessment of the impact on viability, benefit/cost assessment and risk/readiness assessment of new technologies.

- *They are unable to handle the dimensionality issues presented by multi-objective, multi-constraint problems associated with rotorcraft design.* This limitation deals directly with the creation and use of metamodels at the system level in the probabilistic design environment. Multiple constraints/objectives requiring different sets of design parameters limit the approximations of complicated analyses under traditional statistical analysis codes/methods. This leads to an enabling technology, in the context of probabilistic design, called Fast Probability Integration which allows for efficient analysis with a significantly larger number of design variables.

The methodology presented in this paper is the link between an appropriate probabilistic design formulation and providing a robust affordable product to the customer. This paper will provide a detailed discussion of the methodology to determine and open feasible and viable design space. Probabilistic techniques and enabling technologies such as Response Surface Methodology (metamodels), Robust Design Simulation and Fast Probability Integration will be introduced and briefly explained where appropriate. A discussion on benefit/cost assessment and risk/readiness assessment for new technologies is also presented.

Probabilistic Design Essentials

In probabilistic design, the outcome sought is either a cumulative distribution function (CDF) or a probability density function (PDF) for each design objective or constraint. These distributions represent the outcomes of every possible combination of synthesized designs so it is a representation of the feasible design space against which the decision maker can now compare a desired target value. Based on these results, decisions concerning relaxation of targets, relaxation of constraints or infusion of new technologies can be made. The generation of these distributions entails the linking of complex computer codes with statistical techniques. Fox[10] lists three methods that incorporate such complex computer programs in a probabilistic systems design approach:

1. Link a sophisticated design code directly to a random number generator such as a Monte Carlo Simulation to obtain the PDF or CDF of all desired code outcomes
2. Approximate the sophisticated analysis code with a metamodel (e.g. Response Surface) and link it with a Monte Carlo Simulation
3. Link the sophisticated analysis code with an approximation of the Monte Carlo Simulation

Method 1 is considered to yield the most accurate representation of the probabilistic behavior for a given objective. Since the Monte Carlo Simulation requires 5000 - 10^6 cases (depending on the dimensionality of the problem and the desired accuracy at the tails of the distribution) to approximate the CDF or PDF (for the level of accuracy needed at the system level) linking it directly with the analysis code (Method 1) is found to be both time consuming and computationally intense.

Method 2 proposes the approximation of the analysis code with a metamodel such as a Response Surface leading to significantly reduced execution time. Response Surface Methodology (RSM) is a multivariate regression technique developed to model the response of a complex system using a simplified equation. RSM is based on a design of experiments methodology. Typically, the response is modeled using a second order quadratic which includes cross product terms. When this model fails to accurately predict the behavior of the complex analysis code other methods such as independent or dependent variable transformations or artificial neural networks based metamodeling can be used. When the number of design variables is manageable (12-15), as in the case of single discipline formulations, this process provides excellent results. However, as mentioned previously, rotorcraft design and for that matter the design of any complex system is viewed as a multi-attribute, multi-constraint, multi-objective problem requiring different sets of design parameters. Thus this method is limited in its use for systems level design.

Method 3 takes a different approach. It avoids the simplification of the sophisticated analysis and it attempts to approximate the Monte Carlo Simulation results so as to yield results similar in fidelity while using only a handful of calculations These calculations are based on the exact analysis code, not on approximations (i.e. metamodels). This approach is greatly facilitated through the use of a method referred to as the Fast Probability Integration technique. This probability estimation method is based on the Most Probable Point (MPP) analysis technique, and it is very efficient in assessing multi-attribute and multi-constraint problems. A brief description of the technique is provided below and the reader is referred to References 2, 3 and 4. for more information on the theory and application of FPI.

FPI [3] may be viewed as a tool box of probabilistic algorithms developed by researchers at the Southwest Research Institute (SwRI) for the NASA Lewis Research Center for use in structural reliability analysis. The aforementioned MPP analysis utilizes a desired response $Z(\mathbf{X})$ (which in this case is obtained analytically) that is a function of several random variable distributions ($\mathbf{X}_i$). Each point in the design space spanned by the $\mathbf{X}_i$'s has a specific probability of occurrence according to their joint probability distribution function. Thus, each point in the design space corresponds to one specific response value $Z(\mathbf{X})$ which has a given probability of occurrence.

In problem formulations involving random variables, it is often desirable to find the probability of achieving response values below a critical value of interest z_0. This critical value can be used to form a limit-state function (LSF),

$$g(\mathbf{X}) = Z(\mathbf{X}) - z_0 \qquad (1)$$

where values of $g(\mathbf{X}) \geq 0$ are undesirable. The MPP analysis calculates the cumulative probability of all points that yield $g(\mathbf{X}) \leq 0$ for the given z_0.

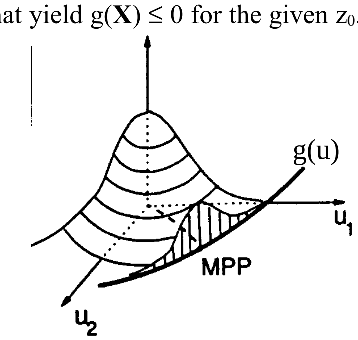

FIGURE 1: MOST PROBABLE POINT LOCATION [3]

Since the LSF "cuts off" a section of the joint probability distribution (Figure 1), a point with maximal probability of occurrence can be identified on that LSF. This point is called the Most Probable

Point. Figure 1 shows the joint probability distribution in the U-space where the FPI code actually determines the MPP. FPI employs a transformation of the original random vector **X** to a standard, uncorrelated normal vector **U** to take advantage of the properties of the standard normal space. In U-space, the joint probability distribution function is rotationally symmetric about the origin and decays exponentially with the square of the distance from the origin.

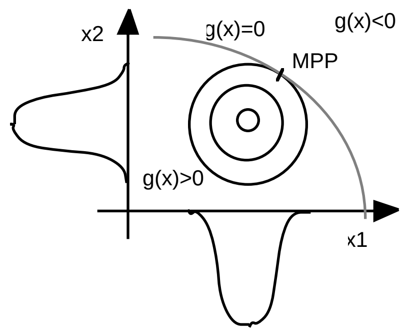

FIGURE 2: VISUALIZATION OF MPP [3]

Figure 2 provides a simple two dimensional illustration of the Most Probable Point location in the random vector space. Once the MPP for a given probability is identified, the process can be repeated for several z_0 values allowing construction of a cumulative probability distribution (CDF).

When constructing a cumulative probability distribution, the Advanced Mean Value (AMV) method option in the Fast Probability Integration code is employed. The Advanced Mean Value method utilizes the following procedure to calculate the CDF which is illustrated in Figure 3:

1. Run center-point case [1 case]
2. Perturb one variable at a time to calculate point sensitivities to create linear metamodel [*n* cases]
3. At user specified p-levels (z_0) use the actual design code to calculate responses and adjust the CDF to account for non-linear effects [*m* cases]

The sensitivities calculated in Step 2 are used to construct a linear approximation (metamodel) of the cumulative probability distribution (Equation 2).

$$R = a_o + \sum_{i=1}^{n} a_i x_i \qquad (2)$$

The additional cases are run at user specified p-levels **(z_o)** and use the actual design code to provide responses to better fit the CDF created in Step 2. Thus the AMV method approximates the exact cumulative probability distribution using ($n + m + 1$) function calls for *n* random variables and *m* p-levels (Equation 3).

$$R = a_o + \sum_{i=1}^{n} a_i x_i + H.O.T. \qquad (3)$$

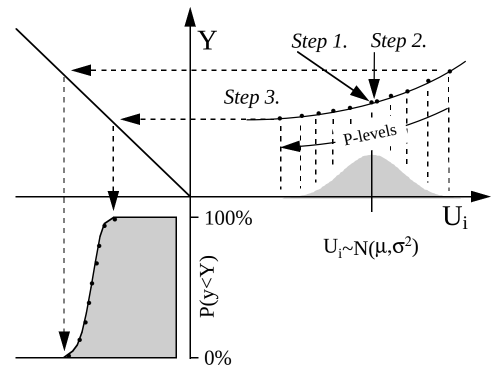

Figure 3: Creating CDF With AMV Method

The shifting of the linear approximation, as shown in Figure 4, accounts for the higher order terms (H.O.T.) or non-linear effects included in Equation 3. Notice in Figure 4 that the CDFs are pivoted around the mid-point corresponding to the 50% p-level. This occurs since this process is a Taylor series expansion around the mid-point. Thus one would expect no effects from higher order terms.

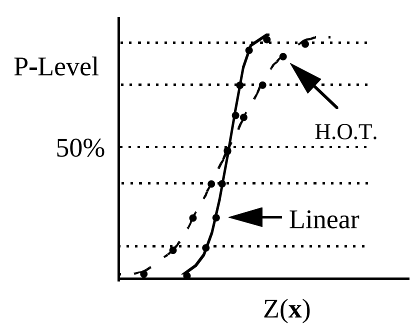

FIGURE 4: THE EFFECT OF HIGHER ORDER TERMS

This method provides a significant time and resource savings over Response Surface Equation (RSE) /Monte Carlo Simulation methods for multi-disciplinary, multi-constrained problems where hundreds of cases are needed to create the RSEs. However, RSEs serve a valuable complementary tool that can be used to gain information about the behavior of the underlying design space. Once the CDF is created it can be differentiated to obtain the probability density function (PDF) of the response.

Technical Feasibility and Viability

Technical feasibility is a measure of a system's ability to meet performance goals and satisfy imposed performance constraints. It is assessed by varying control variables only and generating cumulative distribution functions for each performance objective/constraint. Economic viability is a measure of a system's ability to achieve affordability goals and satisfy imposed economic constraints. It is assessed by varying control and noise variables and generating cumulative distribution functions for economic objectives/constraints. Technical feasibility must be established before economic viability is assessed. The steps required to determine if feasible and viable design space exists and open these design spaces, if necessary, is presented in Figure 5. The steps in this methodology are:

1. Problem Definition
2. Determine System Feasibility
3. Examine Feasible Space
4. Infuse New Technologies
5. Robust Design Simulation

The following discussion describes each step in the methodology in detail and provides information on the actual implementation process.

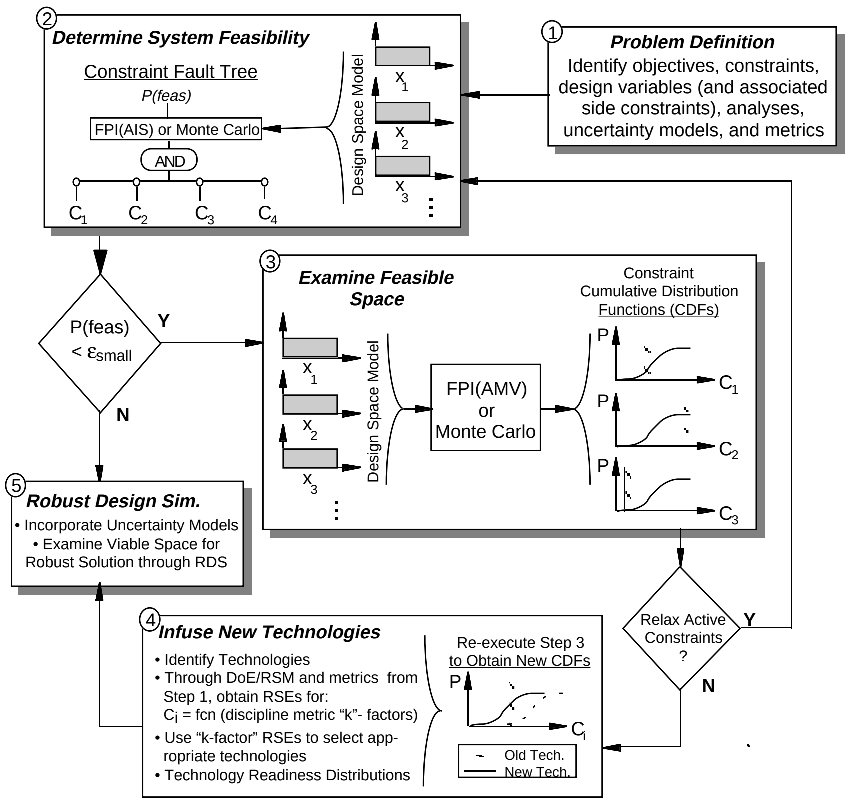

FIGURE 5: OVERALL METHODOLOGY FLOWCHART [9]

Problem Definition

The first step in the process calls for the identification of objectives, constraints, design variables (including ranges), suitable analytical tools for each discipline, and metrics (if known) pertinent to the design problem (Step 1 in Figure 5). As in any engineering design problem, the setup of the problem is perhaps the most important step. The casting of customer requirements into appropriate objectives, constraints and design variables in the early stages of the design avoids problems down the line and may avoid some cases of requirement ambiguity.

Suitable objectives for rotorcraft applications will include economic considerations to reflect the emphasis on the life-cycle and the interests of the manufacturer, airline and the passenger, and design considerations which account for all customer requirements and/or desirements and regulatory/design constraints.

The selection of design variables must be consistent with the objectives and the analysis code being used. Design variables will fall into two categories: control variables and noise variables. Noise variables are those variables that the designer has no control over such as fuel prices, utilization, load factors, etc. These variables tend to be economic variables. The choice of metrics becomes important for the infusion of new technologies to open the design space. Often the metrics needed to represent the effect of a new technology are unknown or unavailable since the need for the new technology has not yet been established.

Tables 1-4 provide an example of this step for a notional Civil Tiltrotor Transport. The objectives include both system and subsystem level attributes. In this case the subsystem chosen for illustration is the propulsion system. An abbreviated list has been given for the control variables but the example serves its purpose. This formulation is used later in the paper to provide a sample of the results expected for subsequent steps in the methodology.

TABLE 1: OBJECTIVES AND CONSTRAINTS

Objectives	Target
System Level	
Takeoff Gross Weight (TOGW)	*minimize*
Weight Empty	minimize
Weight Fuel	minimize
Horsepower (VROC,HOGE)	minimize
Cruise Speed	maximize
Noise	minimize
Subsystem level (Propulsion)	
Specific Fuel Consumption (SFC)	minimize
Engine Power Loading (Cont,IRP,MCP)	minimize
Weight Engine	minimize
R & D Cost	minimize
Development Cost	minimize
Support Cost	minimize
Dimensions	minimize
Economic System	
R&D Cost	minimize
Acquisition Cost	minimize
O $ S Cost	minimize

TABLE 2: SYSTEM AND SUBSYSTEM METRICS

System Level Metrics	
ω	Disk Loading
W/S	Wing Loading
L/D_{CR}	Aerodynamic Efficiency
η_{PROP}	Propeller Propulsive Efficiency
FM	Hover Rotor Figure of Merit
W_{WING}/ft^2	Wing Areal Weight
W_{FUES}/ft^2	Fuselage Areal Weight
SFC	Specific Fuel Consumption
SHP/W_{ENG} (Cont) SHP/W_{ENG} (IRP) SHP/W_{ENG} (MCP)	Engine Power Loading for Various Power Settings
Δ R & D Cost	Change in R & D Cost
Δ Prod Cost	Change in Prod Cost
Δ O & S Cost	Change in O & S Cost

Subsystem Level Metrics	
P_{REC} Inlet	Press Recovery @ Inlet
η_{comp} η_{comb} η_{turb}	Component Efficiencies
% Cooling	Cooling Percentage
K_{SFC} K_{MTBF} K_{MTTR} $K_{MMH/FH}$ K_{RD} etc.	Technology Factors

TABLE 3: CONTROL VARIABLES

Variable	minimum	maximum
Blade Solidity	.10	.13
Number of Blades	3	5
Blade t/c	.11	.125
Blade Tip Speed (ft/sec)	680	750
Wing Span (ft)	50	60
Wing Chord (ft)	5.5	7.0
Wing t/c	.18	.25
Number of Passengers	30	50
Range (nm)	200	700
HT AR	3.6	4.4
HT Sweep (degrees)	6.0	7.5
HT Area (ft^2)	100	125
VT AR	1.6	2.0
VT Area (ft^2)	110	135
VT Sweep (degrees)	12	15

TABLE 4: ECONOMIC (NOISE) VARIABLES

Variable	minimum	maximum
Airline ROI	5%	15%
Manufacturer's ROI	10%	20%
Economic Range (nm)	200	600
Fuel Cost	$.54/gal	$.88/gal;
Mfg. Learning Curve	74%	84%
Production Quantity	300	600
Utilization (trips/year)	2000	3000
Passenger Load Factor	45%	85%
Insurance Rate	.5%	1.5%

Determining System Feasibility

Next, one must investigate the entire design space for occurrence of combinations of design parameters which result in the satisfaction of *all constraints* (Step 2 in Figure 5). The designer is searching for an estimate of the percentage of the design space which contains feasible alternatives. This is formulated as a reliability problem, utilizing fault tree analysis. Uniform distributions are assigned for each control variable, so no bias is introduced since no uncertainty exists in these parameters. The constraints are applied to each sampling of the design space to determine the feasible design space. The result is a single number expressed as the Probability of Feasibility, P(feas).

$$P(feas) = \frac{\#\ of\ configurations\ satisfying\ constraints}{total\ \#\ of\ configurations\ in\ design\ space}$$

This step can be implemented in two ways using the probabilistic methods described earlier. Using the Response Surface Methodology with a suitable design of experiments, a metamodel (response surface equation) is created which represents each objective and constraint as a function of the control variables. The statistical validity of these metamodels is checked and the models are valid within the ranges of the control variables set by the designer in Step 1. A sufficiently large sampling of the design space is taken via a Monte Carlo Simulation and the P(feas) determined. Normally, this task could be computationally expensive for large numbers of design variables. However, through the use of the Adaptive Importance Sampling (AIS) technique from the FPI family described in Reference 3, the search can be done relatively quickly. Thus, the Fast Probability Integration (AIS) technique can provide an estimate of the feasible design space efficiently and it may provide information as to the optimum configuration. In the case of the metamodels, the response surface equations can be used in the next step in order to create the cumulative distribution functions needed for active constraint isolation.

Examine Feasible Space

The threshold tolerance for the Probability of Feasibility is at the discretion of the designer. If the current system achieves a high P(feas), this indicates a sufficiently large feasible design space for robust solutions to exist and one can proceed to robust optimization (Step 5 in Figure 5). If the current system achieves a low or zero Probability of Feasibility, an investigation must be performed to isolate the active constraints. This is done through, what will be called here, component feasibility problem. Unlike the system feasibility problem, component feasibility is concerned with only open responses. There is no fault tree structure. The control variables are once again given uniform distributions and a cumulative distribution function for each objective/constraint is formed.

As mentioned above, the CDFs can be constructed using the metamodels created in Step 2 subjected to a Monte Carlo Simulation. The AMV technique, as discussed previously, provides a more efficient and powerful approach by linearizing the problem and finding response values for given probability levels. It then runs several more cases to adjust the cumulative distribution function for any non-linear effects. Once the CDFs are constructed the designer can overlay the constraint values and immediately determine the active constraints. Figure 6 provides a generic illustration of the results of this step.

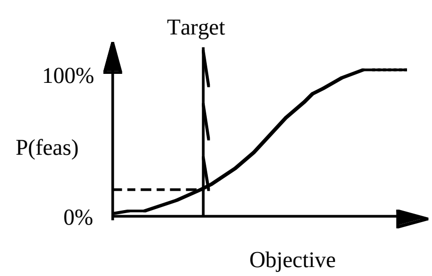

FIGURE 6: CONSTRAINT VIOLATION

By overlaying the constraint, the percentage of the design space satisfying this constraint becomes evident. Once this identification is made, there are two avenues available to "open the feasible space": 1) relax the active constraints and/or 2) infuse new technologies. In the case of the latter option, the power of the Fast Probability Integration technique is exploited since this technique not only constructs the CDFs but provides probabilistic sensitivity derivatives. These sensitivity derivatives provide insight into the most important variables for each constraint and a starting point for the decision maker in choosing a new technology aimed at a specific constraint.

Infusing New Technologies

The need for the infusion of a technology is required when the manipulation of the variable ranges has been exhausted, optimization is ineffective, constraints are relaxed to a minimum, and the maximum performance attainable from a given level of technology is achieved. The maximum level of a given technology is essentially the natural limit of the benefit, displayed in Figure 7. This implies that the maturation variation with time remains constant. When this limit is reached, there is *no other alternative* but to infuse a new technology.

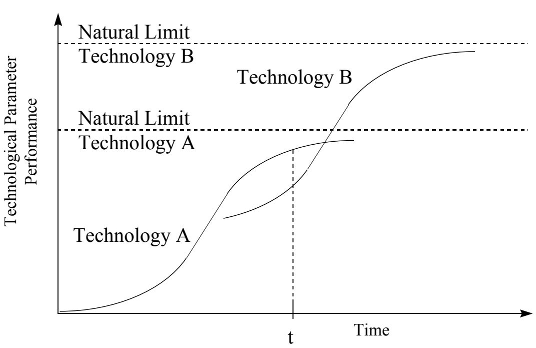

FIGURE 7: TECHNOLOGY INFUSION

Formulation of new technologies in terms of elementary variables does not lend itself to disciplinary or multidisciplinary technology assessment. Hence, the assessment of new technologies must be addressed through the metrics they affect since sizing/synthesis tools are typically based on regressed historical data, limiting or removing their applicability to exotic concepts or technologies and higher fidelity tools cannot always capture the physics associated with a new technology. The solution is to model and define technology metrics for the new technologies as a delta with respect to current technology based on subjective experience. In practical terms, technology metric "k" factors are introduced into the analysis or sizing tool to infuse a hypothetical enhancement or degradation associated with the new technology. In effect, the "k" factors simulate the discontinuity in benefits or penalties associated with the addition of a new technology.

The cumulative distribution functions are now re-evaluated with the metric "k" factors as additional control variables. The CDF "shift to target" is illustrated in Figure 8. This figure shows the opening of the design space caused by the infusion of the new technology as an increase in the P(feas) with the same constraint value overlaid. As previously discussed though, the "k" factors are introduced to produce beneficial as well as degradatory effects. The result in Figure 8 would be typical of the results for the objective or constraint at which the new technology is directed. However, new technologies cannot be assessed from a benefit viewpoint alone. The effect on other disciplinary metrics must be included to see how the new technology penalizes the various objectives and constraints and how it affects the design space.

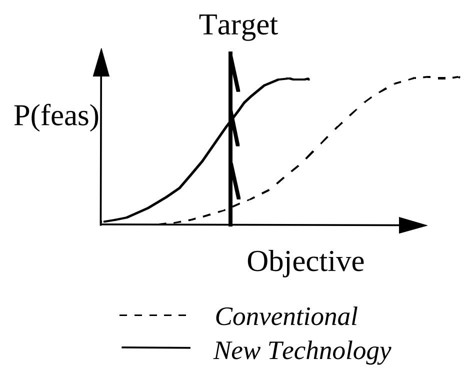

FIGURE 8: NEW TECHNOLOGY IMPROVEMENT

As an example, one can examine the impact of the Variable Diameter Tiltrotor (VDTR) on conventional tiltrotor technology. This "new technology" may be used to provide improvement in the propeller propulsive efficiency. However this isolated improvement would be misleading if the effect of this new technology on other objectives was not included. The effects on weight, R&D cost, production cost, maintenance hours, availability must be factored into the equation by degrading the other metrics accordingly. Thus the improvement from a new technology can be qualified while ensuring that its penalties do not make the new technology prohibitively expensive. If a "k" factor for a given technological metric is shown to improve the system objectives and constraints with minimal penalties, that technology impact can be identified as worthy of further investigation. An actual technology must be identified which can provide the "k" factor projections. This method is essentially forecasting the impact of a technology. This technique provides a very efficient means of identifying design alternatives around concept "show-stoppers". As a result, technologies capable of counteracting the show-stoppers aid in the correct allocation of resources for further research and development of the project.

Technology Impact Forecasting

In the above discussion on new technology infusion the Fast Probability Integration technique is described for implementation of this step. Although computationally more expensive, the implementation of this step using the Response Surface Method provides analysis capabilities not available when using FPI. In this step, response surface equations are created which relate each objective and constraint to the metric " k " factors. Using this formulation the impact of "k" factors on the system objectives and constraints can be assessed qualitatively through a linear or higher order sensitivity analysis depending on the level of detail desired. The analysis can be performed with the prediction profile feature of the JMP statistical package [11].

This example shows the ability of this methodology to be applied at all levels of the design process. In Figures 9-11, the Civil Tiltrotor example has been decomposed down to the component level. These profiles are interactive allowing the decision maker to adjust the "k" factors in any combination and immediately see the effect on the various objectives/constraint. The factors at the component level (e.g. K_{PROD}) can be fed to the subsystem level to determine the effects in real time. At the subsystem level, factors such as specific fuel consumption can be fed to the system level analysis and the cascade from component to system level is complete. This is a powerful tool for resource allocation and new technology decision making.

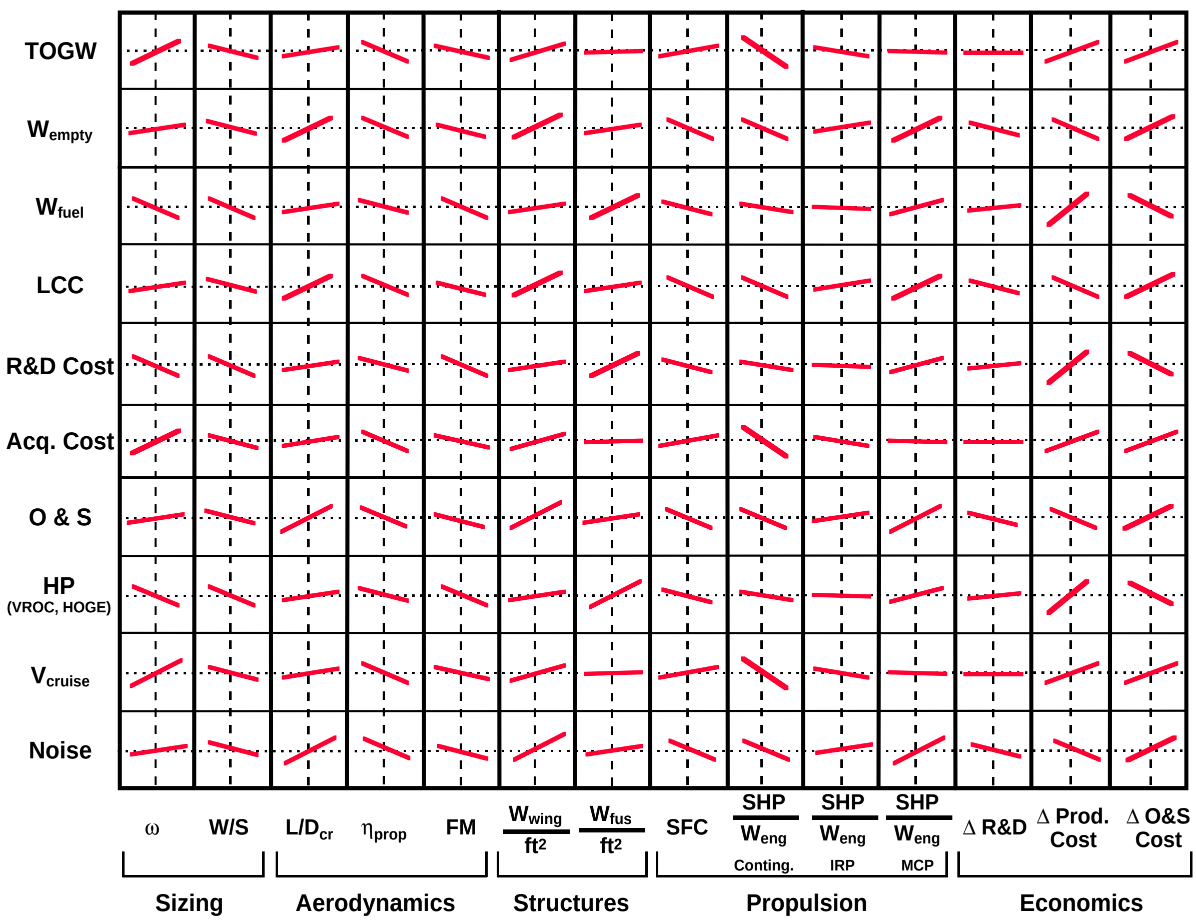

FIGURE 9: SAMPLE PREDICTION PROFILE - SYSTEM LEVEL

Note : All trends are for illustration purposes only.

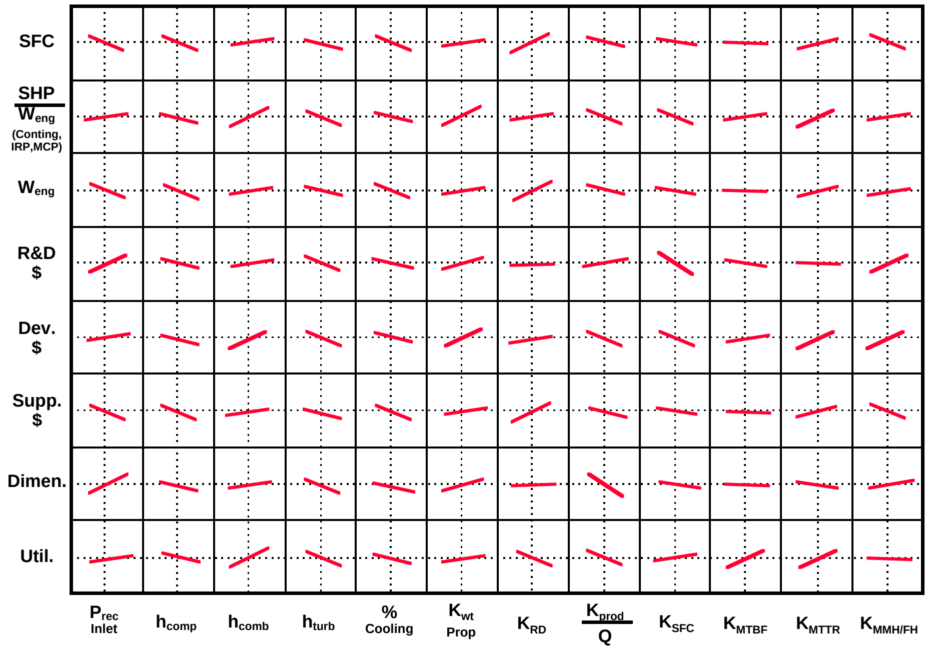

FIGURE 10: SAMPLE PREDICTION PROFILES - SUBSYSTEM LEVEL

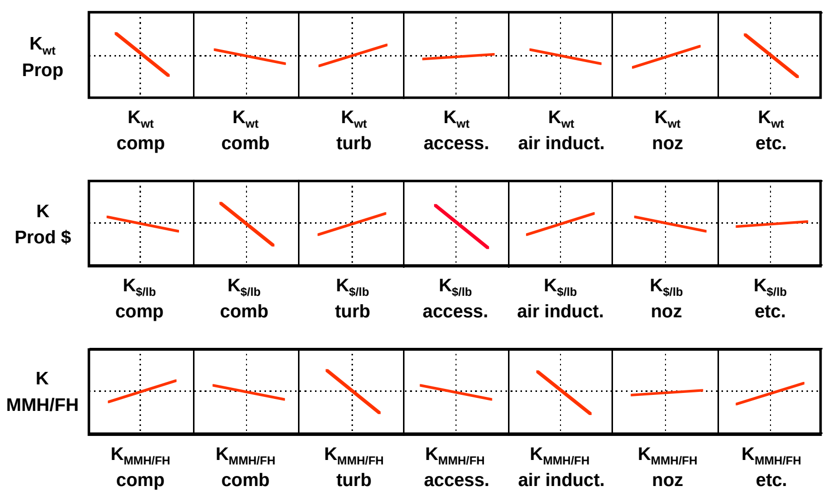

FIGURE 11: SAMPLE PREDICTION PROFILES - COMPONENT LEVEL

The value of this tool for Technology Impact Forecasting is readily apparent when viewing the Department of Defense's Technology Development Approach (TDA). The TDA sets goals in the form of discipline and system level metrics. Until now there has been no methodology that allows the horizontal integration of the goals across the disciplines or the vertical integration of the discipline goals to the system level. This new methodology provides a means to accomplish these integrations.

Another important analysis capability using the Response Surface Methodology is the determination assessment of variability due to forecast confidence. To this point of the discussion the metric "k" factors have been treated as fixed values when injected into the assessment of new technologies. Once the proper "k" factor level is set by the decision maker (i.e. enough feasible design space exists), there will be some uncertainty associated with this "k" level. By using the relations created between the objectives/constraints and the metrics, the metrics can be described with a step change in the mean value as well as an associated variability which reflects the uncertainty defined by the decision maker. Thus for each technology, a cumulative probability distribution can be generated for each objective which reflects the variability due to forecast confidence.

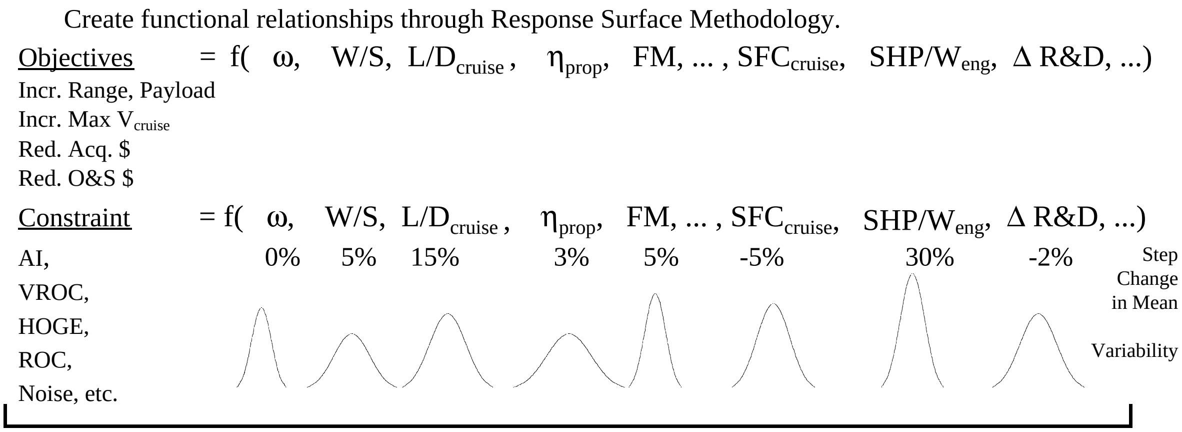

FIGURE 12: ASSESSING VARIABILITY DUE TO FORECAST CONFIDENCE

Robust Design Simulation (RDS) [12]

Steps 1-4 above are concerned with feasibility, since only constraints are considered. Once a large enough feasible space is found, the space is searched for robust solutions. Robust Design Simulation is a systematic procedure for finding settings of design variables which maximize the probability of meeting or surpassing a target for the objective, while satisfying the constraints. RDS is the part of the probabilistic design environment where the system level analysis takes place, while accounting for uncertainty business practices, economics, synthesis and sizing, technology and environmental constraints. It is through RDS that the uncertainties associated with noise variables (i.e. economic variables) are applied in order to determine system viability. This process is much like the search for feasible design space and may require the relaxation of economic constraints and/or infusion of new technologies to enhance the affordability of the system.

Risk/Readiness Assessment

To this point, the discussion of new technologies has avoided the subject of risk. For complex systems, the ability to accurately predict the tradeoffs between alternative technologies from a benefit, risk, and affordability viewpoint is of tremendous value to the decision maker. The creation of Response Surface Equations in Step 4 allows the decision maker to account for the risks associated with technology readiness and fidelity uncertainty. Benefit/Risk/Cost investigations for new technologies can now be carried out, in a probabilistic manner, by providing probability distributions for the metric “k” factors which are based on technology readiness. This yields targets for the metrics which must be met for a feasible design space to exist.

Concluding Remarks

This paper provides a methodology for the rapid and inexpensive assessment of technically feasible and viable design spaces in the context of probabilistic or stochastic design. This methodology is motivated by the belief that affordable rotorcraft systems can only be assessed through the inclusion of uncertainty, ambiguity and conflict which permeates the design environment when design for affordability is emphasized. This paper has provided an in depth explanation of the steps required to determine the existence of a feasible design space as well as an outline of the steps needed to open the design space if required. This space of feasible designs can now be searched for viable alternatives using Robust Design Simulation. The outcome of the described process is a probabilistic search methodology for feasible design alternatives and a technique for creating design feasibility where it did not exist through the introduction of new technologies. The means by which new technologies may be assessed in a more realistic manner was also outlined. Finally, several steps in the methodology were highlighted through the example of a notional Civil Tiltrotor Transport.

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