A ROBUST CONCEPT EXPLORATION METHOD FOR ENHANCING PRODUCTIVITY IN CONCURRENT SYSTEMS DESIGN

WEI CHEN[1], JANET K. ALLEN[2] , AND FARROKH MISTREE[3]

ABSTRACT

Productivity is of major economic significance in the current competitive global market. Due to growing costs and globalization of the marketplace, improvements in productivity require the creation of a reliable design through concurrent systems analysis in the shortest possible time. This is particularly important for designing complex engineering systems such as aircraft, automobiles and ships. The Robust Concept Exploration Method (RCEM) embodies a systematic approach that can be used to enhance design productivity by both increasing design knowledge in the early stages of designs and maintaining design freedom throughout the design process. Given the overall design requirements and the systems analysis packages with high fidelities, the RCEM is used to evaluate quickly the design alternatives and to develop comprehensive, robust, flexible, and modifiable top-level specifications. Central to the RCEM is the integration of robust design techniques, Suh's design axioms, and the Response Surface Methodology within the framework of a mathematical construct, called the compromise Decision Support Problem, for multi-objective design problems. The high speed civil transport (hsct) aircraft is used as an example to demonstrate our approach.

KEY WORDS: design productivity, design freedom, robust design, axiomatic design, response surface methodology, Decision Support Problem, complex systems, hsct.

TITLE'S SHORT FORM: RCEM for Concurrent Systems Design

WORD COUNT: 5859

---

[1] Assistant Professor, Department of Mechanical Engineering, Clemson University, Clemson, SC 29634-0921. Phone (864) 656-5641, Fax (864) 656-4435.

[2] Senior Research Scientist, Systems Realization Laboratory, George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, Georgia 30332-0405. Phone (404) 894-8168, Fax (404) 894-9342.

[3] Professor, Systems Realization Laboratory, George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, Georgia 30332-0405. **Corresponding Author.** Phone (404) 894-8412, Fax (404) 894-9342.

Version: June 15, 1997
Conditionally accepted: Concurrent Engineering: Research and Applications

NOMENCLATURE

d_i^+, d_i^-	Deviation variables in the compromise DSP
$\hat{y}$	Estimated response
μ	Mean value of response
σ	Statistical standard deviation.
? x_i	Deviation of a design variable (control factor)
?	General representation for variance of performance
BPRDES	Bypass Ratio
BURNEFF	Burner Efficiency
CDT	Compressor Discharge Temperature
C_{dk}	The design capability index, the general representation is C
RANGE	Aircraft Flight Range
FAROFF	Take-off Field Length
FLAND	Landing Field Length
FPRDES	Fan Pressure Ratio
FUEMAX	Fuel Weight
GW	Gross Weight
LOD(L/D)	Lift to Drag Ratio
LRL	Lower Requirement Limit
NPT	Number of Passengers
OPRDES	Overall Pressure Ratio
PI	Productivity Index
SFC	Specific Fuel Consumption at Cruise Speed
SW	Wing Loading
SWEEP	Sweep Angle
TCA	Thickness-Chord Ratio
TET	Engine design point turbine entry temperature
THRUST	Thrust-Weight Ratio
TNOX	Nitrous Oxide Emissions
TR	Taper Ratio
TTRDES	Engine Throttle Ratio
URL	Upper Requirement Limit
VAPP	Approach Speed

1. ENHANCING DESIGN PRODUCTIVITY IN CONCURRENT SYSTEMS DESIGN

In response to the increasing pressures from global competitiveness there is a growing investment of effort to enhance design productivity by implementing principles embodied in concurrent engineering [1-3]. Applying concurrent engineering principles is particularly significant, however, challenging in developing complex systems that require a large investment of resources, have long life cycles, and in which multidisciplinary working groups are involved. Examples of such systems are aircraft, automobiles, ships, and electric power generation plants. Improvements in industrial productivity are strongly related to improvements in design productivity which require the creation of a reliable design through concurrent systems analysis in the shortest possible time.

Means for improving design productivity vary in the literature. Related to the primary team issue of CE is the decomposition of tasks. Michelena and Papalambros [4] propose to use a model-based decomposition methodology that would decompose the original design model into smaller coordinated submodels to reduce the size of a complex problem and improve the speed of optimization. Recent years have seen promising applications of advanced computing technologies to CE, such as the use of virtual reality [5-6], rapid prototyping [7], and parallel computing [8] for assisting designers to make quick and reliable decisions. Various developments in improving design productivity are more or less associated with the enablers for seven influencing agents (7Ts) of CE (talents, tools, task, teamwork, technology, techniques, and time) as defined by Prasad [3]. In general, as stated by Pennell and Slusarczuk [9], CE provides an initiative of the product development community that has the goal of reducing the length of the product design and manufacturing cycle time by allowing teams of engineers to develop design modules concurrently from their perspectives.

Based on CE principles, the design of a competitive complex system in the early stages requires the prediction of system responses and performance with high fidelities. This is a challenging task because in addition to facing the situations where the problem is very demanding in terms of computational resources, designers also encounter difficulty due to a lack of information in the early stages of design. Although computing technology continues to grow, analysis codes seem to keep pace so that the computational time still remains non-trivial. It is our primary interest in this paper to develop a methodological approach (*Techniques* agent of 7Ts) that could support the use of high fidelity analyses in the early stages of designing complex systems. To further improve the design productivity, we are also interested in examining the means for developing initial design specifications that could accommodate the changes that a design is subject to during the entire design process or a product's normal life. Specially, we address two means for enhancing design productivity in designing complex systems concurrently. They are:

(1) increasing design knowledge in the early stages of design,

(2) maintaining design freedom through the design process.

Increasing design knowledge facilitates making early decisions more *comprehensive* based on better information. It is widely accepted that the *quality* of a design can be improved if down-stream information is used when making up-stream decisions. This calls for more effort to be invested earlier in a system realization time-line. The benefits of introducing the sophisticated integrated systems analysis program in the early stages of design is schematically illustrated in Figure 1. In a traditional design process, sophisticated analysis tools are used by specialists in individual disciplines and in the later design stages. The fidelity of design analysis is thus low in the early stages; numerous design changes cannot be avoided when it comes to the final stages of full scale development. After introducing the sophisticated integrated systems analysis, it is anticipated that the comprehensiveness and fidelity of design analyses can be significantly improved; the number of design changes can thus be reduced.

Insert Figure 1 here

Figure 1 – Sophisticated Integrated Systems Analysis for Reducing the Number of Design Changes

Maintaining design freedom facilitates minimizing the effects of changes which may occur in the later design stages. We propose the following ways to provide flexibility and maintain design freedom, including: (1) searching for *robust* early design specifications which are insensitive to *small adjustments* in later design stages, (2) finding *flexible* early design specifications as system parameters which are allowed to vary *within a range*, and (3) making early design decisions *modifiable* to adjust and adapt to *large changes*.

The potential ramifications of increasing design knowledge and maintaining design freedom in order to improve design productivity are also demonstrated schematically using the design time-line in Figure 2. When the early decisions are more comprehensive and based on sophisticated integrated systems analysis, the position of the knowledge curve is raised. As the comprehensive decisions which are based on better information eliminate dysfunctional iteration and avoid rework, the total development cycle, including concept design, preliminary design, detail design, prototype and rework, will be shortened. When the early design decisions are *robust*, *flexible* and *modifiable*, designers have more freedom in adapting to changes and the position of the design freedom curve is raised. The build-test-fix rework that under traditional development is minimized as well as potential product time savings are achieved and eventually design productivity is improved.

Insert Figure 2 here

Figure 2 – Enhancing Design Productivity by Increasing Design Knowledge and Maintaining Design Freedom[4]

[4] Our focus here is to schematically demonstrate the benefits of increasing design knowledge and maintaining design freedom in the early stages of design, but not to accurately represent the curvature of the knowledge and freedom behavior curve.

Though efforts have been made for developing design systems for designs in a complex domain [10-11], most of these programs are either domain specific or purely optimization-based so that little insight into the problem itself can be obtained by using them directly. Additional methods are needed to extend designers' capabilities in using sophisticated analysis tools and making robust, flexible and modifiable decisions in concurrent analysis. In this paper, our aim is to introduce a methodological approach called the **R**obust **C**oncept **E**xploration **M**ethod (RCEM), which is independent of the domain of application. Given the overall design requirements and the systems analysis programs with high fidelities, the RCEM can be used to evaluate quickly the design alternatives and generate top-level specifications[5] with quality considerations[6]. The criteria used in quality engineering to measure the quality of a product, such as "mean on target" and "minimizing performance deviations", are modified to measure the robustness and flexibility of a design decision. Suh's independence axiom is adopted to measure the capability of a decision to be modified. In Section 2, the technological background of our approach is reviewed. The RCEM is presented in Section 3. In Section 4, the high speed civil transport (hsct) aircraft design is used as an example to demonstrate our approach. Section 5 is the closure.

2. OUR TECHNOLOGY BASE

The key feature of our method is to apply Taguchi's quality engineering principles [12] to the development of *robust* and *flexible* top-level specifications and, to develop *modifiable* specifications using a modified version of Suh's axioms [13]. Note we propose to use separately the Taguchi method and Suh's design axioms to adjust design changes at different magnitude. Specifically, while Taguchi's robustness requires insensitivity to small changes, Suh's independence axiom defines conditions for acceptable levels of interactions or couplings such that

[5] Top-level design specifications are those design variables used to describe the system at the early stages of design.

[6] Comprehensive, robust, flexible and modifiable design decisions are referred to as decisions with quality considerations in the rest of this paper. Quality is considered from the perspective of being good for the entire design process in reducing time to market.

large changes are isolated in a small number of components or product modules. Techniques for statistical experimentation, specifically, the Response Surface Methodology (RSM) [14] are also incorporated to improve the computational efficiency when using sophisticated integrated system analysis programs. Central to our method is the integration of robust design techniques, Suh's design axioms, and the RSM within the framework of the compromise Decision Support Problem [15], which is a mathematical construct for formulating multi-objective design problems involving tradeoffs.

Insert Figure 3 here

Figure 3 – Integration of Metrics, Tools Within the Compromise Decision Support Problem Framework

2.1 Improving Design Efficiency and Effectiveness by Statistical Experimentation

When faced with a complex, real-world problem in design, extensive computational resources are needed for an integrated systems analysis. To improve computational efficiency, some kind of heuristics should be applied to generate an approximation of system behavior. From the point of view of improving productivity, we believe that using approximations is an efficient approach. Many different techniques for approximations have been proposed, they range from Taylor series approximations [16] to the Design of Experiments (DOE) [17] with fitted response surfaces and the applications of neural nets [18]. For complex problems in which the number of design variables is large, computational demands are excessive for methods involving Taylor series or neural nets. In this work DOE is used as an approximation technique. Among various DOE techniques, the Response Surface Methodology is a collection of statistical techniques which support the design of experiments and fitting a response model [19-20]. Within the RCEM approach, DOE techniques provide an effective way to formalize design knowledge by studying the significance of different design factors through experiments - or computer simulations - and data analysis. The direct relationship between the performance space and the decision space of a complex system established by the response surface models could be used to replace the complicated, computationally expensive analysis program, and to serve as a fast analysis module.

Obviously, using the design of experiments approach, there is always a trade-off between the number of experiments used and the accuracy of the estimated model. A designer must be able to appropriately balance the accuracy of the approximations against the efficiency in generating design information. A common strategy is to use sequential experimentation, i.e., to perform a low order screening experiment first in order to study the whole possible design space to find an appropriate region of interest, and then to build a higher order response model over this reduced region, probably for a reduced number of factors. A detailed sequential experimentation strategy for concurrent systems analysis is reported in [21].

2.2 Extending Robust Design: The Making of Robust and Flexible Early Decisions

Robust design, often called the "Taguchi Method", is concerned with minimizing the variation of system performance from a desired target value, and therefore maximizing the quality of the product [12], [22]. Although this technique has been widely used in industry to design quality into products and processes, Taguchi's methods have some limitations. The two major limitations are associated with the inner and outer array approach for experimentation and the use of the signal-to-noise ratio for robust optimization. A detailed review of these two limitations is provided in [23]. In the same paper, we proposed a robust design procedure as a variation to the approaches suggested by Taguchi and further developed by others to accomplish robust design. Our approach can be used to model the two major types of robust design applications, namely, (1) robust design associated with the minimization of the deviation of performance caused by deviation of noise (uncontrollable) factors, and (2) robust design associated with the minimization of the deviation of performance caused by deviation of control factors (design variables).

The robust design procedure proposed in [23] is extended in this work for making flexible and robust design decisions in the early stages of design. Type I applications are applied here to determine robust early design decisions which are insensitive to small adjustments in later design stages. The uncertain design parameters (small adjustments) are modeled as noise factors ***(z)*** and the values of control factors ***(x)*** are found to dampen the noise effects through robust design. In addition to the goal of bringing the mean of performance to the desired target, the *robustness* of design decisions is achieved by minimizing the deviation of performance caused by deviation of noise factors. Type II applications extend to finding flexible early design decisions which are allowed to vary within a range. The flexible design decisions are modeled as control factors with deviations (? x). The *flexibility* is achieved by finding the mean of the control factors (x_m) that results the minimum deviation of performance, in addition to the goal of bringing the mean of performance to the desired target. Therefore, instead of looking for a point solution, a designer searches a range of solutions.

How is the robust design related to the statistical experimentation methods introduced in Section 2.1? Using the Response Surface Methodology (RSM) introduced in Section 2.1, system performance may be represented by a single, formal model of the type

$$\hat{y} = f(\mathbf{x}, \mathbf{z}), \qquad (1)$$

where $\hat{y}$ is the estimated response and **x** and **z** represent the settings of control and noise variables. When the sources of variation include both variations of control and noise variables, the following equations can be used to estimate the mean and variance of each response.

Mean of the response

$$\mu_{\hat{y}} = f(\mathbf{x}, \mu_{\mathbf{z}}) \qquad (2)$$

Variance of the response

$$\sigma^2_{\hat{y}} = \sum_{i=1}^{k} \left(\frac{\partial f}{\partial \mathbf{z}_i}\right)^2 \sigma^2_{\mathbf{z}_i} + \sum_{i=1}^{l} \left(\frac{\partial f}{\partial \mathbf{x}_i}\right)^2 \sigma^2_{\mathbf{x}_i} \qquad (3)$$

where μ represents mean values; k and l are the number of noise factors and control factors. The standard deviation associated with noise and control factors are σ_{Zi} and σ_{Xi}, respectively. Eqn. 3 is a simplified function of variance based on the assumption that the noise variables are independent.

Using our proposed robust design procedure**,** a robust/flexible design decision is modeled using a compromise DSP with two separate objectives for bringing the mean on target and minimizing the deviation of system performance instead of using Taguchi's signal-to-noise ratio. The advantages of using our approach is detailed in [23] and will not repeated here. The compromise DSP is a multiobjective mathematical construct which is a hybrid formulation based on mathematical programming and goal programming [15]. It is used to determine the values of the design variables which satisfy a set of constraints and achieve as closely as possible a set of conflicting goals. In the compromise DSP, each goal, A_i, has two associated deviation variables d_i^- and d_i^+ which indicate the extent of the deviation from the target, G_i. To effect a solution, on the basis of preference, goals may be rank-ordered into priority levels using the lexicographic minimum [24]. In the work reported in this paper, the compromise Decision Support Problem is used to find the values of control variables **x** (robust and flexible design decisions) that can bring the system performance into the range of overall design requirements. One benefit of using the compromise DSP is that goals may either be weighted in an Archimedean solution scheme or, using a preemptive approach, rank-ordered into priority levels to effect a solution on the basis of preference. Differences between the Archimedean and preemptive deviation functions are discussed in detail in [15] and is not repeated here.

2.3 Make Modifiable Early Decisions Using Suh's Axiom

Taguchi's robust design is useful for achieving design quality by reducing the sensitivity of system performance with respect to variations of design parameters; however, this is usually effective when the “noise” parameters vary within a small range. In other words, it might not be appropriate to apply Taguchi's robust design when the variations of noise factors are very large. The question becomes how to make early design decisions which can be readily adapted in response to large changes in design requirements?

In this work, we seek to apply Suh's independence axiom to model design decisions which occur early on a time-line to be *modifiable* to adjust and adapt to *large changes* . Suh describes a design equation which links functional requirements for a specific design to the design parameters:

$$\{\mathbf{FR}\} = [\mathbf{A}]\,\{\mathbf{DP}\} \tag{4}$$

where {**FR**} is the vector of functional requirements

{**DP**} is the design parameter vector.

[**A**] is the design matrix which specifies the mapping from the functional requirements to the design parameters. Based on this design equation, Suh offers two axioms for use in design [13]:

Axiom 1: The independence axiom

In good design the independence of functional requirements is maintained.

Axiom 2: The information axiom

Among designs that satisfy Axiom 1 the best design is the one that has the minimum information content.

What is relevant to this work is Suh's independence axiom, which is useful for modeling design decisions that can be readily adapted in response to large changes in customer requirements. A part of the author's investigation, namely, the effect of Suh's independence axiom on achieving a modular product for a hierarchical system is reported in [25]. It is concluded that the Independence Axiom could play a major role in the design of modular systems when the change of design requirements is huge, since the axiom defines conditions for acceptable levels of module interactions or couplings. In this paper, independence axiom is used to model the *modifiability* of a design decision early along a time-line. To assess the degree of independence quantitatively, Suh provides two quantities, namely, reangularity (R) and semangularity (S) [13, p.116] to measure functional independence for an **n** dimensional problem. In the nonlinear case, the design matrix **[A]** is a normalized coefficient of the linearized formulation for FRs and DPs at a particular point. For uncoupled designs, both R and S are equal to one. Maximizing R and S with a target value of one (1) can be incorporated as a goal in the compromise DSP in order to achieve functional independence for finding an uncoupled design.

3. THE ROBUST CONCEPT EXPLORATION METHOD

The RCEM embodies a step-by-step approach for quickly evaluating different design alternatives and generating top-level design specifications with quality considerations. In Figure 4, a flow chart of the RCEM steps is presented, as well as the detailed activities occurring during each major step and their relationships to the computer infrastructure for RCEM implementation. The computer infrastructure for implementing the RCEM (Figure 5) is composed of four generic processors, B, D, E, F, surrounding a central 'slot', C, for inserting the simulation programs. The simulation programs, which are existing integrated system analysis programs, evaluate the performance of a few conceptual designs. The point generator, processor B, is used to design the essential screening experiments. The experiments analyzer, processor D, evaluates the screening results and assists in planning additional experiments. The response surface model processor, E, creates response surface models, and the compromise DSP processor, F, is used to determine *robust*, *flexible* and *modifiable* top-level design specifications. The relationships between the four major steps and the use of different processors are further described in Figure 4.

Insert Figure 4 here

Figure 4 – Relationships between RCEM Steps and the Computer Infrastructure

Insert Figure 5 here

Figure 5 – The Computer Infrastructure of the RCEM

Classify Design Parameters (Step 1 Using Module A): In this step, the initial concept exploration space is defined and the problem is formulated as a robust design. Design variables are grouped as either control factors which are under a designer's control, or noise factors which are not under a designer's control. Ranges of values are specified. The performance measures, responses, are also identified, along with performance goals, or signals. To reduce the problem, a range of interest for each response is determined. Performance predictors must be identified and introduced in simulator C.

Sequential Experimentation (Steps 2 and 3 Using Modules B, C, D, E): Step 2 is the initial stage of sequential experimentation using low order screening experiments. This reduces the size of the problem and provides information for the secondary experiments in Step 3. After simulating conceptual designs, the results are analyzed and significant design factors (design drivers), and insignificant parameters are identified. In Step 3, the results from Step 2 are used to elaborate response surface models which replace the original expensive analysis programs with a fast analysis module. Response surface equations map the factor / response relationship. Higher order experiments are performed as necessary; when a satisfactory order of experimentation is attained, the results are analyzed using regression analysis and ANOVA (ANalysis Of VAriance) to determine significance. Results from secondary experiments can be used to further examine interactions between design factors. Combining Steps 2 and 3 produces a sequential experimentation strategy to improve iteratively the accuracy of response surface models [21]. Thus, the number and order of experiments gradually increases while problem size is gradually reduced.

Generate Top-Level Specifications with Quality Considerations (Step 4 Using Module F): Using the fast analysis module from Step 3, top-level design specifications with quality considerations are determined in Step 4. This step involves the integration of robust design principle, Suh's independence axiom, and the compromise DSP, a multiobjective mathematical construct which is to integrate priorities and make tradeoffs. The values of control factors identified in this step become the top-level design specifications. Different design scenarios can be explored rapidly by changing goal priority levels in the compromise DSP, see Section 2.2**.**

4. HIGH SPEED CIVIL TRANSPORT (HSCT) DESIGN USING THE RCEM

Our use of the RCEM has been verified for a variety of engineering design problems: a structural design problem, thermodynamic systems design problem and an aircraft design problem [26]. These problems represent different types of analyses, different degrees of computational complexity and different sizes of the design model in terms of the number of design variables, number of constraints and objectives. Some results from the hsct design problem are presented here to illustrate our approach. In general, the problem for concept exploration of an integrated airframe/propulsion hsct system design is stated:

> *Given mission requirements, the engine cycle concept and a generic HSCT baseline, determine the appropriate number of passengers, flight range, and develop concurrently airframe configuration and propulsion system top-level specifications which meet HSCT overall design requirements including performance requirements, economic competitiveness, and environment considerations, as well as downstream design considerations.*

In Figure 6, the system descriptors of a compromise DSP such as "Given", "Find", and "Satisfy" are used to represent the information flow of this design problem. As the "Given" part of this design problem, the mission profile, the mixed flow turbo fan of the engine concept, and the baseline model developed by the Aerospace Engineering Department of Georgia Tech are taken as the starting point in this concept exploration process. The FLight OPtimization System (FLOPS) [27] is the integrated systems analysis program (Module C in Figure 5) which integrates the engine cycle analysis, the overall vehicle synthesis and mission analysis. FLOPS is a multidisciplinary system of computer programs including nine analysis modules: weights, aerodynamics, engine cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis and program control. Although FLOPS is quite comprehensive for the design simulations necessary for aircraft system analysis, it is seldom used for aircraft synthesis (optimization) because it is a very large program requiring several hundred input parameters and extremely large computational resources for executing optimization. In this work, instead of repeated iterations of FLOPS, the RCEM is used to improve the efficiency and effectiveness of aircraft system synthesis. The "Find" part of this problem are the to-be-determined top-level specifications.

Insert Figure 6 here

Figure 6 – The HSCT Case Study

Step 1 – Classify the design parameters

Following the steps of the RCEM, the design parameters for the integrated airframe/propulsion system design are first classified as either control factors, noise factors or responses (Module A, Figure 5). As demonstrated in the P-diagram (see Figure 7), the twelve to-be-determined top-level design specifications, including the number of passengers (NPT), range (RANGE), airframe and propulsion specifications are considered as the control factors. The turbine inlet temperature (TET) and burner efficiency (BURNEFF) are considered as noise factors because they are uncertain downstream design considerations related to technological factors. The ten responses are parameters used to evaluate system performance based on the overall design requirements.

Insert Figure 7 here

Figure 7 – P-diagram of the HSCT Design System

Steps 2, 3 – Sequential experimentation for creating response surface models

To reduce the problem size by eliminating trivial design factors, a sequential experimentation strategy is used. Then response surface models are developed for the most significant design factors. The results of the initial experiments could also be used to determine the values for discrete top-level specifications through data analysis. Secondary experiments could then be designed for fitting the models of continuous variables. Through our study, the Plackett-Burman experiment [19] has been found to be an effective design for screening, or initial experiments, Module B of Figure 5. As an example, the design solution for the discrete variable NPT would be obtained based on the results from the initial experiments. In Figure 8, the effects of NPT are plotted for responses such as gross weight, GW, fuel weight, FUEMAX, etc. On the horizontal axis, 1, 2 and 3 represent the lower, middle and upper levels of NPT (250, 300, 350), respectively. The vertical axis represents the normalized effects of each factor level based on the range specified in the overall design requirements. From Figure 8 it is noted that the middle level of NPT (NPT=300), level 2 in Figure 8, is favorable for minimizing gross weight, fuel weight, emissions, take-off field land and maximizing productivity index and specific fuel consumption. Therefore NPT will be set to 300 passengers. Data analysis of the screening experiments, Module D of Figure 5, also indicates that the thickness-chord ratio, TCA, and sweep angle, SWEEP, are insignificant because they contribute less than 1% to the responses. These two factors are fixed at their middle levels and are used as constants in the secondary experiments.

Insert Figure 8 here

Figure 8 – The Effects Plot of Number of Passengers

In secondary experiments, second-order response surface models are generated as functions of seven significant control factors and two noise factors, Module E of Figure 5. Tests have been conducted to check the accuracy of these fitted models by ANOVA and comparing the results with those simulated using the original analysis program, FLOPS.

One of the benefits of using the Central Composite Design (CCD) for the fitting second-order response surface model is that after normalization of the design factors, the coefficients of the quadratic equation directly indicate the significance of the first-order effects (linear terms), interaction effects (interaction terms), and second-order effects (quadratic terms) and thus provide more insight into the problem. In Figure 9, the contributions of the nine main factors (first-order effects) to all 8 performance variables are shown. Factors 1, 2, 4, 6 7 and 8 (aspect ratio, thrust-weight ratio, overall pressure ratio, bypass ratio, engine throttle ratio and turbine entry temperature) contribute more than Factors 3, 5 and 9 (wing loading, fan pressure ratio and burner efficiency).

Insert Figure 9 here

Figure 9 – Significance of Linear Effects from CCD

Step 4 – Developing robust, flexible and modifiable top-level specifications

As the final step in the application of the RCEM, the compromise DSP shown in Figure 10 is used as a multiobjective mathematical construct for developing robust, flexible and modifiable top-level design specifications using the fast analysis modules obtained in steps 2 and 3. The formulation in Figure 10 is different from the conventional compromise DSP. In order to develop flexible top-level specifications, control factors are assumed to be uniformly distributed within a specified range. After normalizing the bounds of the control factors from [-1, 1], the normalized deviation ranges become $?_{X1} = ?_{X2} = ?_{X3} = ?_{X4} = ?_{X5} = ?_{X6} = ?_{X7} = 0.1$. Therefore, top-level design specifications are flexible specifications which are allowed to vary between $X-?_X$ and $X+?_X$. To develop robust top-level specifications that could reduce the impact of uncertain downstream design considerations, the engine turbine entry temperature and burner efficiency are modeled as uniformly distributed design parameters with means at their middle levels $\mu_{X8} = \mu_{X9} = 0$, and a normalized variance of $?_{X8} = ?_{X9} = 0.1$.

Insert Figure 10 here

Figure 10 – Mathematical Formulation of the Compromise DSP for Multiple Quality Considerations

Since system performance variations are caused by variations of both control and noise factors, instead of using a single value for the target of a goal, a range of specifications [LRL, URL] is considered, e.g., the target value for gross weight GW is specified as 850,000 lbs = T_{GW} = 945,000 lbs. Design capability indices C_{dk} are utilized to assess the capability of a robust design solution to satisfy a *ranged* set of design requirements. Design capability indices are based on the concept of process capability indices in statistical process control and provide a single objective, alternative approach to the use of Taguchi's signal-to-noise ratio [28]. In brief, C_{dk} is computed using Eqn. 5, and C_{dk} is taken as the minimum of C_{dl} and C_{du}.

$$C_{dl} = \frac{\mu - LRL}{\Delta y}\ ;\ C_{du} = \frac{URL - \mu}{\Delta y}\ ;\ C_{dk} = \min\{C_{dl}, C_{du}\}. \qquad (5).$$

Using the compromise DSP, the target value is one (1) for the maximization of C_{dk} to ensure that variations of system performance fall within a specified region. To calculate C_{dk}, the variance of system performance, i.e., $?_{y(\mathbf{X})}$, could be derived using Eqn. 3.

To maximize the independence of functional requirements and incorporate considerations for developing modifiable top-level specifications, several easy-to-satisfy constraints are eliminated based on the initial experiments. The five overall design requirements, namely, gross weight, fuel weight, NO_x emissions, SFC, and lift-over-drag ratio are assumed to be the functional requirements **FR**s. Since Suh's equation for calculating semangularity, S, is useful only for a square design matrix, the design variables **DP**s, that is, the control factors, must be reduced from seven to five. In Step 3 and Figure 9, factor 3, wing loading, and factor 5, fan pressure ratio, have been found to be relatively insignificant so their values are fixed. Therefore, in addition to maximizing the design capability index C_{dk} for each design requirement, goals 6, 7 and 8 are added to maximize reangularity, R, and semangularity S, and to minimize the difference between R and S to achieve functional independence, Figure 10. The values of R and S are calculated based on the design matrix, A, which could be derived using response surface models.

In the compromise DSP, tradeoffs between multiple objectives are implemented by minimizing the total deviation function Z, Figure 10. When the objective needs to be maximized (or minimized), deviation variable d_i^- (or d_i^+) is used in the deviation function. When the objective is to achieve as close as possible to the target, $(d_i^- + d_i^+)$ is used in the deviation function. In this problem, except that the goal of minimizing the difference between R and S is represented by minimizing $d_8^- + d_8^+$, the rest of goals are desired to be maximized (minimizing d_i^-). f_1 through f_8 in the deviation function represent different priority levels assigned to the eight goals. Initially, when the deviation function Z in Figure 10 is an Archimedean function with equal weights for each goal, the results of the top-level design specifications are given in Table 1.

Insert Table 1 here

Table 1 – Top-Level Design Specifications with Quality Considerations

It is noted from Table 1 that, except the two discrete top-level specifications (NPT and RANGE), results of the other specifications are in ranges rather than single values as developed in a conventional problem. Since the factor effects of TR and TCA are found to be trivial in the screening experimentation, ranges of solutions for these two factors are the same as their initial design ranges. This indicates that any value within the initial given range is acceptable. In Table 2, the achieved system performance is compared to the ranges of demands and wishes specified originally. Unlike the results of a conventional optimization problem without quality considerations, the system performance achieved here has ranges associated with the performance mean values. This variation (delta) is contributed by both the deviation of top-level design specifications (control factors) and the variance of uncertain technological factors (noise factors). For example, with deviations of control and noise factors, the system performance parameter gross weight GW will be 924,463 ± 40,037 lbs, which means the mean of GW will be 924,463 lbs while the variation is ± 40,037 lbs. GW will thus vary within the range [884,426, 964,470] lbs. Since the demands on GW is between [791,667, 1108,333] and the wishes on GW is [850,000, 945,000], see Figure 10, it is noted that within the range of performance variation, demands can always be satisfied while wishes may be violated for certain situations. This verifies the use of design capability index C_{dk} and the compromise DSP. The design capability index represents the extent to which the wishes are satisfied. For example, the achieved C_{dk} for GW in this case is 0.513, while 1 is the target. As for achieving the functional independence, both R and S, are far away from their targets "1" under both deviation functions. Especially the S which measures the alignment of the DP-axes with the corresponding FR-axes is very low. Though the current design solution has been maximized with respect to R and S, the results indicate that the system is still strongly coupled. To further increase the functional independence and therefore to enhance the modularity, it is necessary to apply Suh's independence axiom upfront in a design process to obtain a decoupled system by choosing the best set of FRs and DPs. This topic is not within the scope of this work.

Insert Table 2 here

Table 2 – A Comparison of the Achieved Performance with Design Requirements

5. CLOSURE

In this paper we have illustrated the efficacy of using the Robust Concept Exploration Method to enhance design productivity by increasing design knowledge and maintaining design freedom early-on along a design time-line. The design knowledge is increased by implementing sophisticated integrated systems analysis in the early stages of design and making decisions based on better information. We maintain design freedom through developing robust, flexible and modifiable early design specifications. Our approach offers an alternative to improving the computational efficiency for design problems involving sophisticated and time-consuming concurrent systems analysis. Thus we expect improved designs as well as the reduction of time and therefore the cost of doing design concurrently for complex systems such as aircraft and ships. The RCEM can be applied to various kinds of engineering problems; in this paper we have illustrated our approach for a hsct aircraft design problem. Other examples include the design of a general aviation aircraft [29] and aircraft engines [30].

In this paper, using the HSCT as an example, we show that statistical experimentation methods provide an effective way of formalizing design knowledge in the early stages of design. We illustrate that Taguchi's parameter design can be applied in the early stages of design for developing robust top-level specifications which are insensitive to *small adjustments* in later design stages; the method of robust design can be further extended to developing flexible top-level specifications which are allowed to vary *within a range*. We also demonstrate that Suh's independence axiom can be incorporated into the compromise DSP in addition to the robust design considerations to achieve independence of overall design requirements and therefore reduce the impact of design adjustments in response to large changes in design requirements. The creation of response surface models has facilitated the independence measurement by providing the information of a design matrix.

It is important to note the limitations of the method presented here. First, the goal and constraint functions used in the compromise DSP (Module F in Figure 5) are approximate functions using the methods of statistical design of experiments and specifically quadratic models. There are cases in which the performance is highly nonlinear and a second-order model is not good enough even within a reduced region. A combined RSM and neural network approach has been proposed to overcome this limitation [31].

Acknowledgment

We thank Rudi Cartuyvels (cartuyvl@imec.be) for providing us with a copy of NORMAN® to automate the process of creating response surface models. We are grateful to Tim Simpson for his help in some of the figures in this publication. We appreciate the Aerospace Systems Design Laboratory at Georgia Tech for providing us the HSCT baseline model. Wei Chen was supported by the G.W. Woodruff School of Mechanical Engineering at the Georgia Institute of Technology during her graduate study. We gratefully acknowledge NSF grant DDM-93-96503 and NASA Grant NAG-1-1564.

References

[1] R. I. Winner, J. P. Pennell, H. E. Bertrand and M. M. G. Slusarczuk, *The Role of Concurrent Engineering in Weapons System Acquisition,* IDA Report R-338, Institute for Defense Analysis, Alexandria, Virginia, 1988.

[2] K. Hutchison and D. R. Hoffman, "Implementing Concurrent Engineering", *High Performance Systems,* 1990, pp. 40-44.

[3] B. Prasad, *Concurrent Engineering Fundamentals: Integrated Product Development*, Vol. 1 & Vol. 2, Prentice Hall PTR, Upper Saddle River, New Jersey, 1996.

[4] N. Michelena and P. Papalambros, Optimal Model-Based Decomposition of Powertrain System Design , *Trans. ASME, Journal of Mechanical Design*, Vol. 117, No. 4, December 1995, pp. 499-505.

[5] S. Springer and R. Gadh, “State of the Art Virtual Reality Hardware for Computer Aided Design,”, *Journal of Intelligent Manufacturing*, Chapman & Hall, 7(6), December 1996, pp. 457-465.

[6] J.M. Vance, "Research in Implementing a Virtual Environment for Engineering Design", *Proceeding of the First Work Shop On Simulation and Interaction in Virtual Environments* (SIVE95), University of Iowa, July 13-15, 1995, pp. 251-255.

[7] G. Fadel, D. Crane, L. Dooley and R. Geist, "A Link between Virtual and Physical Prototyping" Presented at the SME Rapid Prototyping and Manufacturing Conference, Detroit, Mi, May 2-4, 1995, *Proceedings of the SME RP conference*, May 1995

[8] J.C. Townsend, R.P. Weston, and T.M. Eidson, "A Programming Environment for Distributed Complex Computing: An Overview of the Framework for Interdisciplinary Design Optimization (FIDO) Project", *NASA Technical Memorandum* 109058, NASA Langley Research Center, December 1993.

[9] J. Pennell and M. Slusarczuk, "An Annotated Reading List for Concurrent Engineering,", Technical Report HQ 89--034130, Alexandria, VA: Institute for Defense Analysis, 1989.

[10] S. Amarel, "Artificial Intelligence and Design", *Proceedings of the 5th Jerusalem Conference on Information Technology,* Los Alamitos, CA, pp. 315-333, 1990.

[11] J. D. Nicklaus, S. S. Tong, and C. J. Russo, "Engineous: A Knowledge Directed Computer Aided Design Shell," *The Third Conference on Artificial Intelligence Applications,* Kissimmee, FL, 1986.

[12] M. S. Phadke, *Quality Engineering Using Robust Design,* Prentice Hall, Englewood Cliffs, New Jersey, 1989.

[13] N. P. Suh, *Principles of Design,* Oxford University Press, Oxford, U.K., 1990.

[14] A. Khuri and J. A. Cornell, *Response Surfaces: Designs and Analysis,* Marcel Dekker Inc., New York, 1987.

[15] F. Mistree, O. F. Hughes and B. A. Bras, "The Compromise Decision Support Problem and the Adaptive Linear Programming Algorithm", *Structural Optimization: Status and Promise,* edited by M. P. Kamat, AIAA, Washington, D.C., 1993, pp. 247-286.

[16] G. V. Reklaitis, A. Ravindran and K. M. Ragsdell, *Engineering Optimization – Methods and Applications,* John Wiley and Sons, New York, 1983.

[17] G. E. P. Box, W. G. Hunter and J. S. Hunter, *Statistics for Experiments,* John Wiley & Sons, New York, 1978.

[18] P. Hajela and L. Berke, "Neural Networks in Structural Analysis and Design: An Overview", *Intl'l J. for Computing Systems in Engineering*, **3**(1-4), 1992, pp. 525-539.

[19] D. C. Montgomery, *Design and Analysis of Experiments,* John Wiley & Sons, New York, 1991.

[20] G. E. P. Box and N. R. Draper, *Empirical Model-building and Response Surfaces,* Wiley Series in Probability and Mathematical Statistics, John Wiley & Sons, New York, 1987.

[21] W. Chen, J. K. Allen, D.P. Schrage, and F. Mistree, "Statistical Experimentation Methods for Achieving Affordable Concurrent Design", *AIAA Journal*, 35 (5), May 1997, pp. 893-900.

[22] G. Taguchi, "Off-Line and On-Line Quality Control Systems", *Proceedings of the International Conference on Quality Control,* Tokyo, Japan, 1978.

[23] W. Chen, J. K. Allen, K-L. Tsui, and F. Mistree, "A Procedure for Robust Design" *Transaction of the ASME Journal*, *Journal of Mechanical Design*, 118, 1996, pp. 478-485.

[24] J.P. Ignizio, "Multiobjective Mathematical Programming via the MULTIPLEX Model and Algorithm," *European Journal of Operational Research*, Vol. 22, 1985, pp. 338-346.

[25] W. Chen, D. Rosen, J. K. Allen, and F. Mistree, "The Modularity and Independence of Functional Requirements in Designing Complex Systems" ASME Winter Annual Meeting, Chicago, IL. Published in Concurrent Product Design, (R. Gadh, Ed.) ASME DE-Vol.74, November 1994, pp. 31-38.

[26] W. Chen, "A Robust Concept Exploration Method for Configuring Complex Systems", Ph.D. Dissertation, Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, Georgia, 1995.

[27] L. A. McCullers, *Flight Optimization System, User's Guide,* 1993. NASA Langley Research Center. email: amccul@avd00.larc.nasa.gov.

[28] W. Chen, T.W. Simpson, J. K. Allen, and F. Mistree, "Using Design Capability Index for Satisfying a Ranged Set of Specifications," *1996 ASME Design Automation, Conference,* Irvine, California, August 1996. Paper Number 96-DETC/DAC-1090.

[29] T.W. Simpson, W. Chen, J. K. Allen, and F. Mistree, "Conceptual Design of a Family of Products Through the Use of the Robust Concept Exploration Method", AIAA/NASA/USAF/ISSMO *Symposium on Multidisciplinary Analysis and Optimization,* Bellevue, Washington, September 4-6, 1996.

[30] Koch, P.N., Barlow, A., Allen, J.K. and Mistree F., "Configuring Turbine Propulsion Systems using Robust Concept Exploration," *1996 ASME Design Automation, Conference,* Irvine, California, August 1996. Paper Number 96-DETC/DAC-1285.

[31] W. Chen and S. Varadarajan S., "Integration of Design of Experiments and Artificial Neural Networks for Achieving Affordable Concurrent Design", *38th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference,* Kissimee, FL, AIAA paper No. 97-1230, April 1997, pp. 1316-1324,

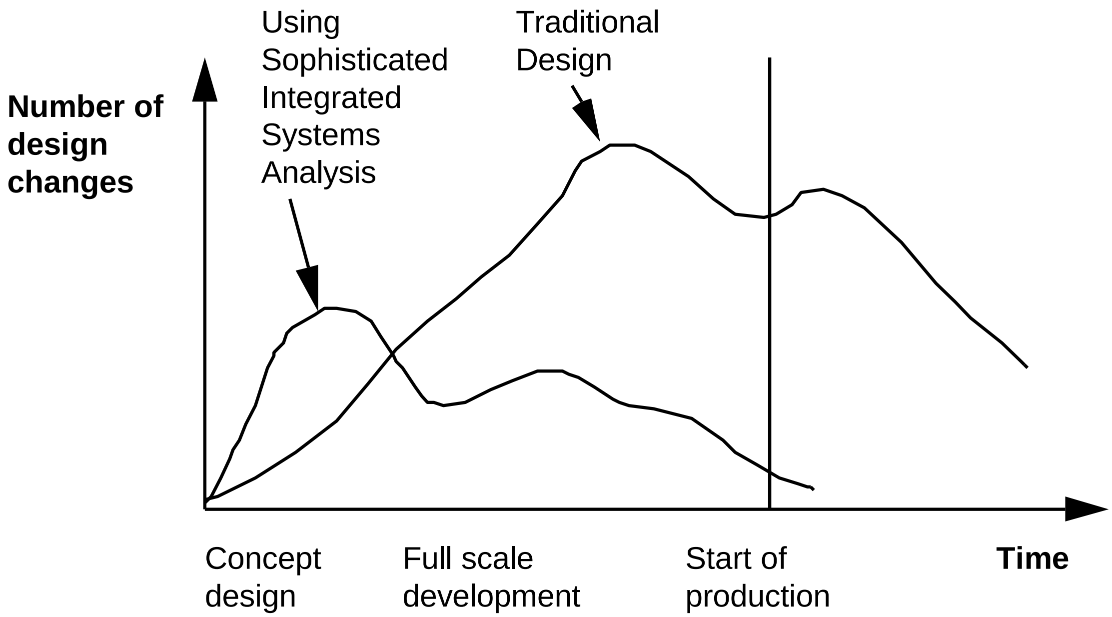

Figure 1 – Sophisticated Concurrent Systems Analysis for Reducing the Number of Design Changes

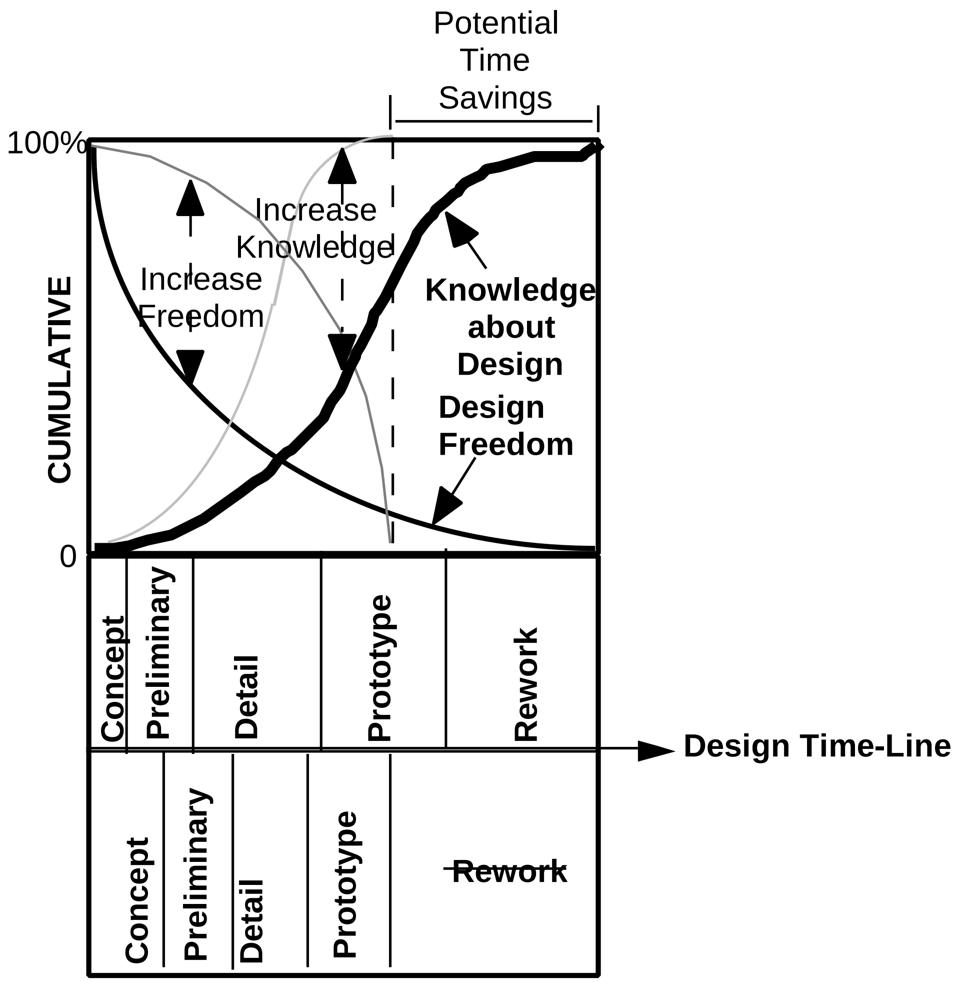

Figure 2 – Improve Design Productivity by Increasing Design Knowledge and Maintaining Design Freedom

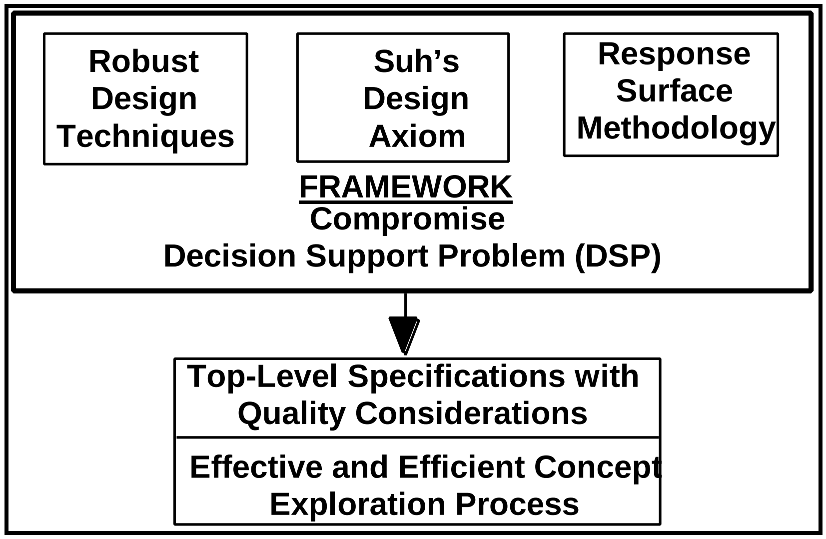

Figure 3 – Integration of Metrics, Tools and the Compromise DSP Framework

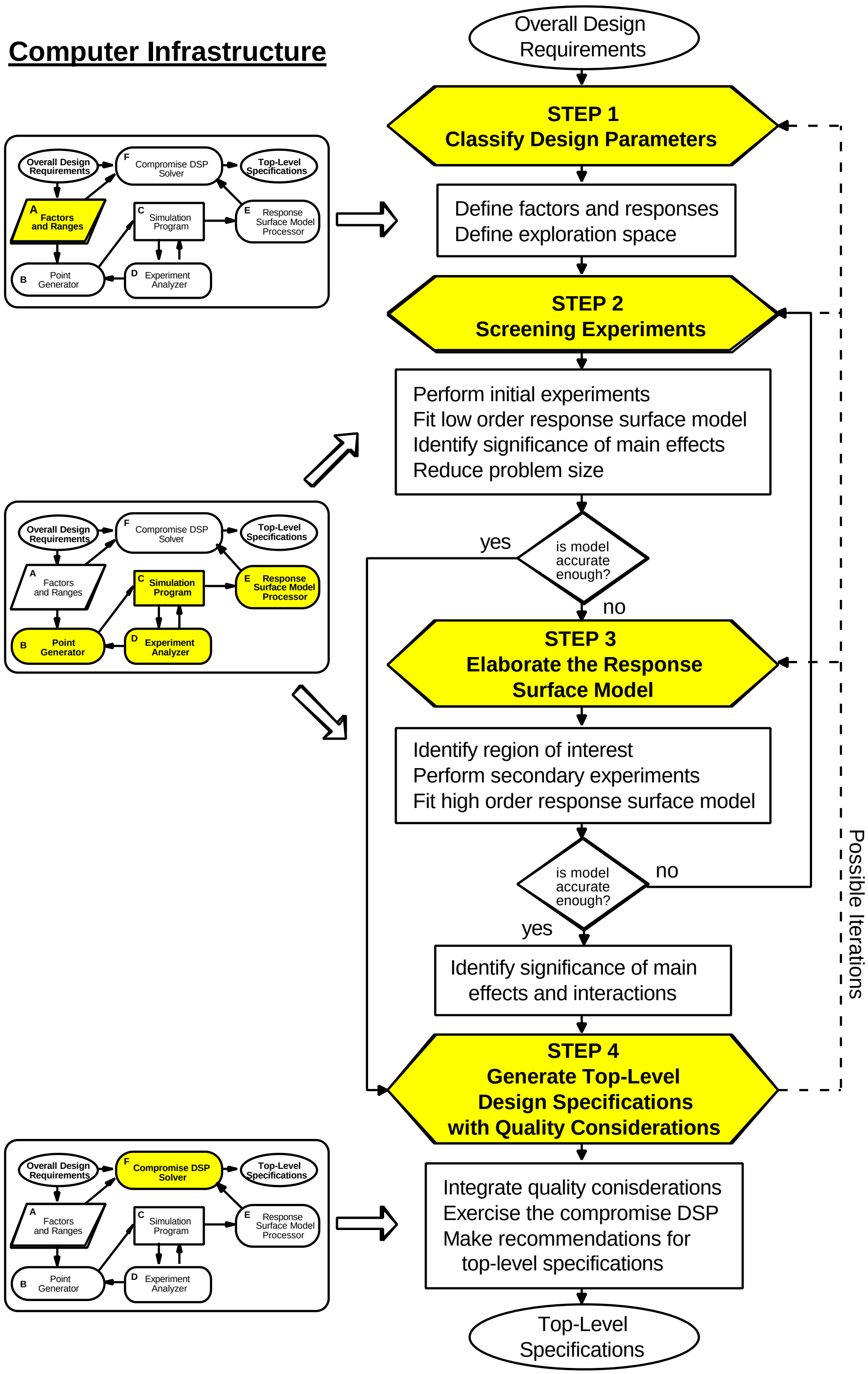

Figure 4 – Relationships between RCEM Steps and the Computer

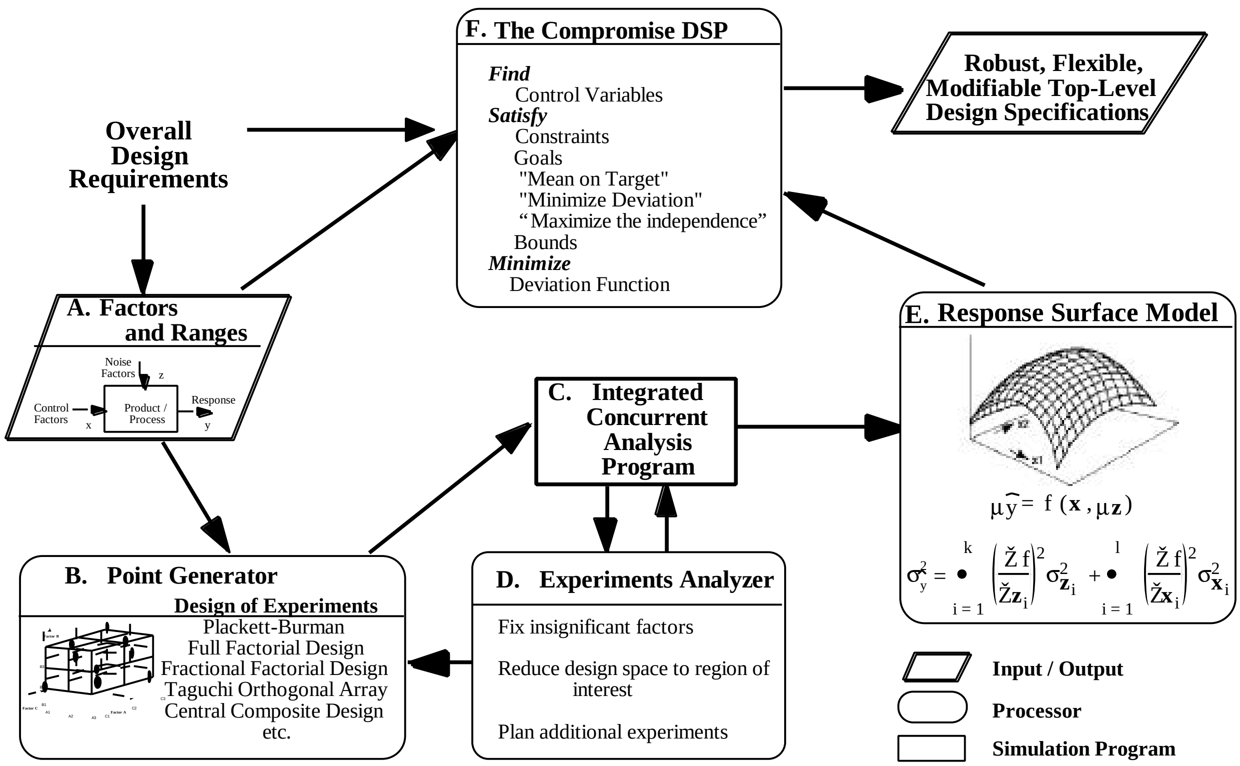

Figure 5 – The Computer Infrastructure of the RCEM

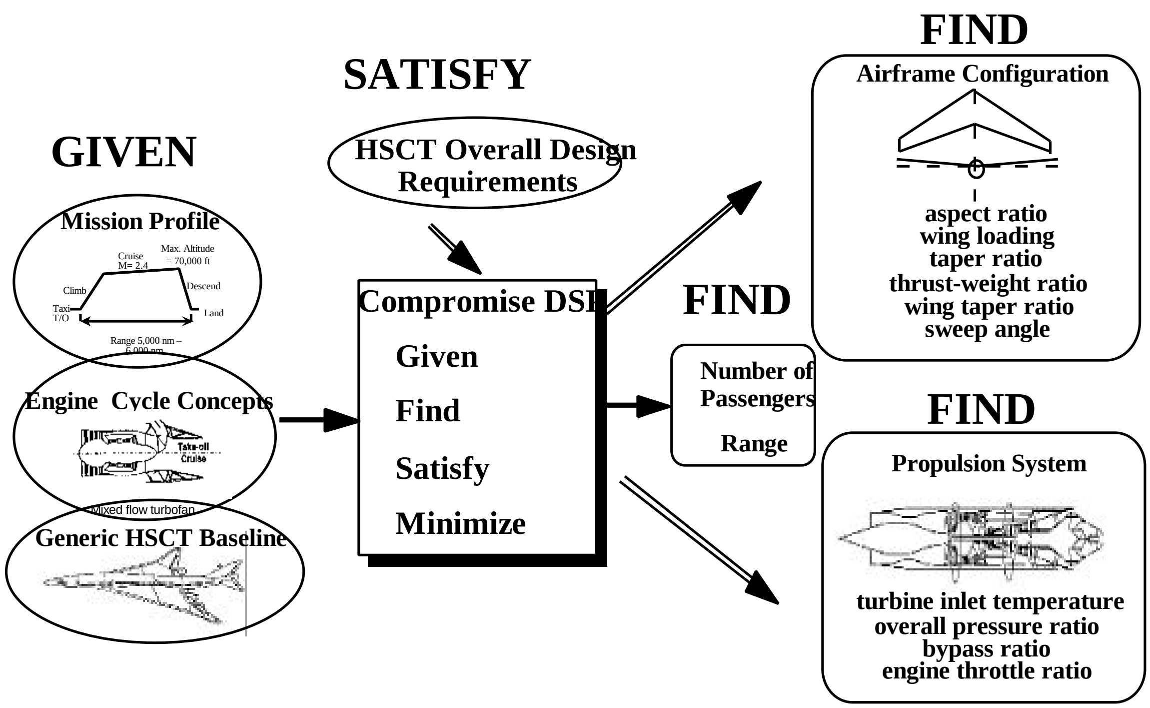

Figure 6 – The HSCT Case Study

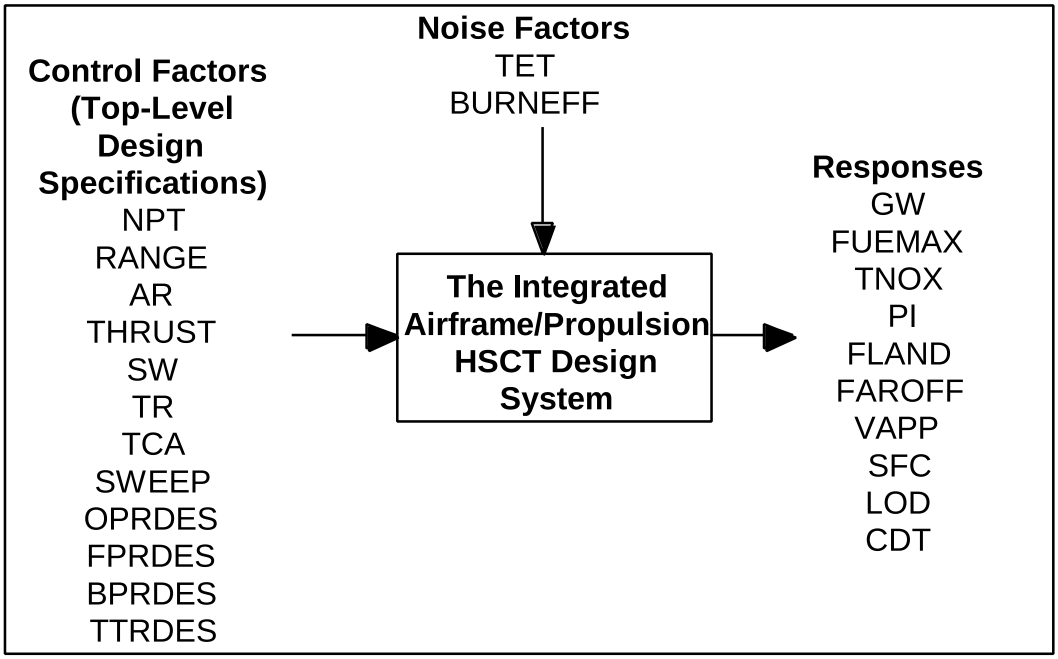

Figure 7 – P-diagram of the HSCT Design System

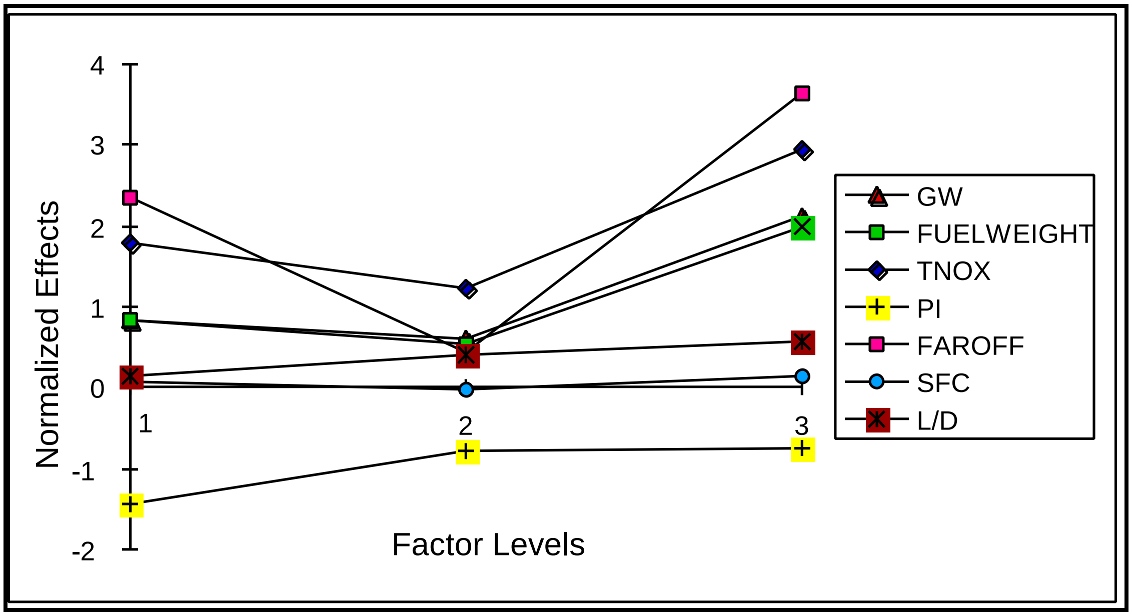

Figure 8 – The Effects Plot for Number of Passengers

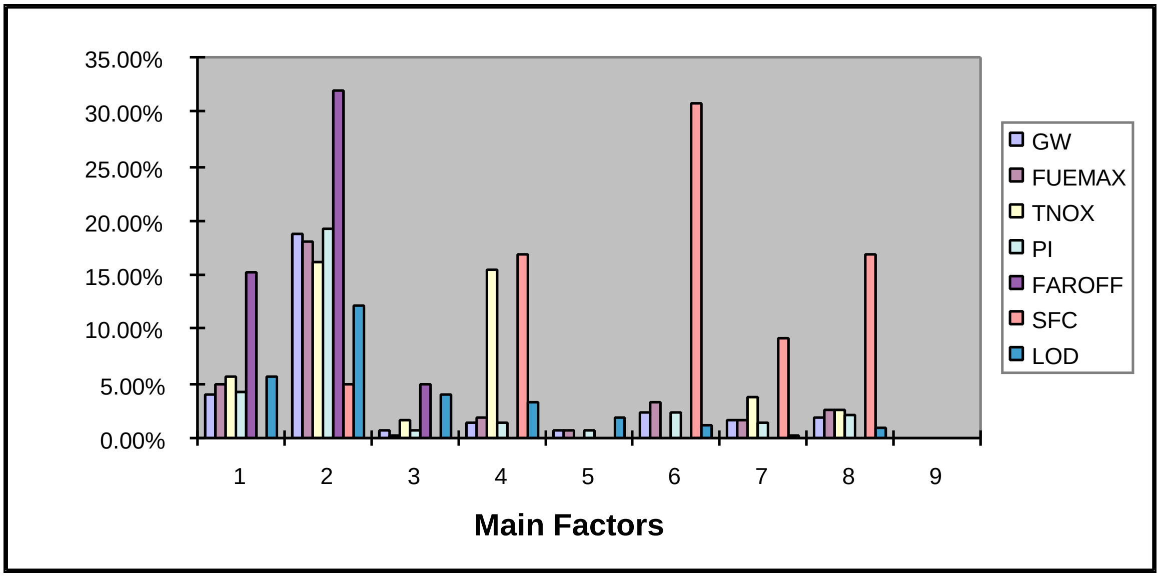

Figure 9 – Significance of Linear Effects from CCD Experiments

Given:

- Response Surface Models of performance obtained from Step 3 of the RCEM
- Number of passengers NPT = 300,
- Range DRANGE = 5000 nm
- Mission profile (altitude, range, reserve fuel, etc.)
- Engine type= mixflow turbo fan
- Generic HSCT baseline configuration
- Overall Design Requirements
- Two control factors (wing loading and fan pressure ratio) are constant: X_3 = -1, X_5 = 0.5 (normalized)
- Noise Factors (turbine entry temperature and burner efficiency) are uniformly distributed within the given range, with means at their middle levels, X_8=X_9=0, deviation $?_{X8}$ = $?_{X9}$ = 1
- Control factors (system variables) are uniformly distributed within a specified range, with deviation $?_{X1}$ = $?_{X2}$ =$?_{X3}$ = $?_{X4}$ =$?_{X7}$ = 0.1 (normalized)
- The Range of *Targets* for overall design requirements
  Gross Weight: 850,000 lbs = T_{GW} = 945,000 lbs NOx emission: 5,700 lbs = T_{NOX} = 6,300 lbs
  Fuel Weight: 480,000 lbs = T_{FUE} = 504,000 lbs SFC 1.340 lb/lb-hr=T_{SFC}=1.367 lb/lb-hr
  Lift-over-drag ratio 7.25 = T_{LOD} = 7.4
- The target for reangularity and semangularity T_R=1, T_S= 1

Find:

- The system variables (top-level design specifications), $\mathbf{X}_i$, i=1, 2, 4, 6, 7
  - The wing aspect ratio: AR X_1
  - The thrust-weight ratio: THRUST X_2
  - The overall pressure ratio: OPRDES X_4
  - The bypass ratio: BPRDES X_6
  - The engine throttle ratio: TTRDES X_7
- The values of the deviation variables associated with goals G(**X**): d_i^-, d_i^+, I=1, 8.

Satisfy:

- The system constraints, C(**X**)
  - gross weight GW(**X**) + $?_{GW}$(**X**) = 1108,333 lbs GW(**X**) - $?_{GW}$(**X**) = 791,667 lbs
  - fuel weight FUEMAX(**X**) + $?_{FUE}$(**X**)= 641,667 lbs FUEMAX(**X**) - $?_{FUE}$(**X**)= 458,3333 lbs
  - emission TNOX(**X**)+$?_{NOX}$(**X**) = 8,167 lbs TNOX(**X**) - $?_{NOX}$(**X**) = 5,833 lbs
  - productivity index PI(**X**) +$?_{PI}$(**X**)= 99 knots PI(**X**) -$?_{PI}$(**X**) = 71 knots
  - Take-off field length FAROFF(**X**) +$?_{OFF}$(**X**)= 11000 ft
  - Specific Fuel Consumption SFC(**X**) +$?_{SFC}$(**X**)= 1.382 lb/hr/lb SFC(**X**) -$?_{SFC}$(**X**) = 1.298 lb/hr/lb
  - lift-over-drag ratio LOD(**X**) +$?_{LOD}$(**X**)= 7.53 LOD(**X**) - $?_{LOD}$(**X**) = 6.87
- The system goals, G(**X**),
  - Maximize design capability index for gross weight, GW:
    $C_{GW}(\mathbf{X}) + d_1^- - d_1^+ = 1.0$ $C_{GW}(\mathbf{X})=\{945000.0-GW(\mathbf{X})\}/?_{GW}(\mathbf{X})$
  - Maximize design capability index for fuel weight, FUEMAX:
    $C_{FUEMAX}(\mathbf{X}) + d_2^- - d_2^+ = 1.0$ $C_{FUEMAX}(\mathbf{X})=\{504{,}000-FUEMAX(\mathbf{X})\}/?_{FUE}(\mathbf{X})$
  - Maximize design capability index for NOx emission, TNOX:
    $C_{TNOX}(\mathbf{X})+ d_3^- - d_3^+ = 1.0$ $C_{TNOX}(\mathbf{X})=\{6300-TNOX(\mathbf{X})\}/?_{NOX}(\mathbf{X})$
  - Maximize design capability index for specific fuel consumption, SFC:
    $C_{SFC}(\mathbf{X}) + d_4^- - d_4^+ = 1.0$ $C_{SFC}(\mathbf{X})=\{1.367-SFC(\mathbf{X})\}/?_{SFC}(\mathbf{X})$
  - Maximize design capability index for lift-over-drag, LOD:
    $C_{LOD}(\mathbf{X}) + d_5^- - d_5^+ = 1.0$ $C_{LOD}(\mathbf{X})=\{LOD(\mathbf{X})-7.25\}/?_{LOD}(\mathbf{X})$
  - Maximize reangularity, $R(\mathbf{X}) + d_6^- - d_6^+ = 1.0$
  - Maximize semangularity, S $S(\mathbf{X}) + d_7^- - d_7^+ = 1.0$
  - Minimize the difference between R and S, $R(\mathbf{X}) - S(\mathbf{X}) + d_8^- - d_8^+ = 1.0$
- The bounds on the system variables: n.m.u.–no meaning unit
  -1 = AR = 1 [n.m.u] -1 = THRUST = 1 [n.m.u.] -1 = SW = 1 [n.m.u]
  -1 = OPRDES = 1 [n.m.u.] -1 = TTRDES = 1 [n.m.u.]

Minimize : • The sum of the deviation variables associated with the goals

$$Z = \{f_1(d_1^-), f_2(d_2^-), f_3(d_3^-), f_4(d_4^-), f_5(d_5^-), f_6(d_6^-), f_7(d_7^-), f_7(d_8^-+d_8^+)\}$$

Figure 10 – Mathematical Formulation of the Compromise DSP for Multiple Quality Considerations

Table 1 – Top-Level Design Specifications with Quality Considerations

	TLDS	**Levels or Range**
System Level Concepts	Number of Passenger, NPT	300
	Range, RANGE	5000 nm
Airframe Configuration	Aspect Ratio, AR	2.13073 ± 0.008
	Thrust-Weight Ratio, THRUST	0.409619 ± 0.01
	Wing Loading, SW	115 ±0.5 lbs/sq. ft
	Taper ratio, TR	[0.06 – 0.08]
	Thickness-Chord Ratio, TCA	[0.02 – 0.04]
	Sweep Angle, SW	[55 – 75] degree
Propulsion System	Overall Pressure Ratio, OPRDES	18 ± 0.2
	Fan Pressure Ratio, FPRDES	4.45 ± 0.015
	Bypass Ratio, BPRDES	0.255231 ± 0.01
	Engine Throttle Ratio, TTRDES	1.1 ± 0.004

Table 2 – A Comparison of the Achieved Performance with Design Requirements

	Achieved Performance	Demands	Wishes	Cpk
GW (lb)	924463 ± 40037	[791, 667, 1108,333]	[850,000, 945,000]	0.5123
FUEMAX (lb)	506051 ± 19552	[458,3333, 641,667]	[480,000, 504,000]	-0.105
LOD	7.27236 ± 2.23911	[6.87, 7.53]	[7.25, 7.4]	0.578
TNOX (lb)	6129.02 ± 296.00	[5,833, 8,167]	[5,700, 6,300]	1.3548
PI(knots)	82.6143 ± 3.933	[71, 99]		
FAROFF (ft)	10656.5 ± 343.8	= 11000		
SFC	1.34897 ± 0.01331	[1.298, 1.382]	[1.340, 1.367]	0.9988

List of Figures

List of Tables

Authors' Biographical Information

Dr. Wei Chen became an Assistant Professor in the Department of Mechanical Engineering at Clemson University in 1995. She is the co-director of the CREDO lab (Clemson Research in Engineering Design & Optimization Lab, http://www.eng.clemson.edu/dmg). Her research goal is to advance the design theory, methods, and tools for those designs with a magnitude of complexity, in the context of globally competitive markets and the need to quickly respond to the change. Her current research involves issues such as robust design, decision analysis and support, multidisciplinary optimization, uncertainty analysis, and simulation-based distributed cooperative systems design. Dr. Chen received her Ph.D. from the Georgia Institute of Technology in 1995. This paper is published based on her doctoral dissertation which won the 1996 Georgia Tech Sigma Xi Doctoral Dissertation Award. Dr. Chen is a member of ASME, AIAA, and ASQC.

Dr. Janet Allen became a Senior Research Scientist in the Woodruff School of Mechanical Engineering at Georgia Tech in 1992. Her specialty is mechanical engineering design; she is interested in the understanding how design products and processes evolve over time. This naturally leads to an interest in decision making and the decision structures necessary to design engineering systems. Dr. Allen also has a strong interest in design pedagogy; she is one of the co-developers of the Design Learning Simulator (www.srl.gatech.edu/DLS/). Dr. Allen received her Ph.D. from the University of California at Berkeley in 1973 and her S.B from the Massachusetts Institute of Technology in 1967.

Professor Farrokh Mistree's design experience spans mechanical, aeronautical, structural, industrial and software engineering. His research focus is on learning what happens when concurrent engineering principles are applied to the design, deployment, operation and support of *open engineering systems*. He is committed to developing a design pedagogy that is rooted in Decision-Based Design and adaptive action learning. It is in this context that he enjoys experimenting with ways in which design can be learned and taught. Professor Mistree is responsible for two books and over 180 technical publications. Since 1992 he is a Professor at Georgia Tech. He received his Bachelor of Technology with Honours from I.I.T. Kharagpur, India in 1968 and his M.S. and Ph.D. from the University of California, Berkeley in 1970 and 1974, respectively. He is a Fellow of ASME and a Senior Member of AIAA.