A NEW MODEL FOR THE AEROSPACE DESIGN PROCESS BASED ON A CONTROL SYSTEM ANALOGY

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Abstract

A novel approach to the modeling and control of aerospace system design problems is presented. By integrating recent advances in probabilistic robust design and technology assessment methods with a traditional control system feedback architecture, the approach is intended to establish a unified structure for managing complex design problems under uncertainty. The notions of plant, state variables, feedback, and compensation are adapted from the realm of control theory to this new setting. A specific aspect of the paper addresses methods for categorizing and computing the plant's sensitivity to modeled uncertainty in the feedback system. An example problem is executed and described to illustrate probabilistic sensitivity analysis as well as one possible avenue for arriving at an optimal compensator. Since this topic is in the initial research stages, the near term challenges with regards to refining and improving the approach are identified throughout the paper. Two such challenges include constructing a valid plant model and the optimal selection of a compensator.

Introduction

Aerospace design problems are becoming increasingly difficult to solve due to increasing *complexity* of systems, increasing customer emphasis on *affordability* (introducing a multi-objective, multi-constraint problem involving the balance of acceptable performance and cost), and, due to these first two, an increasing need for *new technologies*. With all of these aspects comes uncertainty, and it is this uncertain environment that demands a more innovative approach to modeling and management of the design process. Such an approach, if achieved, will be extremely valuable in directing *where resources should be invested to improve eventual success (partially through risk reduction) of new products*.

Thus, the goal of the research reported herein is to model and control the *design process itself*, as opposed to the more typical task of modeling and control of the *product of design*. For example, the discipline of flight control seeks to accurately model and design real controllers for real aircraft. The ideas contained in this paper, in contrast, seek to model the process of using knowledge and human decision-making together to model and control the very process of designing and developing that real aircraft.

What are the challenges to implementing this kind of approach? First, a realistic, explicit system model of a very heterogeneous, uncertain, non-physical dynamic system must be constructed. Next, uncertainty sources of various sorts and types must be identified and represented. Finally, simulation of a potentially computationally intense system must be accomplished. Where appropriate, analogies to concepts, tools and techniques from the field of control systems are employed to deal with these challenges. However, recognizing that the current problem has significant differences than the control of actual systems, inappropriate linkages to traditional approaches are to be avoided. In this spirit, this paper serves as an exploration and initial look into what appears to be a logical and apparently promising problem formulation.

An Uncertainty Model

The roots of moving towards a control system analogy for the complex system design process lie in the common denominator of uncertainty management. The entire field of robust product design, especially for complex systems such as aerospace vehicles, is predicated upon an understanding and proper modeling of uncertainty. The state of the art in this field was summarized in Ref. [1]. Similarly, classical and modern control theory has continuously sought better methods for modeling and combating uncertainty without undue conservatism. Along these lines, a framework for modeling design uncertainty in complex systems was presented in Ref. [2], adapted from the well-known control system model.

This framework is shown in Figure 1. Within it is a taxonomy that describes the mechanisms by which various types of uncertainty enter the design process. The framework is important in that it proposes a categorization of the relevant classes of uncertainty for the aerospace design problem: input, model parameter,

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measurement, and operational/environmental. These classes are organized in the figure, with parenthetical references to their aircraft control system "analogies". Input uncertainty arises when the requirements that define a design problem are imprecise, ambiguous, or not well defined. Model parameter uncertainty refers to error present in all mathematical models that attempt to represent a physical system. Measurement uncertainty is present when the response of interest is not directly computable from the math model (i.e. it must be inferred indirectly from other measurements). Finally, operational/environmental uncertainty is due to partially unknown and usually uncontrollable external disturbances that affect the model's prediction. Each of these uncertainty sources can cause the model-based predictions to differ from reality, which forms the crux of our definition of uncertainty. In the field of control system design, managing uncertainty has been achieved through formal mathematical constructs and identification of where in the "loop" it enters the system. *In aerospace vehicle synthesis and design, no such established framework exists, thus providing the motivation for this on-going research.*

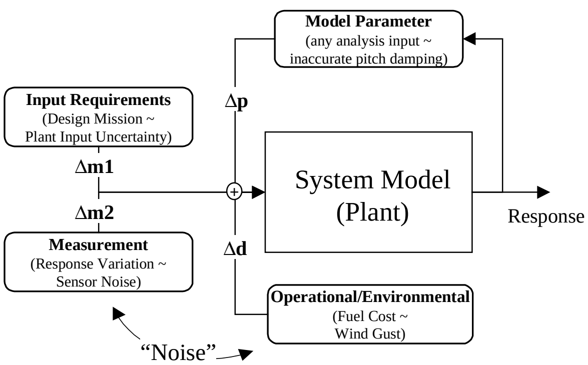

Figure 1: A Preliminary Model for Design Uncertainty

In addition to the clear link to classical and modern control theory, the proposed approach also has roots in the areas of statistical process control (SPC) and other so-called quality engineering methods. In SPC, sampling data from the production line was "fed back" to production engineers who sought to identify sources of variability and take action to tighten tolerances and increase average quality, thus reducing rework and cost. Taguchi methods (Ref. [3]) for robust product design have their heritage in this realm and were explored extensively in the past two decades. In fact, the terms signal-to-noise ratio and control variables common in the Taguchi approach have their equivalents in the method proposed in this paper. Since the introduction of Taguchi's methods, numerous groups in the design methodology community have contributed relevant and important ideas concerning robustness and quality. However, such approaches tended to be "open-loop", one-pass-through formulations. In the current approach, the goal is to explore the time-dependent design process, again through the extended control model. The work described in Ref. [1] and Ref. [4] are examples of the relatively few forays into this task of combining traditional control and design objectives.

Traditional approaches to the modeling challenge of this kind typically fall into the domain of systems dynamics. A typical systems dynamic model attempts to simulate the flow of information or decisions through some kind of free-form network architecture. Nodes in the network might be assigned a cost or performance value, and critical paths are sought or input-output behavior is observed. One shortcoming of this approach is that the models of the actual system are usually very crude. Further, its main advantage, the freedom to create a model of practically any structure, also means that the ability to obtain universal and standard results for various applications is difficult.

In summary, there are two objectives of this paper. The first is to introduce and explain a new modeling framework for the complex system design process based on a control system analogy, beginning with the concept of Figure 1. The second is to examine the character of various types of uncertainty in this framework and to better understand the impacts of this uncertainty on conceptual design solutions. This second task introduces the notion of "reliability" in conceptual design, a term most usually associated with hardware. In the current research, reliability will be assessed by introducing methods for evaluating the sensitivity of responses to various uncertainty types.

A New Model of the Design Process

While the model in Figure 1 focused on the uncertainty, a more complete depiction of the generic design activity (still through the control system analogy) is proposed in this paper. The concepts of plant, state variables, feedback, and signal network diagrams common in the control system setting are merged with the design activity. The hope is that a useful mechanism will emerge to guide the designer towards achieving a product solution that meets the customer requirements. Since the object is a *process*, this modeling must be *dynamic*, and the task is to move the system from one state to another.

An initial version of this new framework is displayed in Figure 2. The key elements are the plant, G, the compensator, K, and the uncertainty sources. The inter-relation of these elements will be described first, followed by subsequent sections concerning details of each.

The specific objective of the system is for the output, y(t), to follow or track the input command c(t). The signal x(t) contains the states, the signal

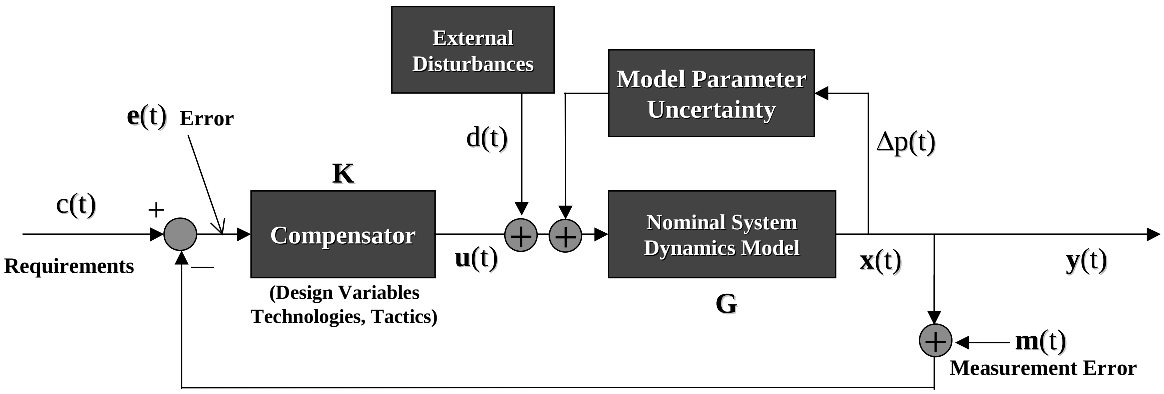

Figure 2: Feedback Model for Design

$y(t)$ are the system responses (a subset of the states, as defined by the matrix C), and $c(t)$ are the commanded requirements. It is desired to feedback state information in order to compare with the command, thus forming an error signal $e(t)$. This error signal is then used by the compensator K to form the control input $u(t)$. Unfortunately, this input is corrupted by external disturbances $d(t)$ and uncertainties in the plant itself, Δp. Further, the true state of the system, $x(t)$, cannot be measured exactly, and thus there is measurement error, $m(t)$. Therefore, the information into and out of the plant is imperfect, which complicates the objective of tracking $c(t)$ properly. In addition, the set of commands themselves are often not known precisely, unlike the typical control setting where the commands are known. This customer command ambiguity is yet another hurdle to achieving the tracking objective of the feedback system. Depending on the type of command, the system may be seeking to follow the command exactly (a nominal the best command) or to be equal to or better than the command (a lower or higher the better command). This was recognized and addressed by Messac et. al in Ref. [4] in the form of physical programming techniques. In any case, understanding the uncertainty that enters the system is key to developing further and more complete formulations. The following relationships can be obtained directly from the structure in Figure 2 and summarize the preceding discussion.

$$y(t) = Cx(t) \tag{1}$$

$$e(t) = c(t) - y(t) + m(t) \tag{2}$$

$$u(t) = Ke(t) \tag{3}$$

$$x(t) = G[u(t) + \Delta p(t) + d(t)] \tag{4}$$

States and the Nature of the Plant

The system model G is referred to as the plant. The plant contains the relationship that determines the behavior of the system. The concept of state is employed to represent this behavior mathematically, since the outputs of the plant are the system state variables. For an aircraft system design model, these state variables might be such things as predicted range, gross weight, fuel weight, take-off field length, endurance, etc. For actual physical systems, the states are obtained by integrating time differential equations which represent the dynamics of the system in question. In the setting of a design process, there are no laws of physics that define this dynamic. Instead, there is a complex combination of disciplinary analyses (based on the underlying physics), performance models, human decision-making elements, historical databases, organizational strategies, etc. Thus, the system model typically consists of disciplinary modeling and simulation in conjunction with vehicle sizing/synthesis that integrates the multiple disciplines to obtain vehicle performance (and possibly cost), as depicted in Figure 3. It is in the plant that the traditional emphasis on multidisciplinary analysis and optimization (MA&O) is placed, either directly, or through approximating equations which capture the essence of more sophisticated models. The modeling of this heterogeneous nature of the plant poses one of the greatest challenges to the success of the overall approach.

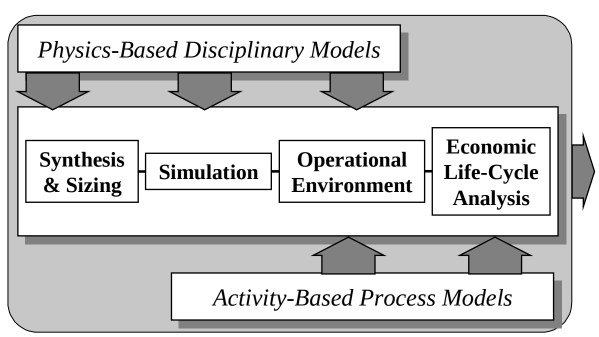

Figure 3: Plant Model (G) for Complex Systems

Since even the best plant model will never perfectly capture the true dynamics, a plant uncertainty model is needed to characterize the range of expected inaccuracies. This uncertainty model, represented by Δp in Figure 2, will change as time elapses in the design cycle, hopefully with the trend of a reduction in the magnitude of this uncertainty as better analysis models, more realistic testing, etc., become available. Such a reduction, however, may come at additional expense. Whenever expense is incurred, the total amount of resources available for compensation is reduced, which compromises performance. The trade-off between combating uncertainty while achieving performance goals becomes evident. In fact, the determination of the closed loop system's sensitivity to the various uncertainty sources is critical to dictating where resources should be expended to reduce or better define the uncertainty.

In a conventional control system model, the uncertainty is dealt with in a worst-case sense. This tactic can lead to overly conservative solutions for normal operating modes. Such solutions may be inappropriate in the design process control setting. Instead, each uncertainty is represented by a random variable with an assigned probability distribution. As a result of these probabilistic inputs, each state variable is also a random variable. The computation of these output state distributions requires probabilistic analysis, which can be computationally expensive. However, there are techniques (both analytical and sampling-based) which can partially overcome this obstacle (Refs. [5], [6]). State variable distributions can be obtained either by combining approximate plant analysis with a very accurate probabilistic routine or by using the actual system plant with an approximate probabilistic analysis. A method for efficient, accurate probabilistic robust design studies was also introduced by the authors in Ref. [2]. An additional fact that ameliorates the computational burden issue is that, unlike a conventional dynamic system (e.g. an airplane, an automobile, etc), the design process operates on a much slower time scale. Updates are measured discretely in days, sometimes months, instead of seconds and milliseconds.

A final challenge of note is that the multitude of possible input and output channels significantly increases the difficulty of the control task. Traditional control system design dealt with control problems one input/output at a time ("close one loop at a time"). This single-input, single output (SISO) approach has been extended in modern control theory to address problems of a multiple-input, multiple-output (MIMO) nature. As one might suspect, MIMO problems are more difficult to solve because of the likely confliction involved in controlling multiple outputs. Unfortunately, nearly all system design problems will be of this MIMO format, and so the trade-off mention previously concerning uncertainty is compounded by the presence of a multi-objective control problem.

Feedback and the Compensator

If no uncertainty is present, a system can be modified through a straight-forward, open-loop architecture. The fundamental role of feedback, however, is to modify the system in the presence of uncertainty. The information fed back is operated on by a *compensator*. At a top level, in a complex system design setting, the human designer has served as the compensator, receiving and acting upon inputs, making decisions, allocating resources, etc., to drive the system forward. This process is repeated until the final product emerges. In this paper, we attempt to formulate a similar process, but at one level below the human designer in the problem hierarchy. At this lower level, the key compensation mechanisms available to the designer include design variable changes (changing the plant parameters themselves), the introduction of new technologies, or re-negotiation of the requirements (commands). In all cases, there is an inherent trade-off involved in selecting the compensator since there is a desire to improve system performance while continually minimizing the impact of uncertainty. This is often a difficult trade-off. In fact, there is often already a conflict between competing performance objectives for multi-objective problems.

The case of compensation consisting solely of a change in the design parameters is akin to a pure gain. When the compensation consists of specific technologies that affect the disciplinary performance metrics or even the states themselves directly, the situation is akin to a compensator with its own dynamics. In this case, a model of the compensator dynamics is needed to predict the technology evolution. Such models are already under investigation by the authors and their collaborators (Ref. [2], [7]). The use of technologies as compensation for design deviates in a sense from the normal control system environment in that technologies actually change the internal behavior of the plant. This nuance is a topic for further study. Later in this paper, an example of how the introduction of technologies as a means of compensation can have negative impacts on overall system sensitivity to uncertainty will be presented.

One particular challenge associated with this formulation typically found also with the control of actual dynamic systems is that the number of compensator options can be vary large. While the command to achieve a roll rate for an aircraft can only be achieved through the use of at most 3 control surfaces in combination, the structure of the compensator has infinitely many possibilities. In the system design setting, the choice of design variable changes or technologies employed can be very large due to the combinatorial nature of the option set. A search must be made to properly select an optimal compensator to operate on the feedback signal after each update. Efforts are under way at finding reasonably efficient and insightful ways to model and conduct such a search.

Understanding the Impact of Uncertainty

Once the uncertainty sources are identified and the specific instance of the framework in Figure 2 is constructed, the designer is interested in starting the simulation. First, however, it is important to investigate the system's sensitivity to the various uncertainties as guidance towards selection of the compensator. The traditional concept of sensitivity analysis in design must be extended to a probabilistic nature in order to quantifiably examine the impact of uncertainty. *As the structure of the uncertainty changes with new information, it is important for the designer to know the impact of those changes*. Metrics for evaluating this impact are often called probability sensitivity derivatives (PSD).

Leverage and Probabilistic Sensitivity

In essence, there are two effects which influence the probabilistic sensitivity of the response to changes in input variability: the input's "leverage" and the input's own variability. These two effects are explained in Figure 4, which was adapted and modified from Ref. [8]. The leverage simply refers to the traditional deterministic sensitivity neglecting uncertainty, as shown in the center of Figure 4. If y is the response random variable in our system, as in Figure 2, and x is the input variable, the leverage is:

$$\frac{\partial P(y \le y_o)}{\partial(x)} \tag{5}$$

The magnitude of the input variability, of course, also impacts the variability of the response. Thus, the overall response sensitivity results from a combination of both effects. In Figure 4, two cases are displayed which illustrate the fact that greater input variability in one input (top figure) over another input (bottom figure) does not necessarily mean that the first input will cause greater variation in the response. A greater leverage in the second input may amplify the uncertainty to such a degree as to cause a larger response variation. Case 2 in the figure is an example of this outcome. The authors in Ref. [9] describe the PSD as a measure of the change in the probability of a selected response with respect to the change in the parameter of a distribution. For most distributions, this change can be defined by two parameters, such as mean and variance. Referring to these generically as (α, β) then, the sensitivities to the parameters which define the uncertainty probability density function (PDF) ($f_x(x)$) for x are:

$$\frac{\partial P(y \le y_o)}{\partial[\alpha(x)]}, \frac{\partial P(y \le y_o)}{\partial[\beta(x)]} \tag{6}$$

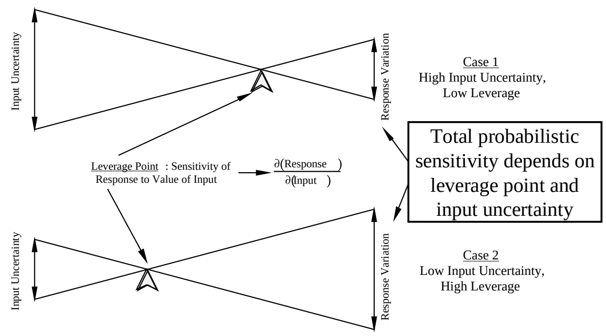

Figure 4: The Definition of Leverage

An Aircraft Design Example

With the tools for plant, uncertainty, and sensitivity modeling in place, the challenges of uncertainty management in designing complex aerospace systems can begin to be systematically addressed. In this initial exploration, the most important characteristics of this approach are its traceability and visualization.

Uncertainty Identification

This section describes three specific examples of uncertainty in the vehicle design process. They are categorized and placed in context within the feedback design framework. In the next section, they will be examined numerically for the aircraft design problem.

Requirements Uncertainty

Class: Input	*Signal: c(t)*	*Nature: Ambiguous*
Distribution: Estimated from user/customer query (non-statistical) and analysis (statistical)		

The most important input to a design problem is the requirements issued by the eventual decision-maker (usually the customer). These requirements specify the mission or purpose of the product to be designed, the objective function(s) by which design options will be evaluated, and the constraints that all successful alternatives must satisfy. Thus, they can be seen as the "forcing function" which drives the evolution of a design artifact. Unfortunately, these requirements are often ambiguous. Ambiguity can be a linguistic type of uncertainty or numerical in nature, and often is difficult to model. Several possible techniques for doing so, however, are emerging and will be described in detail in the paper. For linguistic uncertainty, fuzzy and probabilistic approaches present tremendous potential, as they abandon the "crisp set" notions of probability theory for the concept of partial membership in several sets simultaneously. Ambiguity that is numerical in nature can be addressed through probability distributions, but must be accompanied by knowledge of the parameters and characteristics that define the ambiguous requirement. And so, referring back to Figure 2, the task is to make design decisions so that the system performance (as predicted through the system model with uncertainty) matches this commanded input in a probabilistic sense.

Technology Uncertainty

Class: Model parameter	*Signal: u(t)*	*Nature: Ambiguous + statistical*
Distribution: Estimated from query (non-statistical), test data, historical trends		

A specific type of model parameter uncertainty is that associated with new technologies. New technologies enter the design problem when solutions that meet the requirements are not possible through manipulation of design variables within the design space. In essence, technologies shift the design space itself. However, the performance, development cost, and maturation rate of technologies are all uncertain during the time preceding its operational introduction, as shown in Figure 5 adapted from Ref. [10]. In addition, while the uncertainty associated with a new technology may decrease with time, the uncertainty associated with its integration with the overall system may not decrease at all. The Technology Readiness Level (TRL) is a system of descriptors developed by NASA to standardize the status of a technology with respect to ultimate operational use.

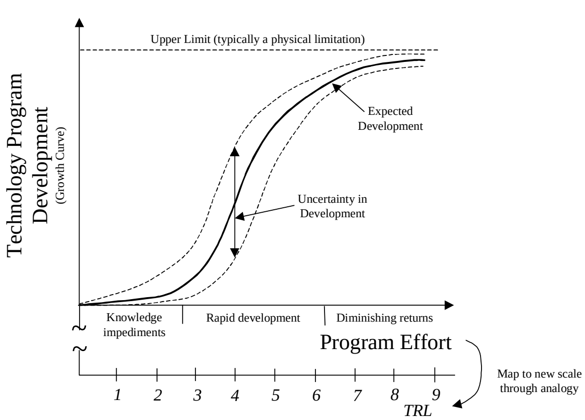

Figure 5: Technology Uncertainty (from Ref. [10])

Several approaches, both recent and not recent, have been proposed for modeling and propagating technology uncertainty. In one respect, many analysis codes already have the necessary kernel for modeling at least the technology performance uncertainty. This kernel is the tuning inputs, or "technology dials", that allow a knowledgeable user to correlate an analysis code to the presence of a new technology. In the world of technology uncertainty, these dials become the tools by which technology impacts can be simulated. In fact, the treatment of these knobs as random variables with intelligently assigned distributions provides a direct mechanism for uncertainty modeling.

Fidelity Uncertainty

Class: Model parameter	*Signal: Δp*	*Nature: Statistical*
Distribution: Estimated from comparison of analysis models with test or historical data		

Another model parameter uncertainty encountered is termed fidelity uncertainty. Fidelity uncertainty arises due to the inability of computer analysis programs to exactly predict physical behavior. This type of uncertainty can be quantified by first understanding the governing assumptions inherent in a given analysis and then conducting a set of calibration simulations to generate data by which an appropriate random variable distribution can be formed. Fidelity uncertainty can be tightly coupled to the technology uncertainty because one aspect of the uncertainty of a new technology is, of course, the inability to precisely predict its physical behavior. Fidelity uncertainty is especially critical during conceptual design, where the tools used are often unsophisticated due to computational issues and lack of detailed knowledge about the system.

Sample Problem Description

The approach is demonstrated on the design of a notional, multi-role, carrier-based aircraft, similar in several respects to the development of the U.S. Navy's F/A-18E/F. In this application example, the goal is to understand the implementation issues of the feedback system formulation and the avenues for examining uncertainty sensitivity. The plant model, constructed in Ref. [[11]], is shown in Figure 6. The Flight Optimization System (FLOPS, Ref.[12]) code was used to size the aircraft taking into account the various constraints introduced by the aircraft carrier environment. In addition, a military life cycle economics capability was included in the plant to predict cost characteristics. This plant can be computationally expensive, and thus response surface equations (RSEs) for this notional fighter example were developed in Ref.[11] and together they serve as the plant. These metamodels better serve the purpose of exploring the proposed design process control approach rather than using the actual modeling and simulation tools depicted in Figure 6. The responses, `y(t)`, to be tracked include performance measures and constraints associated with carrier-based aircraft. These are summarized in Table 1.

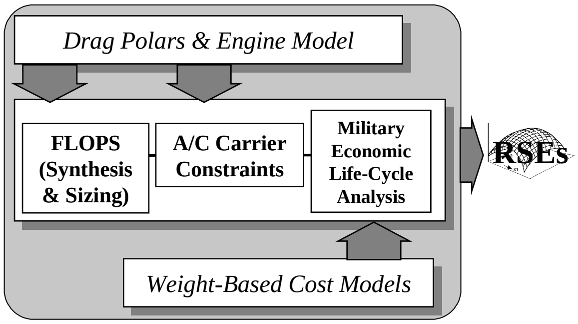

Figure 6: Plant Model for Aircraft Design Example

Table 1: Responses y(t) for Carrier-based Aircraft

Objectives	
$RDTE	Research, develop., test, & evaluation cost
$1st Unit	The production cost of the first unit
$O&S	Operations & support cost for fleet
TOGW	Take-off gross weight
Constraints	
TOWOD LDWOD	Min. takeoff and landing wind-over-deck speeds (a function of aircraft weight, high lift aero, & catapult/arresting gear capacities)
Vapp	Approach speed for carrier landing
Ps	Combat specific excess power
AltRng	Achievable radius for the alternate mission)

Two sets of RSEs for these responses were formed, one as a function of mission parameters and the others as a function of so-called technology k-factors. For the former, seven parameters along with a range of variation for each were chosen in an attempt to capture the range of possibilities that define a mission space for the aircraft. In particular, the mission radius, delta payload (over a baseline value), and need for auxiliary tanks can vary widely between various missions. In the current example, the auxiliary tank variable is set at either zero, one (center fuselage mounted), or two (wing mounted). Depending on the value of this variable, appropriate fuel, weight, and drag values are included in the sizing analysis. The stealth penalty is simply a generic weight penalty assumed to exist for incorporating stealth characteristics. This information, displayed in Table 2, serves as the input to the RSE generation process. The baseline aircraft model in the sizing/synthesis program is used to execute the cases required for the regression data. Note that the thrust and wing reference area variables are included since they are needed to allow for proper scaling of the vehicle for various missions.

Table 2: Mission Parameters/Ranges (inputs to the RSEs)

Mission Parameter	Min	Max
Mission radius (nm)	296	435
Ultimate load factor	6.5	7.9
Combat Mach number	0.9	1.1
ΔMission payload (lbs)	0	1000
ΔStealth penalty (lbs)	0	1000
Auxiliary fuel tanks	0	2
Specific Fuel Consumption (SFC) k-factor	0.9	1
Scaling Variables	**Min**	**Max**
Thrust per engine (lbs)	14500	21000
Ref. wing area (ft^2)	380	520

The purpose of the technology k-factor space is to allow the examination of evolutionary technology insertion as compensation to the feedback system. Actual technologies are modeled in this setting by adjusting the set of technology k-factors (“technology dials”). For the current study, nine technology k-factors and associated ranges were chosen and are displayed in Table 3. These factors were chosen so that two of the most typical generic technology classes that affect performance, i.e. aerodynamic and structural improvements, could be captured in the sizing code.

Table 3: Technology k-factors/ranges (inputs to the RSEs)

Technology k-factor	Range
Induced drag (k_C_{Di})	-10% to 0%
Zero-lift drag (k_C_{Do})	-10% to 0%
Wing weight (k_WingWt)	-15% to +15%
Fuselage weight (k_FusWt)	-15% to +15%
Vert. tail weight (k_VTWt)	-15% to +15%
Horiz. tail weight (k_HTWt)	-15% to +15%
RDT&E cost (k_RDTE)	-20% to +5%
1st unit product. cost (k_T1)	-20% to +5%
O&S cost (k_O&S)	-20% to +5%

The k-factor for propulsion improvements, in the form of specific fuel consumption (`k_sfc`), was included in the mission space described above instead of the technology k-factor space as an example of how mixing can be used for specific trade studies (an example of which was conducted in Ref. [11]). Additionally, three cost-related k-factors are employed. to model a benefit or penalty of the employment of a new technology. The k-factor for research, design, test & evaluation (`k_RDT&E`) is important for capturing the additional cost incurred for maturing a technology. The 1st unit production cost (`k_T1`) is often used to represent process technology improvements. Finally, the operations and support cost (`k_O&S`) k-factor is needed to assess the potential cost impacts associated with maintenance and operations advancements. The variables and ranges for the technology k-factor space are used to create the technology k-factor RSEs.

Leverage- Deterministic Sensitivity

The leverage can be evaluated through a Pareto Plot, which compares the parameter effects in the RSEs, assuming equal variance and no correlation. The Pareto Plots are understood as indicative of the true leverage. When second-order polynomial regression models are used (as is the case here), effects in the RSEs include not only main effects (e.g. `k_O&S`), but also interaction terms (e.g. `k_O&S*k_FusWt`), and quadratic terms (e.g. `k_O&S*k_O&S`). The relative leverage of the mission parameters for the `TOGW` and `O&S` responses is illustrated in Figure 7 and Figure 8. Instead of listing a number corresponding to the leverage, the Pareto Chart is useful in that it rank-orders the effects and gives a percentage contribution to the total leverage. Disregarding the scaling variables (which will always have a large effect), the parameters with the highest leverage appear to be the `k_sfc`, `Radius`, and `AuxTnk`.

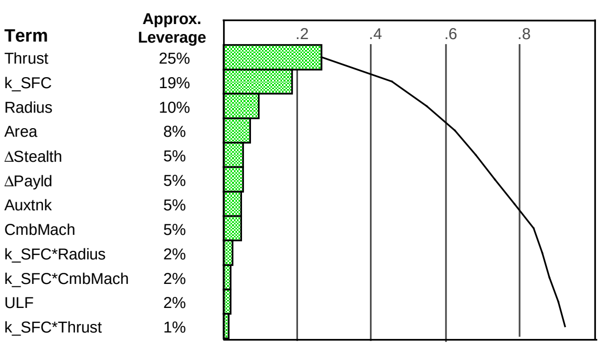

Figure 7: Leverage- Pareto Plot for TOGW vs. Mission Variables

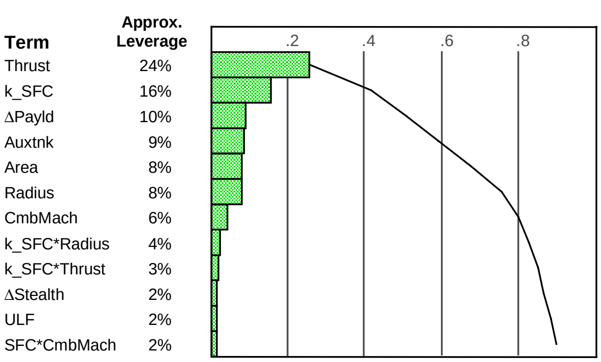

Figure 8: Leverage- Pareto Plot for $O&S vs. Mission Variables

The relative leverage of the k-factors for the `TOGW` and `$O&S` responses is illustrated in Figure 9 and Figure 10. For the `TOGW`, the k-factors with the largest leverage are weight-related, except for the `k_C`$_{Do}$, which ranked third. In contrast, the `$O&S` is logically dominated by its direct k-factor (correctly implying that it is better to affect `$O&S` directly rather than indirectly through weight reduction).

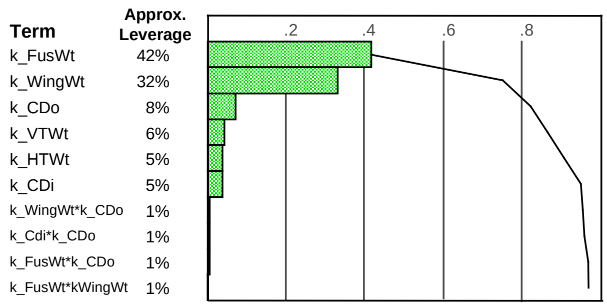

Figure 9: Leverage- Pareto Plot for TOGW vs. Technology k-factors

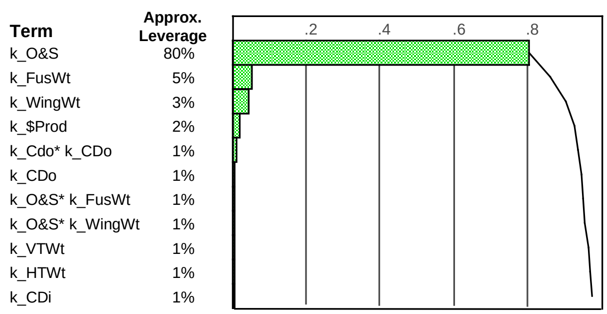

Figure 10: Leverage- Pareto Plot for $O&S vs. Technology k-factors

Probabilistic Sensitivity- Open-Loop Analysis

While the Pareto Charts displayed the leverage (deterministic sensitivity, Eq. (5)), the probabilistic control system formulation requires that the designer understand the combined effect of leverage and input variability, i.e. the total probabilistic sensitivities (Eq. (6)). This total sensitivity (leverage plus variability) can then be compared with the Pareto results. The total probabilistic sensitivity can be obtained by performing a Monte Carlo simulation around the plant, accounting for the various sources of modeled uncertainty. In essence, this amounts to running the system of Figure 2 in open-loop mode (no feedback) and measuring the sensitivities.

In the present case, the RSEs in the plant contain the leverage information, but a specific scenario must be posed that defines the input uncertainty distributions. A simple scenario of fidelity uncertainty is constructed to illustrate this point, as described in

Figure 11 via five PDFs that are sampled during the Monte Carlo simulation. Fidelity uncertainty is represented through `k_WingWt.`, `k_FusWt`, k_C_{Do}, k_C_{Di} as a means of capturing the inability of the analysis in the plant to predict weight and drag, respectively. This is certainly a realistic case, since, for example, structural optimization may give an accurate estimation of the theoretical weight, but says nothing about the "non-optimum" weight, which includes wiring, insulation, etc. Thus, an accurate value for the total wing weight is difficult to compute.

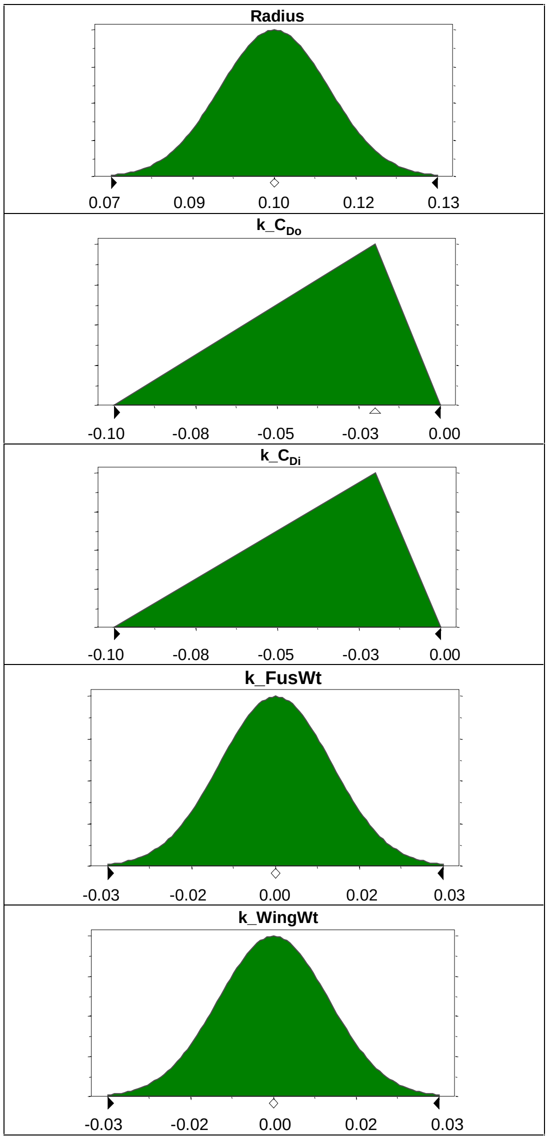

Figure 11: Fidelity Uncertainty PDFs for Sensitivity Scenario

The resulting probabilistic sensitivities are rank-ordered and presented in Figure 12. Note that the rank-ordering differs from the purely deterministic rankings reported in Figure 7 through Figure 9. This is likely due to the rather large variability assigned to k_C_{Do} and k_C_{Di} which more than accounted for the large leverage of `k_FusWt` in the `TOGW` response. These results would lead one to focus on reducing the fidelity uncertainty of the drag prediction, a conclusion that would not have been clear from simply looking at deterministic sensitivities (though possibly expected since the ranges for the uncertainty are different than the total range examined in the Pareto Plots).

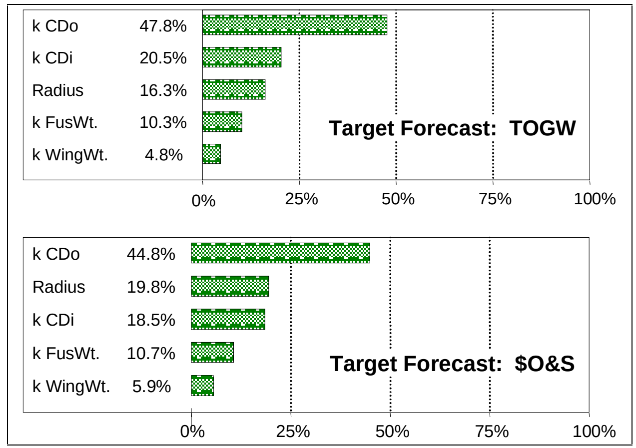

Figure 12: Probabilistic Sensitivity for TOGW and $O&S

Technology Compensator Development

With a plant model obtained, uncertainty models constructed, and sensitivity studies complete, the actual execution of the framework in Figure 2 can be initiated to find a proper compensator. It is important to note that the problem can be approached in *two ways*.

1) First, one could search for the compensator from amongst a group of existing technologies that might, for example, be under development in the corporation or government's R&D laboratory.
2) In contrast, instead of choosing from a specific set of technologies, one could use this framework to find the levels of technological improvement that would be needed to meet certain commanded objectives. These levels can then be used as targets for the science and technology groups to achieve. In other words, determine the compensator characteristics required, and then commence a program (allocate resources) to construct a specific, non-unique solution.

The approach of type 1 has been and continues to be explored, see specifically Refs. [7] and [13]. In this paper, type 2 will be investigated on the notional carrier-based aircraft example described previously.

Computing e(t); Defining a Generic Compensator

Most modes of the current framework will focus on the tracking problem: given a command `c(t)`, develop a compensator that will produce `y(t)` that satisfies `c(t)`. Since both `c(t)` and the feedback of `y(t)` are probabilistic in nature, their comparison (the formation of the tracking error `e(t)`) must be done through the definition of a new random variable. For the case of a "lower the better" command, this random variable is defined as in Eq. (7).

$$\begin{aligned} e(t) &= P\left(\boldsymbol{Resp}_{\boldsymbol{Ach}} - \boldsymbol{Com}_{\boldsymbol{Ant}} > 0\right) \\ &= P\left(y(t) - c(t) > 0\right) \end{aligned} \tag{7}$$

The definition of the error signal in this case is depicted in Figure 13. The PDF on the left represents the range of possible values of `y(t)` that the system is likely to achieve under compensation with uncertainty. The PDF on the right is the range and likelihood of possible commands `c(t)`. The new random variable in Eq. (7) is the probability of not meeting the command, a value that must be determined in order to make design decisions. The probability of "success", then, is simply `(1-e(t))`. In this viewpoint, "reliability" in conceptual design implies finding solutions that satisfy requirements/constraints as represented through this random variable.

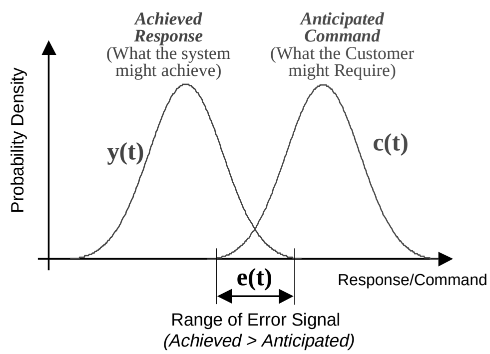

Figure 13: Computation of Error Signal `e(t)`

The problem at hand is of type 1): find an optimal set of k-factors that represent the generic structure of the desired compensator that tracks a commanded distribution for `$O&S` in the presence of the fidelity uncertainty model described in Figure 11. Four k-factors are selected as the components for which an optimal combination will be sought. These are: `k_FusWt`, $\texttt{k\_C}_{Do}$, `k_$O&S`, and `k_SFC`. The associated plant-compensator-uncertainty feedback system for this case is illustrated in Figure 14.

A simple search for the optimal vector of k-factors, however, would lead to an overly optimistic or "benefit only" view. Such an approach neglects the risk inherently present in technology forecasting. But how can such risk be accounted for without the specification of the actual technologies, as was done in the previous section when computing the system's probabilistic sensitivities? One answer to this question is the concept of a "total technology distance" away from the baseline. In other words, while trying to find the compensator that meets the `e(t)` requirement, it is also desired to minimize the total distance away from the baseline (computed simply by adding the individual k-factor distances). Though not specific, this still may be an acceptable way to include risk and perform a risk-adjusted search. If desired, weightings for individual k-factors can be assigned if prior knowledge was available regarding the relative difficulty of, for example, aerodynamic versus structural technologies.

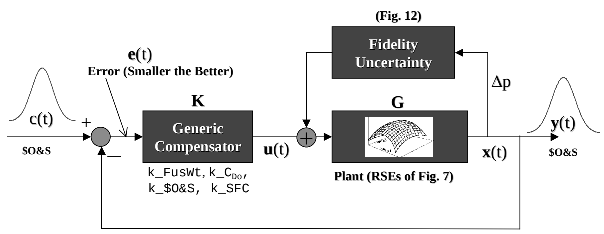

Figure 14: Setting for Aircraft Design Example

The system in Figure 14 is placed within a Monte Carlo simulation environment and the risk-adjusted search for the best generic compensator is begun. At each iteration, the simulator performs the Monte Carlo by sampling from the fidelity uncertainty distributions and computing the new distributions of the state variables. In this particular example, the response to be commanded is the `$O&S` and `e(t)` (probability of not meeting the command) is commanded to be less than 10%. In other words, a compensator is sought which guarantees with 90% reliability that the achieved `$O&S` will be less than the requirement. The results of the search to meet this command while minimizing the "total technology distance" are displayed in Figure 15 and Figure 16. The optimum compensator occurs at iteration 66, where $P[1 - e(t)] \cong 0.905$ and the cumulative distance is `1.346`, computed using the normalized scale indicated in Figure 17. Under this scale, "minimizing the total technology distance" is accomplished by maximizing the sum of the normalized k-factor values. The actual optimal k-factor settings are displayed in Figure 17.

The distance-from-baseline penalty term allows the optimization to take into account the leverage of each input k-factor described in Figure 7 through Figure 10. An interesting result shows that no drag reduction technology is advised, likely because its benefit through leverage (Figure 10) is not enough to overcome the penalties of its large uncertainty (Figure 11) in computing `e(t)` probability. On the other hand, `k_SFC` (for which there was no uncertainty but a large leverage) correctly came out to be the driver in the compensator composition.

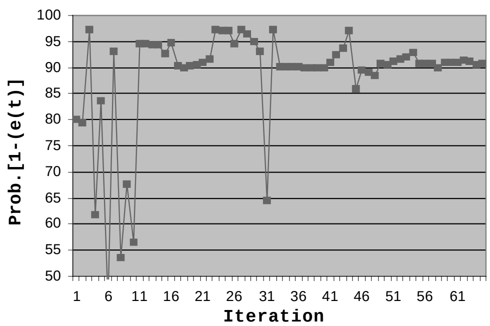

Figure 15: Search History for 1-e(t), Prob. of Success

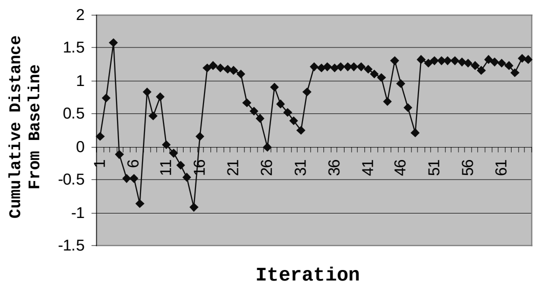

Figure 16: Search History of Technology Distance Metric

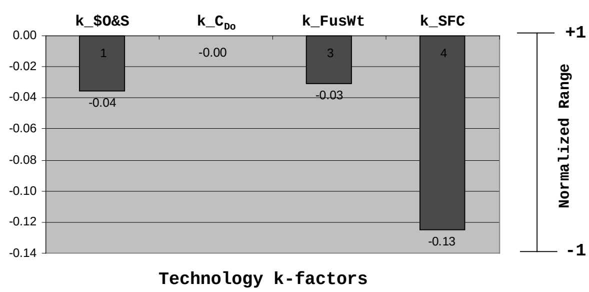

Figure 17: The Best Compensator- Optimum k-factor Values for Risk-adjusted Search

Conclusions and Future Challenges

A new framework for modeling and control of the aerospace system design process was presented. It is predominantly based on a control system analogy, though it builds upon insights gained over the past several years in the areas of robust design simulation, probabilistic technology assessments, and multidisciplinary analysis. The concepts of state, state feedback, and command tracking through compensation were introduced in the context of the system design. A simplified aircraft design example was constructed and posed in the framework to illustrate these concepts. In open-loop mode, the formulation was used to determine the output sensitivity to various forms of uncertainty. In this case it was found that the take-off gross weight and operations/support (O&S) cost states were most sensitive to uncertainty associated with the prediction of vehicle drag. In closed-loop mode, a generic technology compensator was developed to minimize the O&S cost while also minimizing the overall magnitude of technology improvement required.

There are clear challenges ahead. One certainly is the formation of a realistic plant model in the absence of physical laws (e.g. Newton's laws) that define the dynamics of systems. Proper control of the design process can only occur after such a plant (and its associated uncertainty) is modeled. Further, the update rate of this "design process control system" is very low, making compensation potentially very difficult. Finally, the search for an optimal compensator in a vast option space remains an outstanding problem.

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