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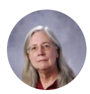
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A CONCEPT EXPLORATION METHOD FOR DETERMINING ROBUST TOP-LEVEL SPECIFICATIONS

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ABSTRACT

In the early stages of design of complex systems, it is necessary to explore the design space to determine a suitable range for specifications and identify feasible starting points for design. Thus, a robust concept exploration method have been developed to improve the efficiency and effectiveness of the process of identifying suitable starting points for the design of complex systems. Using this method, quality concepts (robustness) are introduced into the choice of the initial specifications for design. The Concept exploration is implemented by integrating the Response Surface Method, robust design techniques and the compromise Decision Support Problem. The proposed approach is demonstrated to determining top-level specifications for airframe geometry and the propulsion system for the High Speed Civil Transport aircraft. The focus in this paper is on illustrating the approach rather than on the results *per se*.

Word Count: 6986.

Key words: Concept exploration, robust design, specifications, response surface method, Decision Support Problem.

NOMENCLATURE

d_i^+, d_i^-	Deviation variables in the compromise DSP	
DSP	**D**ecision **S**upport **P**roblem	
HSCT	**H**igh **S**peed **C**ivil **T**ransport	
RCEM	**R**obust **C**oncept **E**xploration **M**ethod	
RSM	**R**esponse **S**urface **M**ethod	
$\mathbf{E}$	Statistical expected value of a function	
$\mathbf{X}$	Control Factors or top-level design specifications	
$\mathbf{Z}$	Noise Factors	
y	Response	
$\hat{y}$	Estimated response	
μ	Statistical mean	
σ	Statistical standard deviation	
CDT	Compressor discharge temperature	deg R
FOFF	Take off field length	ft
FLAND	Landing field length	ft
FPR	Fan pressure ratio	–
GW	Gross weight	lb
MNOx	Mean of NOx	g/kgfuel
MPI	Mean of PI	knots
NOx	Nitrous oxide emissions	g/kg fuel
PI	Productivity index	knots
SFC	Specific fuel consumption	–
TITemp	Turbine inlet temperature	deg R
VAPP	Approach velocity	knots
VNOx	Variance of NOx	$(\text{g/kg fuel})^2$
VPI	Variance of PI	$(\text{knots})^2$

1. FRAME OF REFERENCE

Productivity is of major economic significance in all parts of the industrialized world. Due to growing costs and globalization of the marketplace, in order to improve productivity, the basic objective for the early stages of design is to obtain a reliable design in the shortest possible time. This requires that at the start of a project, a set of top-level design specifications is determined to provide project control and assist in subgroup integration. These specifications must be comprehensive yet general enough to be modifiable. However, due to complexity in analyses, it is not an easy task to include considerations from different disciplines or considerations of downstream life cycle performance. In general, most design automation techniques have concentrated on relatively low levels of design and manufacturing tasks but little has been done to provide assistance in the early stages of design.

A **R**obust **C**oncept **E**xploration **M**ethod (RCEM) is developed in this work to provide assistance in the early stages of the design of complex systems. Given the overall design requirements and integrated analysis packages at different levels of complexity, the method can allow:

- quick evaluation of different design alternatives,
- generation of robust top-level design specifications which incorporate considerations from different disciplines.
- acquisition and shaping of knowledge to reduce or reorganize the design models without risking high costs.

To evaluate design alternatives and generate top-level design specifications, a concept exploration approach was first proposed in the ship design field [1]. Given the mission profile and operating environment, ship performance is simulated for several concepts.

These concepts are represented by a set of principal dimensions (length, beam, draft, depth and form coefficients) which can provide early project configuration control (placement of machinery, type and number of propellers, rudder configuration, etc.). The design concepts are evaluated and the most promising ones are used as top-level design specifications and form the basis for further design. As the generation of concepts is either random or by a grid search, there is no scientific basis for determining how many concepts or in what areas of the design space the concepts should be generated. Because of the amount of computation involved, this is an expensive approach and it is often difficult to find a good starting point.

In recent years, Taguchi's principles of quality engineering and the accompanying statistical techniques, specifically the use of orthogonal arrays for experimental design and the signal-to-noise ratio for quality measurement, have been introduced into engineering design. In our work, the objective of using Taguchi methods is to improve computational efficiency, explore the behavior of a design space, and improve the robustness of the design and, thus the quality of the design. Representative benefits include the reduction in the number of computer runs of a finite element code, ASTROS, for optimum wing structural design [2], design of a LifeSat space vehicle [3] and the use of robust design methods for concurrent concept selection and system synthesis of a solar powered irrigation system [4]. Although Taguchi's complete methodology for quality improvement has been well recognized [5], there are certain limitations to using the Taguchi approach directly for engineering design. These limitations include [6-8]:

- The Taguchi method does not benefit from iteration.
- The experimental designs Taguchi advocates are limited and cannot to deal adequately with interactions.
- More efficient and simpler experiments and methods of analysis are available.

- The arguments for the universal use of the signal-to-noise ratio (loss-model approach) are unconvincing.

Further, in engineering design, it has been found difficult to use the Taguchi approach to find experimental points in the design space where all the engineering constraints are satisfied.

Although there are limitations associated with the Taguchi method, we believe his approach represents a significant advance in the application of experimental designs to the improvement of product quality. We have investigated these limitations and propose to integrate the response surface method (RSM) with the compromise Decision Support Problem (DSP) in developing a general robust design procedure [9]. We also expand this robust design procedure to improve the efficiency and effectiveness of the process of concept exploration itself. In this paper, a Robust Concept Exploration Method (RCEM) which is based on the integration of robust design techniques, RSM and the compromise DSP, is presented. As shown in Figure 1, robustness is introduced into the choice of initial specifications and the proposed method is used to improve computational efficiency in concept exploration. A detailed description of our approach is provided in Section 2.

- INSERT FIGURE 1 HERE -

Figure 1 - The Robust Concept Exploration Method: Components

To demonstrate our approach, the RCEM is applied to determining top-level specifications for airframe geometry and a propulsion system for the High Speed Civil Transport (HSCT) aircraft. The development of a HSCT has been the focus of the High Speed Research (HSR) program which was initiated by NASA researchers and American industry subcontractors in 1986. The preliminary study of such a HSCT has been selected as a pilot project for the implementation of the Integrated Product and Process Development (IPPD) approach proposed by the School of Aerospace Engineering at Georgia Tech [10]. Since the identification of a suitable propulsion system is generally acknowledged to be a key requirement for the successful development of a new airplane, one focus of the HSCT research program is to identify the most promising propulsion system and its associated technologies [11]. The traditional method of engine cycle sizing and optimization is loosely coupled to the overall vehicle synthesis and mission analysis. This results in a time consuming iterative process. Lavelle and co-authors, developed an integrated propulsion/airframe analysis system to address the interactions between propulsion system analysis and overall mission performance analysis in the preliminary stages of design [12]. For a variety of engine cycle types, Geiselhart incorporates the optimization of major engine design variables to introduce design considerations from later design stages (subsystem and component design) into design at the system level [13]. Geiselhart integrates a cycle analysis module into the Flight Optimization System (FLOPS) [14], a multidisciplinary system of computer programs for conceptual and preliminary design and evaluation of advanced aircraft concepts. This allows environmental concerns, e.g., airport noise and emissions, to be addressed early in the design process. However, problem size is limited, the number of design variables permitted is small and the optimization process is time consuming.

Using the FLOPS analysis modules for simulation, it is shown in this paper that an RCEM can be used to explore airframe configurations and propulsion system designs and determine robust top-level design specifications. The relative significance of engine cycle, engine component and airframe design variables are identified with respect to their influence on system performance; the fitted response surface model serves as a fast analysis module and robust top-level design specifications are generated using a compromise DSP. Our focus in this paper is on illustrating our approach rather than on the results *per se*.

2. THE ROBUST CONCEPT EXPLORATION METHOD

In this section, each of the three components of our method, the response surface method, robust design techniques, and the compromise DSP, is described. It is also shown here how they are integrated, Figure 1.

2.1 The Response Surface Method

The RSM is a collection of statistical techniques which support the design of experiments [15-16]. By careful experimental design and analysis, a *response* or *output* variable is associated with levels of a number of *predictors* or *input* variables. This is particularly useful if there are large computer run times associated with design analysis of complex systems because the precise relationships between *input* and *output* are unknown. RSM is a very powerful tool for empirically mapping relationships between independent design variables and their dependent performance functions. The response surface model can be used as fast analysis module, and its normalized function can be used to identify significant input variables. For example, RSM has been applied in aircraft aerodynamic configuration design to select a set of design parameters which have great impact on system performance and to achieve the optimal configuration based on the surface model [17].

Among the various kinds of experimental design for fitting a response surface model, the Central Composite Design (CCD) is probably the most widely used for fitting second-order response surfaces and studying second-order effects [18]. As shown in Figure 2, central composite designs are first order fractional factorial designs augmented by an additional star and centers which allows the estimation of a second order surface. The least squares method is used to fit a quadratic surface model of the following form:

$$f(x_1,\ldots x_n) = \underbrace{\beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n}_{\text{(Linear Terms)}} + \underbrace{\gamma_1 x_1^2 + \ldots + \gamma_n x_n^2}_{\text{(Quadratic Terms)}} + \underbrace{\beta_{12} x_1 x_2 + \ldots + \beta_{n,n-1} x_{n-1} x_n}_{\text{(Interaction Terms)}}$$

- INSERT FIGURE 2 HERE -

Figure 2 - Three Variable Central Composite Design

Using CCD, the number of experiments needed for fitting a second-order model is significantly less than would be required in a three-level full factorial design. The benefit of using this technique increase as the number of factors increases. Another benefit of using RSM lies in its application to robust design to overcome the limitations of the Taguchi method.

2.2 Robust Design Techniques

The method of robust design, sometimes called the Taguchi method, has been developed to improve the quality of a product by minimizing the variations in system response (performance) without eliminating the causes of that variation in the input to the system. In robust design, the relationship between different types of factors is represented in a P-diagram, where P represents either product or process [19]. The three types of input factors to be considered are *Control Factors (x)* – parameters which can be specified freely by a designer, *Noise Factors (z)* – parameters which are not under a designer's control, and *Signal factors (M)* – targets to be achieved for system performance.

As mentioned in Section 1, there are several limitations associated with the Taguchi method. We carefully examined the limitations and propose the integration of the RSM with the compromise DSP in developing a *general* robust design procedure [9]. In addition to minimizing variation in performance caused by variations in noise factors (uncontrollable parameters), for which the Taguchi method has been developed, we expand robust design to include minimizing variations in performance caused by the variations in control factors (design variables). Using our proposed procedure, the response-model postulates a single, formal model of the type

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

where $\hat{y}$ is the estimated response and $\mathbf{x}$ and $\mathbf{z}$ 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 the mean values, k, l are the number of noise factors and control factors with deviations. The standard deviation associated with noise and control factors are σ_{Zi} and σ_{Xi}. In Eqn. 3, it is assumed that the noise variables are independent. Based on the estimated mean and variance of response, robust design is achieved by bringing the mean on target and minimizing the variance of response.

A significant part of this work is the introduction of quality concepts (robustness considerations) into the concept exploration process. To develop comprehensive top-level specifications, downstream design considerations are introduced early in the process. However, some design parameters, particularly those at the component level, may not have been identified in the concept exploration stage. Using robust design, these unknowns are modeled as noise factors and the values of control factors are found to dampen the effects of the unknown information. In order to provide flexible top-level design specifications so that the designer can have more freedom in the later stages of design, control factors in which there is variation are considered. Using robust design, instead of looking for an absolute optimum, we search for a flat region which is close to the target and has the least variation if there are deviations in design variables, Figure 3.

- INSERT FIGURE 3 HERE -

Figure 3 - Developing Robust Top-Level Design Specification

2.3 The Compromise Decision Support Problem

The compromise DSP is a multiobjective decision model which enables a designer to determine values of design variables which satisfy a set of constraints to achieve as closely as possible a set of conflicting goals [20]. The objective is to minimize the deviations of different goals from their desired target values using the concept of lexicographic minimization [21].

As the achievement of robustness (bringing mean to the target and minimizing variance) involves trade-offs, an important aspect of this work is the modeling and handling of multiple trade-offs simultaneously. The standard RSM is useful in searching for the optimum (maximum or minimum) of a single response but is inadequate to address multiple trade-offs and design constraints. The compromise DSP provides a general approach to achieve robust design by enabling a designer to find values of control factors to achieve a performance which is as close as possible to the target values and to minimize variations around these targets, subject to engineering constraints. Using the compromise DSP, it is possible to address individually the issues of maximizing the intensity of the signal on target and minimizing variation around this target. These become separate goals in the multiobjective compromise DSP. This approach can also help a designer to focus on individual contributions to mean and variation and to identify parameters which affect the attainment of specific goals.

2.4 An Integration Scheme for Robust Concept Exploration

The developed concept exploration module consists of a simulator and three processors (point generator processor, response surface model processor and the compromise DSP processor). The relationship between these components is schematically represented in Figure 4. The simulator (module C) is at the center of this structure. It is a numerical processor which takes values of control, noise and held-constant factors as input and generates values of system performance (functional requirements) as output. The simulator is an integrated analysis module composed of several analysis programs at different levels of complexity.

Given the overall design requirements, concept exploration starts from the classification of different design parameters. As shown in Figure 4, module A, different design parameters are either classified as control factors, noise factors and responses. Ranges are specified for control and noise factors, while the targets are assigned to the responses. Then a point generator (module B), based on the design of experiments, identifies simulations to be conducted. RSM is a sequential procedure. Usually, a low-order polynomial function of the independent variables is employed first and a more elaborate model employed subsequently. Further analysis can be performed in a reduced region. Therefore, different experimental designs, e.g., Plackett-Burman, fractional factorial, full factorial, central composite design, and orthogonal arrays are provided to suit different requirements in terms of size of the problem, the order of nonlinearity and the stage of concept exploration.

- INSERT FIGURE 4 HERE -

Figure 4 - The Concept Exploration Module

After simulation, the response surface model processor (module D) is used to fit a surface model which represents a quick mapping from decision space to performance space. Mean and variance of performance can also be predicted based on the surface model. Most importantly, judging from the coefficients of the surface functions, trivial design effects can be removed and the analysis model can be reduced or reorganized without risking high costs. The response surface model processor can also generate information about model accuracy using regression analysis and ANOVA (Analysis of Variance). Thus, creating a response surface model is a sequential process which is iterated until satisfactory accuracy is obtained. NORMAN® [22] is used as the point generator and response surface model processor in this work.

The response surface models are then used by the compromise DSP solver (module E) as the analysis program to determine the robust top-level design specifications. The compromise DSP provides a generic approach to attaining robust top-level specifications by enabling a designer to find values of control factors (module E1) to achieve a performance which is as close as possible to target values and to minimize variations around these targets (modules E2 and E3). The formulation of compromise DSP is influenced by the identifications of factors and their ranges implemented earlier (module A). DSIDES® is used here to solve compromise DSPs [23].

In the following section, the design of an integrated airframe/propulsion HSCT system is used as an example to demonstrate our approach.

3. DETERMINING ROBUST TOP-LEVEL SPECIFICATIONS FOR INTEGRATED AIRFRAME/PROPULSION HSCT SYSTEM

3.1 Technology Base for HSCT Design

NASA's High Speed Research (HSR) program is to develop the technology which will allow the launch of a HSCT aircraft capable of cruising at Mach 2.4 and carrying about 300 passengers in excess of 5,000 nautical miles. The HSCT must be environmentally friendly (i.e., meet FAR Stage III noise regulations, reduce or eliminate sonic booms over land and reduce NO_X emissions which are harmful to the ozone layer). Although these challenges affect all of the various disciplines involved, it is obvious throughout the design analysis that the propulsion system selected for the HSCT will have a major effect on the overall economic and technological viability of the aircraft. As mentioned in Section 1, it is also very important to address the interaction between propulsion system analysis and overall mission performance analysis.

The FLight Optimization System (FLOPS), a synthesis code developed at the NASA Langley Research Center, is used as the simulation program (simulator), module C of Figure 4. FLOPS is a multidisciplinary system of computer programs for conceptual and preliminary design and evaluation of advanced aircraft concepts. More specifically, the program consists of nine different modules: weights, aerodynamics, engine cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis, and program control. As shown in Figure 5, the FLOPS analysis modules are integrated with ENGGEN, a simplified engine simulation code to perform one dimensional steady state thermodynamic analyses of turbine engine cycles to predict design point and off-design point performance for a variety of cycles. This program can be used to study various performance responses (aircraft system, propulsion system and engine components) under different definitions of FLOPS namelists, engine cycles and engine components.

- INSERT FIGURE 5 HERE -

Figure 5 - The Structure of the Simulation Program

In this study, except for the top-level specifications for airframe configuration and propulsion system, the generic Georgia Tech HSCT Double Delta and Arrow Wing baseline configurations are used to define all the necessary design parameters. The configuration is sized for a completely supersonic mission, as shown in Figure 6.

- INSERT FIGURE 6 HERE -

Figure 6 - Baseline Mission Profile

The two most promising engine concepts being examined are the Mixed Flow Turbo Fan (MFTF) and the Turbine Bypass Engine (TBE) [24]. In this study, the MFTF concept is used. The advantages of MFTF include a quieter engine, lower jet velocities during takeoff and landing and low SFC levels due to the higher bypass ratio.

3.2 Integrated Airframe/Propulsion HSCT System Problem Statement

Given the mission requirements, the next step is to develop airframe configuration and propulsion system top-level specifications which can incorporate HSCT overall performance requirements as well as downstream design considerations. In Table 1 the design specifications to be determined for both systems are listed. These correspond to the control factors used in module A and module E1 of Figure 4. To introduce quality into the choice of design specifications, two sources of deviation are considered. One is the uncertainty in design parameters associated with the propulsion system component downselect, e.g., combustor efficiency, Z. This is considered as a noise factor with deviation. The other source of deviation is the deviation associated with control factors when we seek to provide flexible top-level design specifications instead of optimum values, Figure 3. As an example the following two top-level specifications are considered as control factors with deviation.

- the number of passengers, X_{a1}^*.
- the overall pressure ratio, X_{p3}*.

- INSERT TABLE 1 HERE -

Table 1. The Top-Level Design Specifications to be Determined (Control Factors)

The design task is to find values of control factors, or top-level specifications to achieve the design goals as closely as possible and to minimize variations around the targets, subject to the engineering constraints. One of the important control factors is the turbine inlet temperature. Turbine inlet temperature is a significant component design variable and it has always been the subject of a compromised solution; the higher its value, the more efficient the cycle. High temperatures on the other hand demand either a complicated turbine blade cooling method or new materials which can withstand these high temperatures. Both solutions imply the inclusion of new technologies which may come with significant risk both in confidence and readiness. The constraints and goals considered (used in module E2 of Figure 4) are listed in Tables 2 and 3, respectively. The difference between constraints and goals is that constraints are rigid requirements that cannot be violated while goals are soft requirements. Our constraints include considerations of aircraft system performance, e.g., limit on gross weight; limits on takeoff and landing field length; the consideration of subsystem performance (SFC of propulsion system) and component level design requirement (compressor discharge temperature). The Specific Fuel Consumption (SFC) is a very critical propulsion system factor because a supersonic aircraft requires a much greater amount of fuel than a subsonic aircraft to complete its mission. The compressor discharge temperature is also a very critical component design factor because it increases with the flight Mach number.

Maximizing the Productivity Index which is a measure of operational cost is an important goal. The Productivity Index is defined:

$$\text{P.I.} = (PL * VB) / (WF + WE)$$

where,

PL = Payload [lbs],	VB = Block speed [knots]
WF = Fuel weight [lbs],	WE = Empty weight [lbs]

- INSERT TABLE 2 HERE -

Table 2. Limit Values for System Constraints

- INSERT TABLE 3 HERE -

Table 3. Target Value for Goals

3.2 Screening Test for Reducing the Size of the Problem

The purpose of the screening test is to apply a low-order, two level fractional factorial experiment to identify factors which may be significant and reduce the size of the problem. In Table 4, the ranges of factors for experiment are given. In all, there are nine factors including eight control factors and one noise factor (Factor 8). There are two control factors with deviations, Factors 1 and 7. All the other control factors have no deviation. The ranges of propulsion system design variables are based on the study of Seidel and co-authors[24]. Using the response-model approach, both control and noise factors are included in a single array for experiment. NORMAN® [22] is used here to generate the experiments and fit the response surface model (modules B and C of Figure 4). Plackett and Burman (P&B) experimental design [15], a first order, two level fractional factorial design, is used for screening test. For nine factors, thirteen experiments are required. When the number of factors is not small, a P&B design is a very useful for testing the response behavior across a wide design range.

- INSERT TABLE 4 HERE -

Table 4. Factors and Ranges for Experiment

In Table 5, the results of minimum, maximum and average values of the responses are given based on the thirteen P&B experiments. From the range of responses, it is observed that the response FOFF (takeoff field length) and CDT (compressor discharge temperature) always satisfy the constraint requirements, Table 2. To reduce the size of the problem, these two constraints are omitted. The regression model establishes a relationship between the response and the first order main effects (linear effects). Using NORMAN®, ANOVA of the regression analysis is performed, this shows that the accuracy of the first-order response surface model is only satisfactory for VAPP (aircraft approach velocity). Thus more elaborate experiments and higher-order regression models are needed for the other responses. The response model of VAPP based on the P&B experiment is:

$$VAPP = 155.86 + 2.937 * X_{a3} \tag{4}$$

In Eqn. 4, the variable X_{a3}, wing loading, is normalized and varies from [-1,1]. X_{a3} is the most influential factor for the aircraft approach speed. A lower value is preferred to reduce the approaching speed.

- INSERT TABLE 5 HERE -

Table 5. The Range of Responses from the Screening Test

3.3 Central Composite Design for Elaborating the Surface Model

The results of the P&B experiment show that all the factors influence more than one of the responses, therefore none of the factors can be eliminated. Again using NORMAN®, a Central Composite Design (CCD) with 531 experiments for nine factors is used to obtain quadratic response surfaces for GW, FLAND, SFC, PI and NOx. The CCD is a central-composite-inscribed design in which the bounds of variables are used as star points. After normalization, the distance of the full factorial design points to the center point is 0.21.

Based on the CCD results, ANOVA indicates that for all the responses the regression is significant. Therefore quadratic surface models can be used as approximation functions to represent the relationship between design decisions and system performance. In Figure 7, we provide 3-D grid plots of gross weight (GW) as a function of fan pressure ratio (FPR) and turbine inlet temperature (TITemp) while other factors are held at their nominal values. The plot based on the surface model obtained from NORMAN® is compared with the plot based on the actual FLOPS simulations. The difference between these two plots is least at the center while the difference at the corners are high. A higher order surface model or model transformation is needed if a more accurate model is required.

- INSERT FIGURE 7 HERE -

Figure 7 - A Comparison of Response from Surface Model and Simulation

One of the benefits of using central composite design for the response surface model is that after normalization of the design factors, the coefficients of the quadratic model directly indicate the significance of main factors (linear terms), interaction effects (interaction terms) and the curvature of the surface (quadratic terms). This will provide the designer with more insight into the problem. In Figure 7, the contributions of different effects for the responses for gross weight, emission, specific fuel consumption and productivity index are given. The same scale (-20% to 30%) is used for all three effects. Only significant interaction effects are listed while the trivial ones are omitted. For the main effects and second-order effects, the numbers on the horizontal axis indicate the factors whose numbers are included in Table 4. For the interaction effects, the two-digit number on the horizontal axis indicate the two factors involved, for example, "37" indicates the interaction between Factors 3 and 7.

- INSERT FIGURE 8 HERE -

Figure 8 - Contributions of Different Effects

Compared to the main effects and interaction effects, the second-order effects are relatively small for all responses, Figure 8. The interaction between Factor 6 (fan pressure ratio) and

Factor 9 (turbine inlet temperature) is the most significant effect influencing gross weight, specific fuel consumption and the productivity index. For emission, Factor 7 (overall pressure ratio) is the dominant factor; because they are negatively related, a higher overall pressure ratio leads to excessive NOx emission. The sign of the contribution for each effect can also be used to determine whether there will be trade-offs between the achievement of different objectives.

As robust design is used to find controllable design variables to dampen the effects of variations in other factors, the contributions of interaction effects can be used to determine whether it is possible to use them to reduce the effects of noise. For example, in this problem, Factor 8 (combustor efficiency) is considered as a noise factor and Factors 1 (number of passengers) and 7 (overall pressure ratio) are considered as control factors with variation. There is no significant interaction effect related to Factor 1 and Factor 8. This means that it is almost impossible to reduce the variance of performance caused by the deviation of these two factors by merely adjusting the selected design variables (top-level specifications). There are several significant interaction effects associated with Factor 7, i.e. the interaction effect "67" is significant for all four responses. This indicates that it is possible to reduce the variation of performance caused by the variation of Factor 7, the overall pressure ratio, by carefully choosing the value of Factor 6 (fan pressure ratio).

3.3 The Compromise Decision Support Problem for Determining Top-Level Design Specifications

Once satisfactory surface models for performances are established based on the constraints and goals in the problem statement in Section 3.1, the compromise DSP is used to determine values of top-level design specifications. The compromise DSP formulation for this problem is shown in Figure 9.

- INSERT FIGURE 9 HERE -

Figure 9 - The Compromise Decision Support Problem Formulation

In the current design model, the noise constraint is omitted because, with current nozzle and suppression technologies, the stringent noise limits of FAR 36 stage III cannot be meet. When new technology is available, noise will be introduced as a constraint.

In the compromise DSP, a pair of deviation variables d_i^+ and d_i^- are used to indicate the extent of the deviation of a goal from its target. Therefore the overall objective of the compromise DSP is to minimize the total deviation function. The use of both d_1^- and d_1^+ or only one of them in the deviation function depends on whether the goal is to achieve a target performance as closely as possible or whether a maximum/minimum is required. For example, if the goal is to maximize a function, d_1^+ must be minimized in the deviation function. We choose to address separately the issues of bringing the mean on target and minimizing the deviation by modeling them as separate goals in our formulation. In our initial study, all goals are at the same priority level and are assigned equal weights (Archimedian formulation). The deviation function Eqn. 13 becomes:

$$Z = 0.25(d_1^+) + 0.25(d_2^-) + 0.25(d_3^-) + 0.25(d_4^-) \qquad (14)$$

In the above compromise DSP, a general representation for constraints and goals is used, e.g., GW(**X**), MPI(**X**), etc. These functions are derived based on information from the response surface model. To consider the variations of constraints caused by the deviations of controllable or uncontrollable parameters, a worst case scenario is used. In general, if the constraint without robust design considerations has the form $g_j(x, z) \leq 0$, using the worst case scenario, the constraint becomes:

$$E\,[\,g_j(x, z)] + \sum_{i=1}^{k} \left| \frac{\partial g_j}{\partial \mathbf{z}_i} \Delta \mathbf{z}_i \right| + \sum_{i=1}^{l} \left| \frac{\partial g_j}{\partial \mathbf{x}_i} \Delta \mathbf{x}_i \right| \leq 0 \qquad (15)$$

where E represents the statistical *expected value* of a function, Δz_i, which equals $3\sigma_{zi}$ and Δx_i is the deviation of controllable variables. The mean and variance of performance for goals are derived based on Eqns. 2 and 3.

The compromise DSP is solved for four different design scenarios and the results of top-level design specifications are provided in Table 6. The four design scenarios considered are:

- *Scenario I* All the goals are at the same priority level with equal weights.
- *Scenario II* The mean on target goal is placed at a higher priority level than the goal of minimizing the deviation.
- *Scenario III* Minimizing the deviation is placed at a higher priority level than the mean on target goal.
- *Scenario IV* Design without considering robustness. Noise factors are fixed at their nominal values, goals are at the same priority level with equal weights.

- INSERT TABLE 6 HERE -

Table 6. Top-Level Specifications Under Different Design Scenarios

The objective of robust design is to find the values of control factors without deviation (2,3,4,5,6,9) and the mean values of control factors with deviation (1,7) to reduce the variance of the response caused by deviations in Factors 8, 1, and 7. Therefore in Table 6, we include the results of control factors without deviation (2,3,4,5,6,9) and the mean value

± deviation of the control factors with deviation (1,7). The design solutions for thrust-weight ratio (Factor 3), wing loading (Factor 4), engine throttle ratio (Factor 5), and turbine inlet temperature (Factor 9) are quite stable while the rest of specifications vary for different design scenarios. This is a reasonable solution because the contributions of these stable factors are relatively small. Interactions between these factors and the factors with deviation (Factors 1, 8 and 7) are very small. Therefore, whenever robust considerations are introduced or removed or placed at different priority levels, the results for these factors are relatively stable. Results for the overall pressure ratio (Factor 7) are very different when robustness is introduced or removed. For robust design, a higher overall pressure ratio is preferred, while a lower value is preferred if robust design considerations are not introduced. Therefore the region around the upper limit of the overall pressure ratio must be more flat than the region around its lower limit. The fan pressure ratio (Factor 6) is the most unstable design specification for different design scenarios. This confirms our observation in Section 3.2 that Factor 6 strongly interacts with the noise factors.

4. CLOSURE

A Robust Concept Exploration Method (RCEM), which combines robust design techniques, RSM and the compromise DSP, is developed to support the early stages of design of complex systems. Using the HSCT airframe configuration and propulsion system design as an example, it has been shown that the proposed method can be used to examine the character of the design space and determine top-level design specifications. This approach can be used to integrate multidisciplinary analysis with computational efficiency and permit the introduction of downstream design considerations in the early stages of design. To improve the efficiency of the concept exploration process and increase design freedom in later design stages, quality concepts (robustness considerations) have been introduced as the requirements for the choice of the initial specifications. In particular, there are several advantages of using this approach:

- Response models allow the studies of both constraints and objectives. Using the compromise DSP, design constraints can be incorporated and trade-offs among multiple objective functions can be made.
- Based on the response model, a general robust design procedure can be developed by separating models of the mean and variance of the characteristic of interest. This allows a designer to address individually the issues of bringing the mean on target and reducing variation.
- The response model can serve as a fast analysis module to evaluate different design alternatives and develop new top-level specifications whenever the overall design requirements change.

A paradigm shift has emerged in the design methods used to support the early decisions in designing complex systems. Instead of using an optimization procedure for searching for a single correct answer, this method can be used to focus on the systematic identification of the space where potential solutions lie and to determine dependencies among different parameters. This approach makes it possible to keep design options open as long as possible and permits the design model to evolve in an known region of design space while knowledge is gained during the design process.

Although we have listed several benefits of using the response-model approach, we believe there are situations where using Taguchi's signal-to-noise ratio approach is preferable. The former is preferable if it is important and affordable to understand the response relationship and if the relationship is not too complex. The latter is preferred if it is important to quickly identify a setting (rather than a surface) with a better performance.

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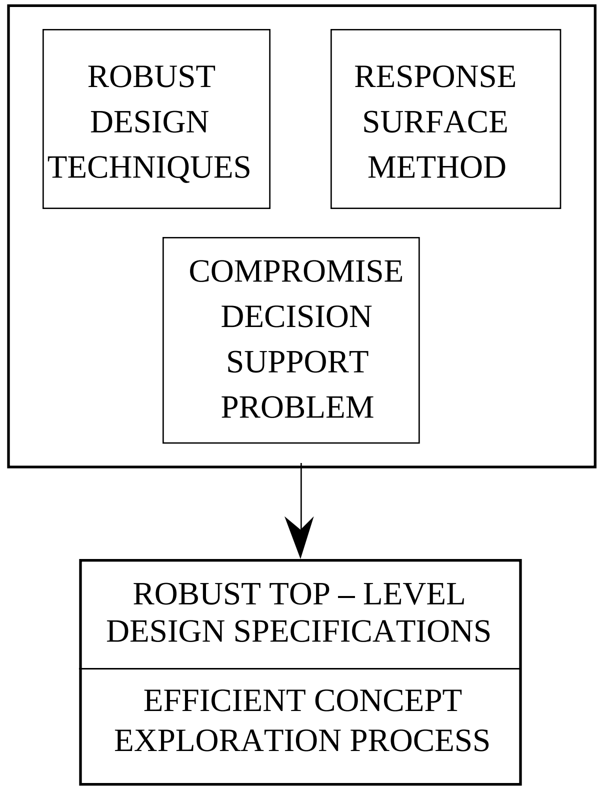


Figure 1 - The Robust Concept Exploration Method: Components

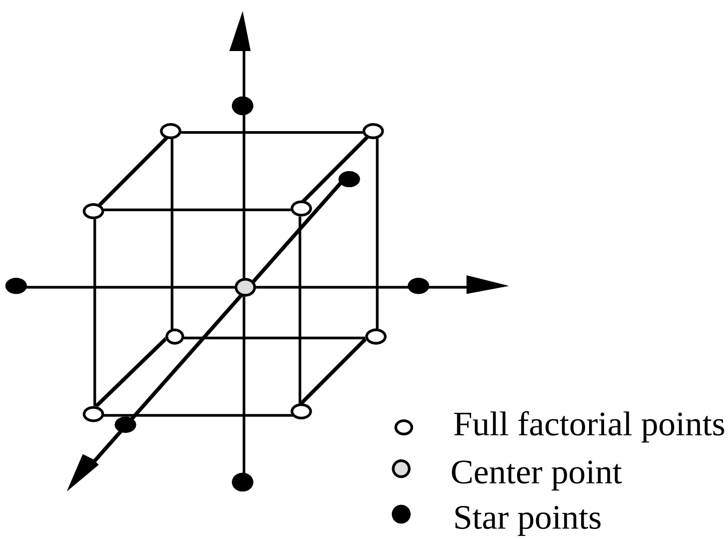


Figure 2 - Three Variable Central Composite Design

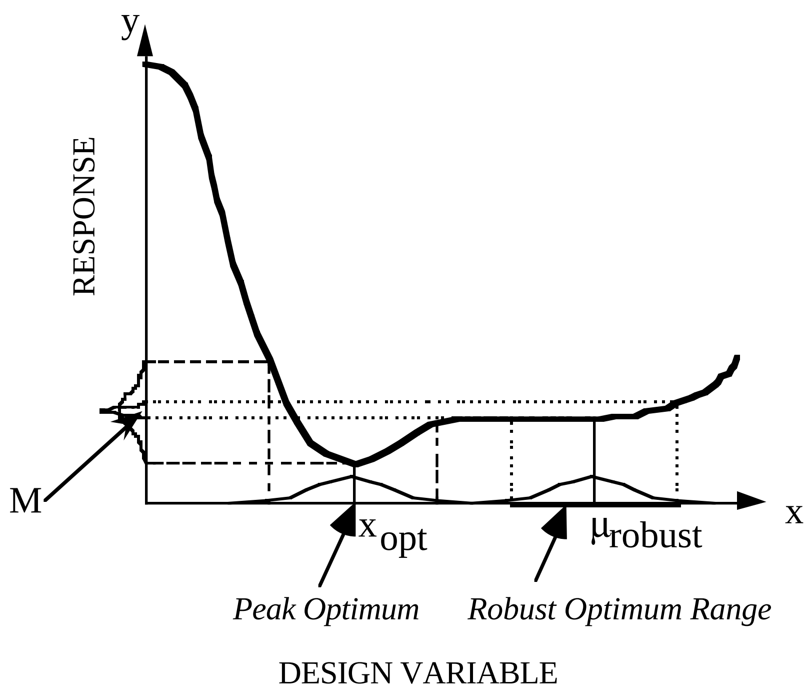
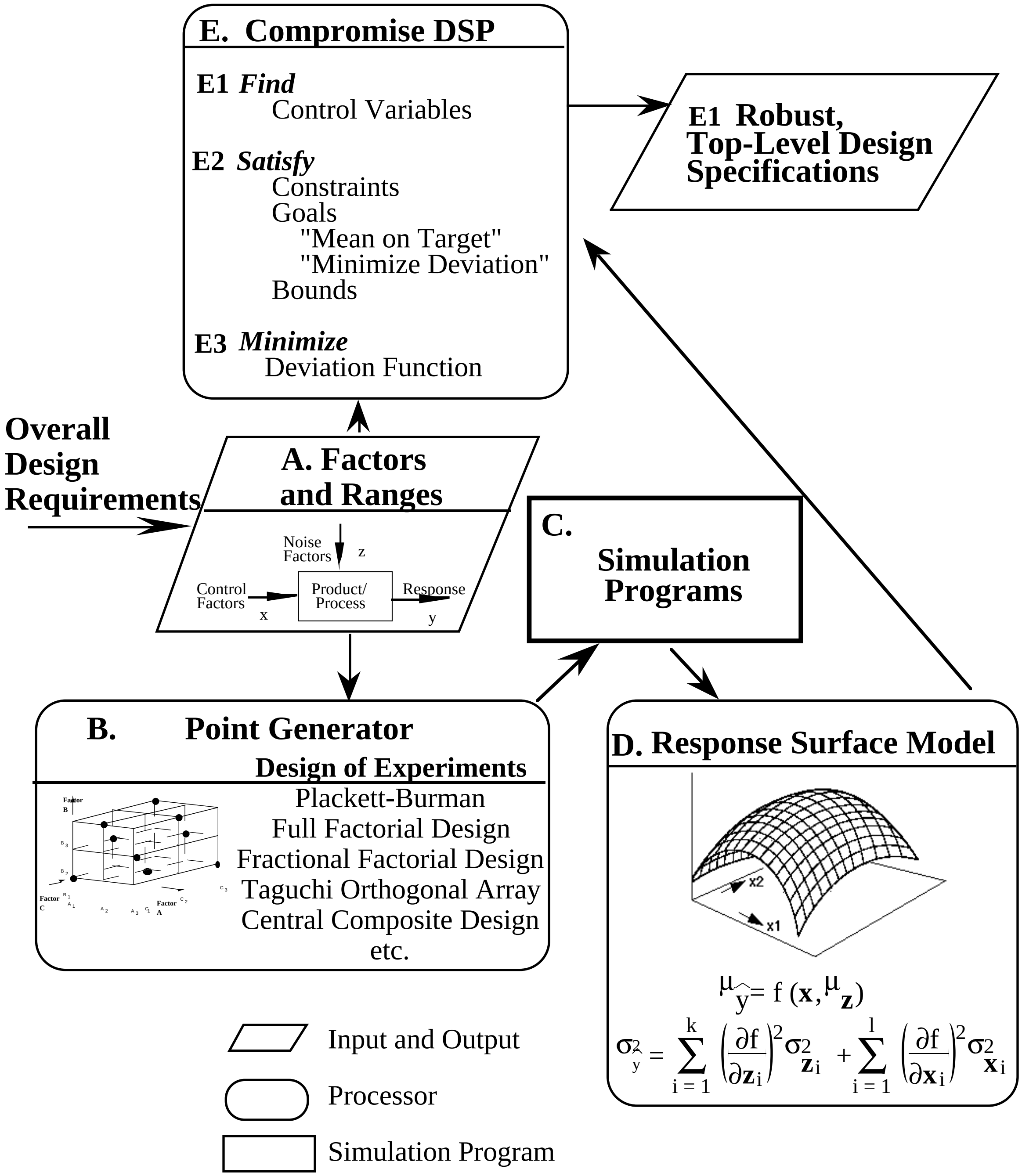


Figure 3 - Developing Robust Top-Level Design Specifications



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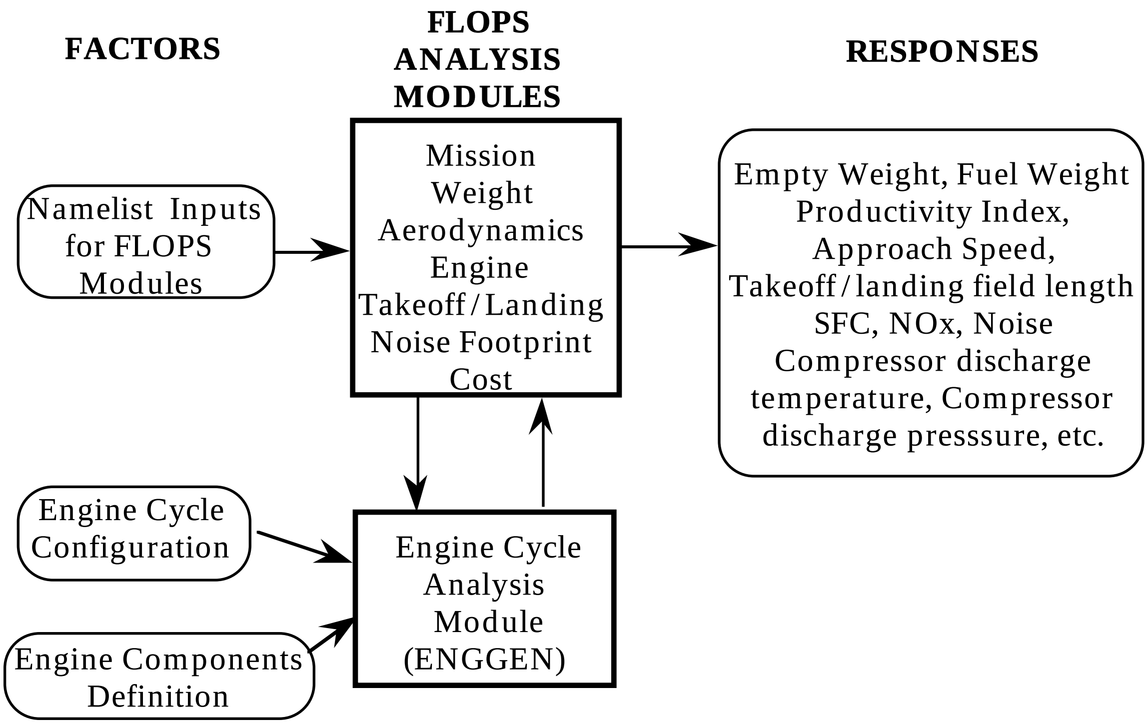


Figure 5 - The Structure of the Simulation Program

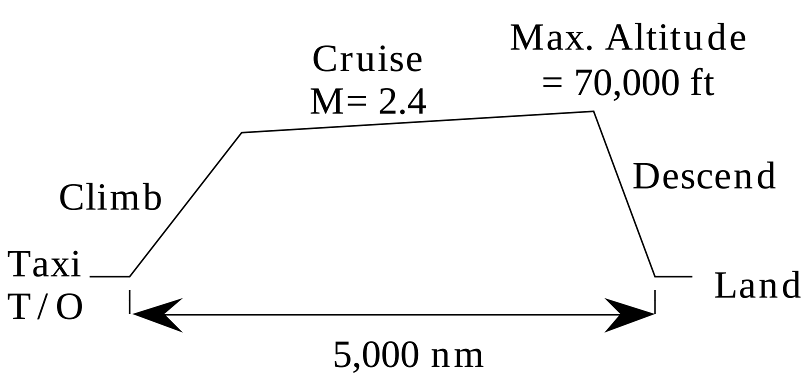
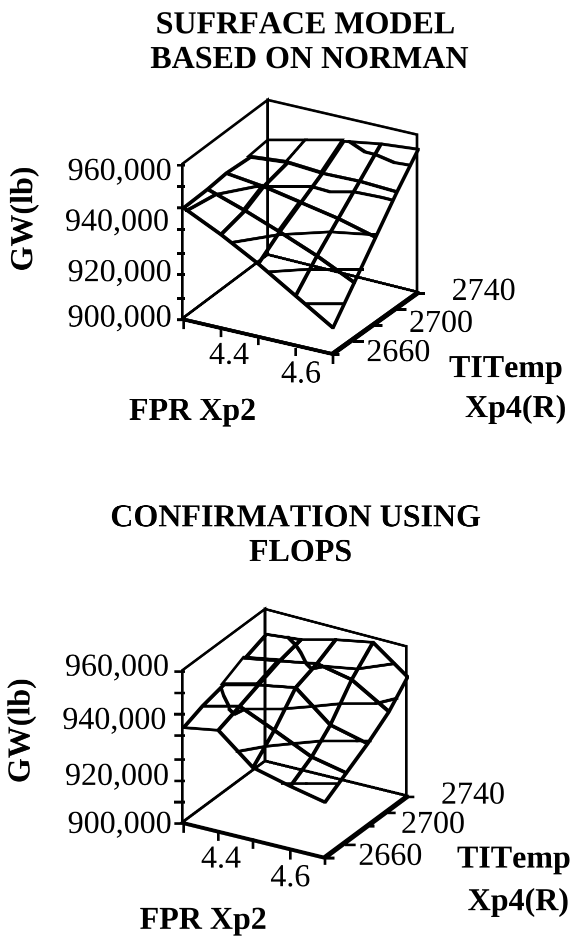


Figure 6 - Baseline Mission Profile



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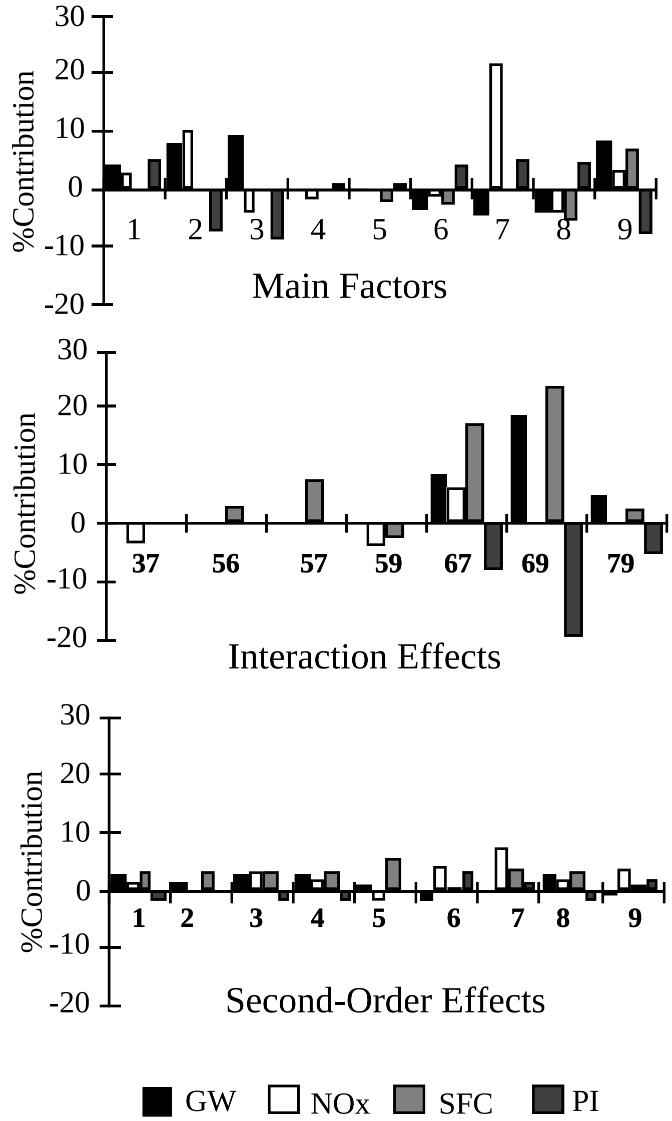

Figure 8 - Contributions of Different Effects

Given

- Response surface models of gross weight, approach speed, landing field length, specific fuel consumption, productivity index and nitrous oxide emission as functions of design variables **X** (X_{a1}^*, X_{a2}, X_{a3}, X_{a4}, X_{p1}, X_{p2}, X_{p3}^*, X_{p4}) and the uncontrollable variable Z
- The mean and standard deviation of uncontrollable variables
  $\mu_Z = 0$, $\sigma_{Za} = 1/3$ (after normalization of variable range).
- The deviation of controllable variable X_{a1} and X_{p3}, $\Delta X_{a1}=0.3$, $\Delta X_{p3}=0.3$
- The limits of constraints: Ugw, Uvapp, Ufland, Usfc, Usfc, etc.
- The target of goals TMPI, TVPI, TMNox, TVNOx

Find

- Values of *system variables*

	X	Units
Mean of Number of Passengers	μX_{a1}	
Wing Aspect Ratio	X_{a2}	–
Thrust-Weight Ratio	X_{a3}	–
Wing Loading	X_{a4}	lb/ft^2
Engine Throttle Ratio	X_{p1}	–
Fan Pressure Ratio	X_{p2}	–
Mean of Overall Pressure Ratio	μX_{p3}	–
Turbine Inlet Temp	X_{p4}	deg R

- The values of *deviation variables* associated with all the goals d_i^-, d_i^+ (i =1, 4)

Satisfy

The *System Constraints*

- Upper limit on gross weight
  $GW(\mathbf{X}) \le Ugw$ (5)
- Upper limit on approach speed
  $VAPP(\mathbf{X}) \le Uvapp$ (6)
- Upper limit on landing field length
  $FLAND(\mathbf{X}) \le Ufland$ (7)
- Upper limit on specific fuel consumption
  $SFC(\mathbf{X}) \le Usfc$ (8)
- Upper limit on takeoff field length*
- Upper limit on compressor discharge temperature*

The *System Goals*

- Maximize the *mean* of the Productivity Index
  $MPI(\mathbf{X})/TMPI + d_1^- - d_1^+ = 1$ (9)
- Minimize the *variance* of the Productivity Index
  $VPI(\mathbf{X})/TVPI + d_2^- - d_2^+ = 1$ (10)
- Minimize the *mean* of nitrous oxide emissions
  $MNOx(\mathbf{X})/TMNOx + d_3^- - d_3^+ = 1$ (11)
- Minimize the *variance* of nitrous oxide emissions
  $VNOx(\mathbf{X})/TVNOx + d_4^- - d_4^+ = 1$ (12)

Bounds on the system variables

$d_i^+ \cdot d_i^- = 0$, with $d_i^+, d_i^- \ge 0$

Objective

Minimize the total deviation function

$Z = [\, f_1(d_1^+), f_2(d_2^-), f_3(d_3^-), f_4(d_4^-)]$ (13)

* these constraints can be eliminated based on the screening experiment results.

Figure 9 - The Compromise Decision Support Problem

List of Tables

Table 1. The Top-Level Design Specifications to be Determined (Control Factors)

Airframe Configuration	Propulsion System
Number of Passenger X_{a1}*	Engine Throttle Ratio X_{p1}
Wing Aspect Ratio X_{a2}	Fan Pressure Ratio X_{p2}
Thrust-Weight Ratio X_{a3}	Overall Pressure Ratio X_{p3}*
Wing Loading (lb/sq.ft) X_{a4}	Turbine Inlet Temp (deg R) X_{p4}

* controllable variables with deviation

Table 2. Limit Values for System Constraints

	System Constraints	**Limits**
System level	Upper limit on gross weight Upper limit on approach speed Upper limit on takeoff field length	$GW \leq 950000$ lbs $VAPP \leq 140$ kts $FOFF \leq 11000$ ft
	Upper limit on landing field length	$FLAND \leq 11000$ ft
Subsystem level	Upper limit on Specific Fuel Consumption	$SFC \leq 1.34$
Component level	Upper limit on compressor discharge temperature	$CDT \leq 1710$ degR

Table 3. Target Value for Goals

System Goals	Target Value
Maximize Productivity Index PI	TMPI = 80 knots
Minimize Variance of PI	TVPI = 0
Minimize nitrous oxide emissions NOx	TMNOx = 0.5g/Kg fuel
Minimize Variance of NOx	TVNOx=0

Table 4. Factors and Ranges for Experiment

Factor		Minimum	Maximum
1	# of Passenger	290	310
2	Wing Aspect Ratio	1.5	3.1
3	Thrust-Weight Ratio	0.42	0.48
4	Wing Loading (lb/sq.ft)	115.0	125.0
5	Engine Throttle Ratio	1.02	1.10
6	Fan Pressure Ratio	4.0	5.0
7	Overall Pressure Ratio	18.0	22.0
8	Compressor Efficiency	0.97	0.99
9	Turbine Inlet Temp (deg R)	2600	2800

Table 5. The Range of Responses from the Screening Test

Response	Minimum	Maximum	Average
GW (lb)	876525	1080940	957746
VAPP (kts)	131.07	151.62	140.86
FOFF (ft)	6531.8	8352.3	7418.3
FLAND (ft)	10775	15711	12799
SFC	1.3272	1.3808	1.3562
CDT (deg R)	1476.1	1550.0	1535.1
PI (knot)	67.726	90.753	80.095
NOx (k/kgfuel)	0.39	0.64	0.51

Table 6. Top-Level Specifications under Different Design Scenarios

	Design Scenario			
Top-Level Specifications	I Achiemedian Robust	II Preempetive Robust	III Preempetive Robust	IV Achiemedian Non-Robust
Number of Passengers*	302±3	302±3	302±3	300
Wing Aspect Ratio	3.04	2.99	3.04	2.10
Thrust-Weight Ratio	0.42	0.42	0.42	0.42
Wing Loading (lb/sq.ft)	119.71	119.99	119.87	121.28
Engine Throttle Ratio	1.10	1.10	1.10	1.10
Fan Pressure Ratio	4.39	4.41	4.43	4.35
Overall Pressure Ratio *	20.92±0.6	20.94±0.6	20.92±0.6	18.25
Turbine Inlet Temp (deg R)	2600.00	2600.39	2600.00	2612.50