Robust Concept Exploration of Propulsion Systems with Enhanced Model Approximation Capabilities

Sriram Varadarajan
Design Engineer
Georgia Power
Atlanta, GA
Former Graduate Research Assistant at
Clemson University

Wei Chen*
Assistant Professor
University of Illinois at Chicago
Former Faculty at Clemson University

Chester J. Pelka
Technical Manager
Advanced Engine Programs
Pratt & Whitney Aircraft
E.Hartford, CT, USA
pelkacj@pweh.com

***Corresponding Author:**
Dr. Wei Chen
Mechanical Engineering (M/C 251)
842 W. Taylor St.
University of Illinois at Chicago
Chicago IL 60607-7022

Phone: (312) 996-6072
Fax: (312) 413-0447
e-mail: weichen1@uic.edu

ABSTRACT

Improvements in industrial productivity require the creation of a reliable design in the shortest possible time. This is especially significant for designs that involve computer intensive analyses. The Robust Concept Exploration Method (RCEM) embodies a systematic approach to configuring complex engineering systems in the early stages of product design by introducing quality considerations based on the robust design principle. Approximation techniques are employed in the RCEM to replace intensive analysis programs for saving the computational time and cost, thereby increasing the efficiency of a design process. In this paper, the applicability of the RCEM for multiobjective complex systems design is examined by applying it to the propulsion system conceptual design process at Pratt & Whitney. Various approximation techniques are studied and a new strategy is proposed to enhance the existing model approximation techniques embodied in the RCEM.

Key Words: Concept Evaluation, Model Approximations, Propulsion Systems Design, Robust Design, Top-Level Design Specifications.

NOMENCLATURE

ANN	Artificial Neural Networks
CET	Combustor Exit Temperature
CCD	Central Composite Design
DOE	Design of Experiments
DSP	Decision Support Problem

FANDIA	Fan Diameter
FBURN	Fuel Burnt
FPR	Fan Pressure Ratio
HPCPR	High Pressure Compressor Pressure Ratio
LPCPR	Low Pressure Compressor Pressure Ratio
LSE	Least Squared Error
OPR	Overall Pressure Ratio
RANGE	Aircraft Range
RSM	Response Surface Methodology
SESDP	Simplified Engine Systems Design Problem
SFCISO	Isolated Pod TSFC
SFCWIL	Streamtube TSFC
SOAPP	State of the Art Performance Program
TSFC	Thrust Specific Fuel Consumption
VJR	Exhaust Jet Velocity Ratio

1 INTRODUCTION

The major portion of the life cycle cost of today's common complex engineering systems such as aircraft, propulsion systems, and automobiles, is determined during the conceptual phase of the design. It is in this phase that the design concepts are evaluated and the *top-level specifications* (design variables used to describe the system at the early stages of design) are determined. To make rational decisions in the early stages of designing complex engineering systems, a great deal of concurrent systems analysis is required. To facilitate multiobjective and often multidisciplinary complex systems design, a departure from the traditional design analysis and the single objective optimization approach is essential in the conceptual stage of design.

The Robust Concept Exploration Method (RCEM) [1-3] is one such approach that can be used to quickly evaluate the design alternatives and to develop top-level specifications with quality considerations based on the robust design principle. In particular, the RCEM can be used to determine top-level specifications that are *robust*, insensitive to adjustments in later stages of design or during operation, and *flexible*, allowed to vary within a range. The RCEM approach has been tested for various engineering design problems [3-8]. These preliminary studies of the RCEM illustrated that the RCEM can be used to integrate multi-functional attributes across disciplines with an improved computational efficiency, to permit the introduction of downstream design considerations in the early stages of design, and to provide flexibility in a design process.

The primary objective of this work is to further verify the validity of the RCEM by applying it to a Pratt & Whitney (P&W) propulsion system conceptual design. Specifically, the applicability of the RCEM for designs that involve complicated thermodynamic cycle behaviors is tested. Our special focus is on enhancing the model approximation capabilities of the RCEM. Through previous applications, it is observed that the Response Surface Methodology (RSM) [9] used in RCEM may not be accurate enough in modeling highly nonlinear behaviors and the improvements to the accuracy of the response surface models are limited. In this work, we investigate other existing approximation techniques such as the Artificial Neural Networks (ANN) [10] and study how they could be used to complement the RSM. A new strategy for model formation is proposed to enhance the current model approximation capabilities of RCEM. In particular, we try to address the following two major research issues in this work:

- How can the existing approximation algorithms be integrated to achieve a better trade-off of accuracy and cost, so that different techniques can take complementary roles in model approximations?
- Why is it important to develop *robust* and *flexible* top-level design specifications in the early stages of designing complex systems? Are these specifications superior to the results obtained from the conventional optimization model?

The paper is organized as follows. In Section 2, the RCEM approach is presented as a step-by-step procedure. This introduction is followed by a review of the two types of robust design for developing *robust* and *flexible* design specifications. A review of the two fundamental approximation techniques used in this work, namely the Design of Experiments (DOE) and the ANN techniques, is presented in Section 3. A new model formation technique is proposed at the end of this Section. In Section 4, the applicability of the RCEM with the enhanced model approximation capabilities is tested for the propulsion system conceptual design process through applications and verifications. Section 5 is the closure of this paper.

2 THE ROBUST CONCEPT EXPLORATION METHOD (RCEM)

The RCEM is a step-by-step approach for quickly evaluating different design alternatives and generating top-level design specifications with quality considerations. Central to the RCEM is the integration of robust design techniques, the Design of Experiments (DOE) techniques [11], and the Response Surface Methodology (RSM) [12] within the framework of the compromise Decision Support Problem (DSP) [13] for multiobjective design problems. The criteria used in quality engineering to measure the quality of a product are modified to measure the *robustness* and *flexibility* of a design decision.

The computer infrastructure of the RCEM is shown in Figure 1. The major components of the RCEM infrastructure include four processors (modules B, D, E and F) and a simulator (module C). The central slot, module C, is the integrated sophisticated concurrent analysis program, which is surrounded by several processors corresponding to the different steps in RCEM. Module A is related to the task of *classifying the design parameters*. Based on the principles of quality engineering, the design parameters are classified as the control factors (design variables), the noise factors (uncontrollable variables), and the responses (performance). The second step of the RCEM is to perform a small number of "*screening experiments*" to identify the least significant factors among all the control and noise factors. Module B, along with the simulator C, perform the screening experiments, which are implemented in the form of computer experiments. This reduces the size of the problem and provides information for organizing the secondary experiments. The third step of the RCEM is to *build the response surface models* that can be used to replace the original, computationally expensive analysis programs with the fast analysis modules (using Modules B, D and E). Higher order experiments, such as the

Central Composite Design (CCD), the full-factorial design, the fractional factorial design, etc., are used to generate the secondary experiments. Based on the response surface models of the original design performance, the mean and the variance of the performance can be derived for robust design. In the final step of the RCEM, "*determine top-level design specifications with quality considerations*", the compromise DSP (module F) provides a generic approach to attain *robust* and *flexible* top-level specifications by enabling a designer to find values of control factors, to achieve a performance which is as close as possible to the target value and to minimize variations around the target. This is further explained in the next paragraph.

***Insert* Figure 1. Computer infrastructure of the RCEM [3]**

The adaptation of Taguchi's robust design principle [14] in the final step of the RCEM relies on a general robust design procedure developed by Chen et. al. [15] for solving two broad categories of robust design problems. These are, Type I–robust design associated with the minimization of variations in performance caused by variations in noise (uncontrollable) factors and Type II–robust design associated with the minimization of variations in performance caused by variations in control factors (design variables). When used for concept exploration, Type I applications are applied to determine *robust* early design decisions that are insensitive to small design adjustments in later design stages; Type II applications extend to finding *flexible* early design decisions that are allowed to vary within a range, which is modeled as the mean of control factors x with it deviation (? x). The word formulations of the compromise DSPs for the Type I and Type II robust design are provided in Figure 2. In the figure, x is used to represent the control factors and z stands for the noise factors. Though the "given" and "find" portions are different, in each type, *robustness* or *flexibility* is achieved by minimizing the deviation of performance σ_y, in addition to bringing the mean of performance μ_y to the desired target. These objectives are modeled as separate goals in a compromise DSP. Different from the conventional optimization approach, in compromise DSP, objectives are achieved by minimizing the difference between the achievable and the desired values of the design objectives. Based on the preference, goals may be either weighted or rank-ordered into priority levels, called Archimedean and Preempetive formulations, respectively [13].

***Insert* Figure 2. Two Types of Robust Design**

3 ENHANCEMENT OF THE APPROXIMATION TECHNIQUES

In RCEM, approximation techniques are used to replace expensive analysis programs by simplified fast analysis modules. There are various forms of approximation techniques in the existing literature, ranging from the approximation of derivatives [16-18] to the approximation of design space [19-21]. The latter is the focus of this study. A comprehensive review of the existing approximation techniques that encompass the DOE [9,11] including the Response Surface Methodology (RSM), the ANN [10], the kriging method [22], and the AI-based inductive learning methods is available in [23], and will not repeated here. Our primary interests in this work are the two most widely used techniques, the RSM and the ANN. In this section, we examine the advantages and the limitations associated with these two techniques. A new strategy, which combines both methods to build a single model, is proposed.

3.1 Design of Experiments and Artificial Neural Networks

The *Design of Experiments* techniques are formal techniques which support the design and analysis of experiments [11]. Among the various DOE techniques, the *Response Surface Methodology (RSM)* [12, 24] is a collection of statistical techniques that support the design of experiments and fitting response surface models. The *Artificial Neural Networks* (ANN) technique is inspired by the cognitive and data processing capabilities that are characteristic of biological neural networks. A basic network (Figure 3(B)) comprises three layers: the input, the hidden and the output layers. It is common to process the weighted sum of the inputs by an activation (sigmoid) function to obtain an output signal Y. Back propagation is a commonly used training process that propagates the error information backward from the output nodes to the hidden nodes. The applications of RSM or ANN for model approximations can be found in many engineering problems [20, 25-27].

***Insert* Figure 3. RSM and ANN**

Through authors' previous studies [1, 2, 28, 29], some insight has been gained on using the DOE and ANN techniques. We note that the ANN perform better than the RSM in modeling the highly nonlinear behavior, while the response surface models have the edge when a large number of experiments are not affordable and the performance is low-order nonlinear [28]. It is also observed that due to the form of the sigmoid transformation function used in the ANN, the ANN model itself provides little information about the design factors and their contributions to the response without any further analyses. The response surface model, on the other hand, is "*transparent*", clearly showing the factor contributions from the coefficients in the regression equation. This knowledge is helpful in identifying the insignificant factors and thereby reducing the size of a complex problem.

3.2 The Combined RSM+ANN approach

In this work, a new approach that combines both the ANN and the RSM techniques to build *a single model* is proposed as an alternative to the existing techniques. This approach is referred to as the Combined RSM+ANN technique, under which RSM is used to fit the polynomial model and the ANN is used to model the "departure".

It is known that when using polynomial response surface models, there exists an error, which is the difference between the predicted and the true values of the performance. In detail, given that $\mathbf{x} = (x_1,..,x_k)$ are the independent variables, or factors, y is the true value of the response, then the relationship between y and $\mathbf{x}$ can be written as:

$$y = f(\mathbf{x}) + \varepsilon$$

where ε represents the noise or error observed in the response y and f(x) is the response surface model which is often expressed as a polynomial function. It is observed that this error ε is often highly nonlinear in nature even though y may be low-order nonlinear. An example of such an error function under a set of data points is shown below in Figure 4 based on the 121 confirmation tests for the performance “fuel burned” in the HSCT problem presented in [28]. It is observed that while the performance itself is moderately nonlinear, the error ε fluctuates and results a highly nonlinear function for the error function itself.

***Insert* Figure 4. A Typical Error Function, e, between the Actual Model and the Predicted RSM (121 Sample Points)**

Since the ANN is found to be effective in modeling highly nonlinear behaviors, it is proposed to combine a response surface model, f(x) modeled by the RSM, plus an error term, modeled by the ANN technique. Hence, the response y is a function of both RSM and ANN,

$$y = f(x)[RSM] + \varepsilon\ [ANN].$$

It may be argued that the model could be built completely based on the ANN technique alone, instead of combining the ANN-based error model with the response surface model. However, it is with our observations that many engineering behaviors are moderately nonlinear, with the form of a polynomial function plus an irregular error term. In such cases, it is recommended to use the ANN+RSM model over the ANN model even in the situation where the accuracy of these two methods is close. This is because when using the combined ANN+RSM approach, the RSM part (polynomial function) shows clearly the contributions of different factors such as main factor effects and interaction effects.

These information provide more knowledge of the system behavior as well as assistance in robust design formulation. On the other hand, the ANN model provides little knowledge of the system without any further analyses. While the actual behavior of the function to be approximated is critical in determining which model is the better of the two, the data necessary for training the network is readily available for both cases. The ANN and our proposed RSM+ANN approaches are therefore included in the RCEM, in addition to the RSM, to enhance the model approximation capability. This is tested and verified for the conceptual propulsion system design provided by Pratt & Whitney.

4 CONCEPT EXPLORATION OF PROPULSION SYSTEM

The design of an aircraft propulsion system is an example of the complex system design processes that are required for today's high technology systems. Since the characteristics of the propulsion system determine approximately 1/3 of the aircraft system direct operating cost and 1/5 of the total operating cost, it is desirable to select the combination of design parameters which produce the lowest reasonable level of cost. There are several dozen fundamental design parameters for the overall system configuration and for the components which make up the system. External requirements and criteria exist from both the airframe manufacturer and from the airline who will operate the aircraft. For example, functional items such as thrust, acoustics and emissions address the suitability to power a particular aircraft; performance items such as fuel efficiency, reliability, and cost are critical to the operating cost for the airline. In addition, internal company requirements must be met. These can include technology and manufacturing capability, manufacturing cost and other profitability parameters, and the potential for adapting existing products to new applications.

The traditional approach to propulsion system design used by Pratt and Whitney, in the conceptual stage is shown in Figure 5. It is a top-down layered approach. In other words, the user has to determine and fix the concepts of one layer before moving to the next one. Starting from the brainstorming procedure in which the scope and objectives of the problem are identified, the thermodynamic cycle design module is then performed to determine the primary cycle parameters. The output from this module is stored in a Performance Table database. The aerodynamics design and the mechanical design modules then use the data from the Performance Table. The results from the aerodynamic design are used in determining the "gaspath" and the "airfoil" geometry. This information flows to the mechanical design module, from which the engine cross-section is determined at the end.

Insert **Figure 5. Traditional Top-down Approach to Engine Design**

It is obvious that, with this top-down approach, the designer has very limited freedom towards the final stages of the design process, since most of the parameters are fixed before moving to the next level of detail. Hence, an *integrated analysis* is required at the system level of the design process with a *concept exploration* in the preliminary stages to determine the best top-level design specifications. The results presented in this paper are based on the studies only using the cycle module SOAPP (State of the Art Performance Program), with additional weight and drag correlation, as the engine simulation program (Module C in Figure 1). SOAPP is a performance simulation system for modeling the thermodynamic and the chemical processes of gas turbines and other fluid-flow systems. Though one simulation of SOAPP program takes close to one minute on a SUN Ultra 1 workstation and could not be considered as computationally expensive, the thermodynamic behavior modeled is the most nonlinear among all the analysis modules for engine conceptual design. Therefore, when tested only for the SOAPP program, the applicability of our approach could be extended to the integrated design and analysis incorporating various behavior models. The conceptual design of a 30,000 lb. thrust propulsion system for a twin-engine commercial transport is selected for this phase of the study.

4.1 Problem Identification and Classification of Parameters

In step 1 of the RCEM, the parameters are classified based on the problem identification. A total of five control factors are considered as the design variables, which are modeled as the to-be-determined top-level design specifications. The upper and the lower bounds of these variables are specified in Table 1a. The three constraints, i.e., Overall Pressure Ratio (OPR), the Fan Diameter (FANDIA), and the High Pressure Turbine Pressure ratio (HPTPR); and four objectives, i.e., streamtube TSFC (SFCWIL), isolated pod TSFC (SFCISO), fuel burned (FBURN), and range (RANGE) are specified in Table 1b.

Six noise parameters are also introduced. The majority of the noise factors considered in this study belong to the efficiency of the propulsion system components, such as the fan, the compressors, etc. The nominal values for each of them, along with the variation, are shown in Table 2. These ranges are determined based on experience in past propulsion system design and development programs. They represent the variations in the final component characteristics after the product design and development.

***Insert* Table 1. Problem Identification and Classification of Parameters**

***Insert* Table 2. Noise Parameters for the Engine Design**

4.1 Screening Experiments

In Step 2, a screening procedure is carried out to understand the significance of the five control factors and the six noise factors (11 factors in total). This is done by using a small number of simulations (17) referred to as experiments (Plackett-Burman design for this case). The effects of the five control factors and the six noise factors on the seven performance parameters are obtained through the statistical analysis. In Figure 6, all the seven responses corresponding to the constraint and objective parameters are listed along the horizontal axis, while the heights of the vertical bars illustrate the percentage contributions of different factors shown in different patterns. The vertical sequence of the factors follows the same order of the parameters listed on the legend. It is noted that compared to the effects of noise factors (prduct, ehpt, elpt, ehpc, elpc, efnod), those of the control factors (FPR, LPCPR, HPCPR, CET, VJR) are much more significant. It is therefore decided to keep all the six control factors as variables in the further study. Among the six noise factors, *efnod* (fan efficiency), *elpc* (low compressor efficiency), and *prduct* (fan duct loss) are consistently less significant than *ehpc* (high compressor efficiency), *elpt* (low turbine efficiency), and *ehpt* (high turbine efficiency) for all the seven responses. Hence, enod, elpc, and prduct are fixed at their nominal values (0.927, 0.90, and 0.0075 respectively) for further simulations, while the rest are treated as noise variables with deviations.

***Insert* Figure 6. Main Factor Effects Including Noise Factors**

4.3 Elaborating the Fast Analysis Models

The next step is to build the second-order response surface models for each of the seven engine performance parameters as functions of the eight most significant factors (five control factors and the three noise parameters). The mathematical expression of the second-order response surface models is of the following form:

$$f(x_1,...x_n) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n + \gamma_1 x_1^2 + ... + \gamma_n x_n^2$$
$$+ \beta_{12} x_{1,} x_2 + ... + \beta_{n,n-1} x_{n-1,} x_{n.} \qquad (1)$$

The Central Composite Design (CCD) is used to generate the experiments for building the response surface models. For eight factors, the CCD generates 273 experiments. The quadratic response surface models (RSMs) are first obtained and their accuracy values are checked before proceeding to robust design. The values of the R-coefficients for the seven RSMs are given in Table 3. The closer the R-coefficients are to unity, the better the approximation is. It is observed that the RSMs are good only for the responses FANDIA, HPTPR and OPR, which, incidentally are the three constraints. For the other four performance (the four objectives), the RSMs are not accurate enough.

***Insert* Table 3. R-coefficients of the Response Surface Models**

4.4 Improving the Approximations

As enhancements to the RCEM approximation capability, the Artificial Neural Networks (ANN) and the combined RSM+ANN approach proposed in Section 3 are applied to the responses for which the RSM is not sufficient. A comparison of the accuracy for models created by different methods are provided in Table 4. The least squared error (LSE), an overall average variation of the estimated values from the actual values, is the metric for this comparison. It is observed that the LSEs are much less for the improved approximation models (either the ANN or the combined RSM+ANN model) compared to that of the RSM.

Insert Table 4. Comparison of the Least Squared Errors

The improvement in the approximations when using the combined RSM+ANN techniques is graphically illustrated in Figure 7. These plots (A, B, C) are based on the output values from the SOAPP, the RSM, and the combined RSM+ANN models, respectively, taking the grid design as the inputs. The X-axis represents the Combustor Exit Temperature (CET) and the Y-axis represents the Fan Pressure Ratio (FPR), the two important design parameters. The other six factors are at their middle values. It is seen that the approximation using the combined RSM+ANN model (Figure 7(C)) is much better than the RSM based approximation (Figure 7(B)) when compared to the actual behavior (Figure 7(A)) of the performance SFCISO. Based on the LSEs, we decide to use RSMs for the performances FANDIA, HPTPR and OPR; use ANN models for FBURN, RANGE and SFCWIL; and use combined RSM+ANN model for the performance SFCISO. The implementation of the robust designs using the compromise DSP is explained in the following section.

***Insert* Figure 7. Grid Plots for SFCISO**

4.5 Generation of Top-level Design Specifications with Quality Considerations

In this step of the RCEM, the selected approximation models are used as fast analysis modules for the multiobjective optimization for developing *robust* and *flexible* top-level design specifications (Module F). As explained in Section 2, the main objectives of robust design is "to bring the mean m on target" and "to minimize the variations s in the performances" due to the deviations in a design system. Both robust design Type I and Type II are applied to the conceptual propulsion system design problem.

4.5.1 Results for Robust Design Type I

In Type I robust design, the values of engine design variables which optimize the engine performance as well as minimize the impact of the deviations of engine components' efficiencies are identified. Using the mathematical construct of the compromise Decision Support Problem [13], there are two sub-objectives (to bring μ on target and to minimize σ) for each of the four objectives, namely, to minimize the FBURN, the SFCWIL, and the SFCISO and to maximize the RANGE. To consider the variability of the constraints caused by the noise factors, the worst case scenario ($\mu + 3\sigma$) is used for the three constraints, namely, FANDIA, HPTPR, and OPR. The mathematical formulation of the compromise DSP for Type I robust design is given below. To calculate the performance deviations (*_DEV) at each optimization iteration, for each setting (design values) of the five control factors, the three noise factors are varied over a Central Composite Design of 27 experiments. The mean m_f and variance of the performance parameters s_f are calculated for this distribution of 27 experiments. In this formulation, the target values for the standard deviations are taken as zero.

***Insert* Figure 8. Compromise DSP for Type I Robust Design**

When considering multiple aspects of quality, designers may have different preferences for whether it is more important to bring the mean on target or to reduce variation. In the compromise DSP, different design scenarios can be modeled by assigning goals at different priority levels (preemptive formulation) or at the same level with different weights (Archimedean formulation). In Table 5, the results of three different formulations of deviation function are given. The results are compared among each other and with the one without robust design considerations.

A general observation from Table 5 is that the values of design solutions vary among different scenarios, with the changes of the HPCPR and LPCPR (high and low compressor pressure ratios) being the most significant. This is consistent with our previous observation that these two are significant design factors. In terms of design performance, Scenario II, under which achieving the mean performance is placed at the first priority level and minimizing the variance is placed at the second level, attains the best mean performance for SFCWIL, SFCISO, FBURN, and RANGE. On the other hand, Scenario III (preemptive formulation with level for variance and Level 2 for mean performance) attains the minimum variance of SFCWIL, SFCISO, FBURN, and RANGE. The solutions of Scenario I (mean and variance at the same level) illustrate a tradeoff between the two aspects of robust design. In all the cases, the variance of the performance are reduced close to zero. Compared to the results from the conventional optimization without robust design considerations, the sacrifice of the design performance under all the three robust design scenarios is reasonable. Note tradeoffs also exist among the multiple design performance parameters.

Insert **Table 5. Engine Design Optimization Results Using Type I Robust Design**

4.5.2 Results for Robust Design Type II

Type II robust design is performed to find *flexible* engine design specifications that are allowed to vary within a range. As outlined in Figure 2, the constraints and the objectives are the same as in Type I. However, there are five more design variables in this case, representing the deviations of each of the five control factors as a part of the solutions. Similar to Type I, three different optimization scenarios are considered. In Table 6, the results for this type of robust design are shown for all the three scenarios. In "design solutions", the ranges of the design variables ? x are also generated as a part of the solutions. The corresponding variations of the goal performance parameters are provided. It is noted that the locations of the flexible design solutions for HPCPR and LPCPR are significantly different from those without robust design considerations. The tradeoffs between achieving the mean performance and minimizing the variance are also observed throughout the three different scenarios.

Insert **Table 6. Optimization Results Using Type II Robust Design**

4.6 Verification Issues

<u>Approximation Techniques</u>

Corresponding to the research questions posed in Section 1, two verification issues are addressed here. The first issue is to verify whether the approximation models are enhanced using the ANN and the combined RSM+ANN techniques. The results shown in Table 4 and the graphs in Figure 7 prove that there is indeed an improvement in the approximation. Further verifications of this approach are done in this section. The first issue is whether the combined RSM+ANN technique is better than the actual RSM. In Table 7, the least squared errors (LSEs) for the two models are compared for various responses from the P&W propulsion system design problem. The grid design for 121 experiments is used as the input to test the LSEs. It is noted that the combined RSM+ANN models are better than the original RSM for all the cases. These results can be logically explained. The RSM has an error associated with it. The ANN-based error model "corrects" this error to a certain extent. This makes the model more accurate, which is a good reason to use this technique.

***Insert* Table 7. Least Squared Errors for RSM and the Combined RSM+ANN**

The second part of verification of the combined RSM+ANN model is see how efficient this approach is compared to using the pure ANN models. It is found that the combined RSM+ANN approach is less sensitive to the number of nodes chosen than the pure ANN approach. This is evident in the comparisons of LSEs made in Table 8. The number of hidden layers is taken as one for all the networks.

***Insert* Table 8. Least Squared Errors for Varying Number of Hidden Nodes**

We have also confirmed the optimization results obtained from the approximation models by verifying them using the real engine analysis program SOAPP. It is found that the error varis from 1%-10% among the different design scenarios tested.

Applications of Robust Design Concept

The second issue is to verify whether the robust and flexible top-level design specifications are better than those results obtained from the conventional optimization model without robustness considerations. As the verification tests, the minimized variations through robust design, either Type I or Type II, are compared with the performance variations of the conventional optimization solutions (without robust design considerations) assuming that the deviations of noise or control factors do exist. The comparison for the Type I robust design is provided in Table 9, while the comparison for Type II robust design is graphically illustrated in Figure 12. In Table 9, the variation under "without robust design" is larger than the one under "with robust design" for each performance. The variations are obtained by exercising the full range of noise factors (see Table 2). Figure 12 illustrates the tradeoff between achieving the mean performance and minimizing its variance under Type II robust design. It is observed that, with the robust design considerations, the performance variations are reduced for both RANGE and SFEWIL (22.373 vs. 33.586 nmi and 0.0047 vs. 0.0059 lb/hr/lb), under the deviations of the range of solutions (see Table 6). The robustness is achieved with reasonable sacrifice in the mean performance.

In the case of “without robust design considerations”, the full range of noise factors and the same range of deviations of design variables are used to simulate the performance variations for Type I and Type II, respectively, under the scenarios of “what if” the deviations exist. It is noted from both types that the *variations in the four objectives for the case when robust design is used are much less than the other case.* This indicates that robustness is achieved. Meanwhile, a reasonable tradeoff between the performance and its variance is also observed.

***Insert* Table 9. Comparison of the Variations - Type I**

***Insert* Figure 9. Comparison of the variations - Type II**

5 CLOSURE

In this paper, the applicability of the Robust Concept Exploration Method (RCEM) to engineering design at a complex domain is examined. By applying the RCEM approach to the thermodynamic engine cycle design during the conceptual stage at Pratt & Whitney, it is illustrated that the RCEM can be used to improve the computational efficiency in concept exploration through building surrogate models for replacing the expensive simulation programs. By introducing the robust design concept, the possible design adjustments (or uncertainties) can be modeled explicitly and a robust design solution can be obtained to reduce the impact of these potential changes in a design process (Type I robust design). The extension of the robust design for designing a range of solutions (Type II robust design) is applied to achieve the improved design freedom and ultimately the reduced amount of design iterations.

The model approximation capability of the RCEM is enhanced by utilizing various existing approximation techniques and developing new ones. The original RCEM features only the DOE techniques with the Response Surface Methodology (RSM) to build the approximation models (response surface models). It is observed that the response surface models are not very accurate in modeling highly nonlinear behaviors, such as the thermodynamic cycle behavior being studied. The proposed approach, referred to as the combined RSM+ANN model, combines both the RSM and the ANN techniques to build a single model. It is observed through the example problem and the verification studies that the RSM approach is more powerful for approximating low-order nonlinear behavior such as quadratic and linear functions, while the ANN is more appropriate for highly nonlinear functions and the combined RSM+ANN technique is good for moderate nonlinear functions. One important benefit of using the combined RSM+ANN method is the absence of the "black-box" effect. The pure ANN model provides little information on the actual system behavior without any further analysis. On the other hand, the RSM part of the combined RSM+ANN model provides clear information on the contributions of different factors towards the response.

Although the computational demand of the P&W thermodynamic engine cycle design module (SOAPP) is less significant compared to the integrated cycle, flowpath, and mechanical design modules, the results from the example problem demonstrate the capabilities of the RCEM and its potential for concurrent propulsion system analysis at a larger scale. Future research in this area will be towards the development of a hybrid concept exploration methodology that combines the DOE techniques, the ANN methods, and the probabilistic search algorithms. The focus will be on examining the methods of constructing mappings for highly nonlinear functional relationships, with a large number of design variables. It is also desired to capture the multiple modeling objectives in concept exploration with the development of a generic methodology that recommends the "best" model formation technique based on the users' specified modeling criteria.

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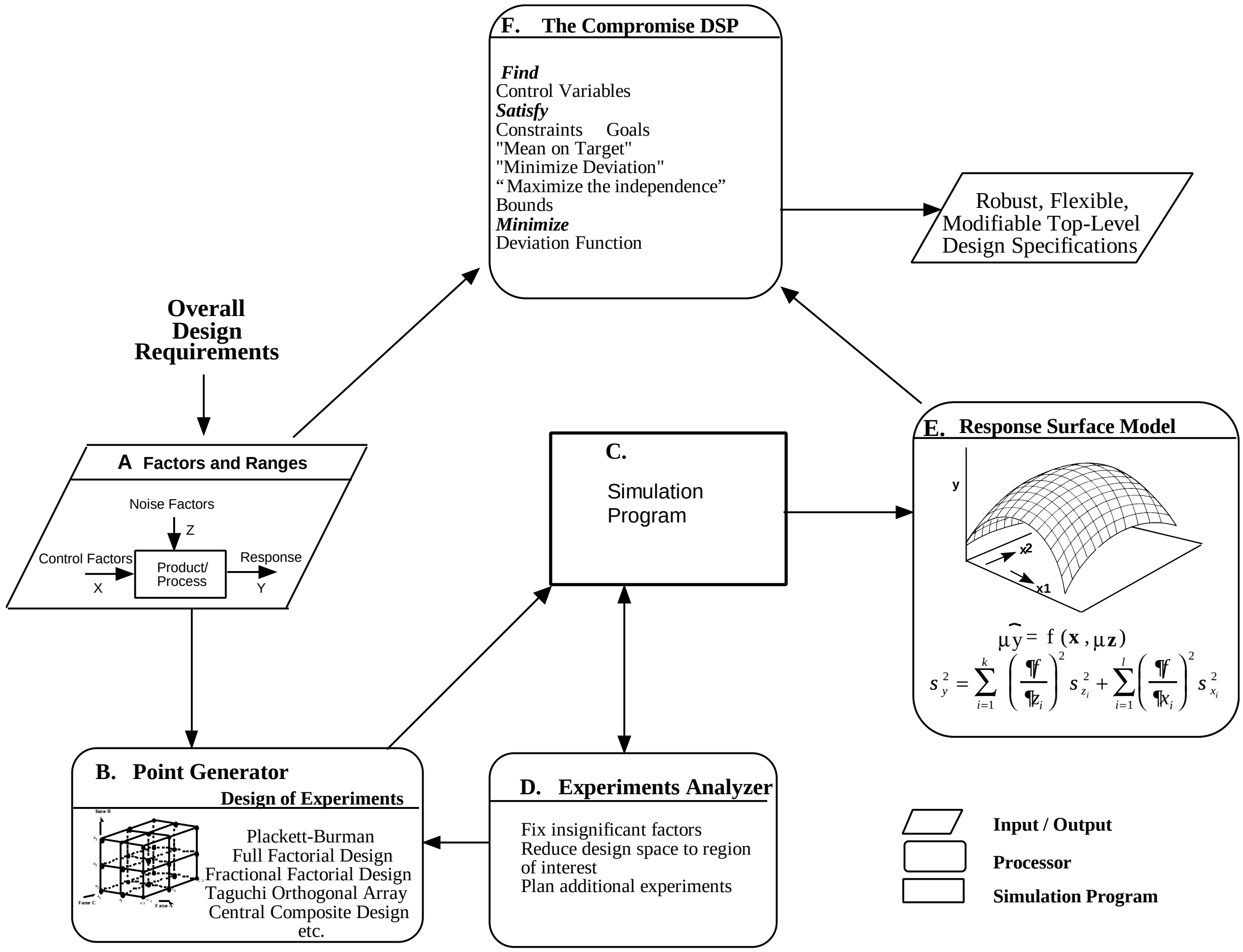


Figure 1. Computer Infrastructure of the RCEM [3]

Type I Robust Design (Robust Specifications)

Given
- Model $f(x, z)$
- Noise factors (μ_z, σ_z)

Find
- Control factors x (top-level specifications)

Satisfy
- System constraints
- Goals
  - Bring the mean μ_y on target
  - Minimize the variance σ_y

Minimize
- Deviation Functions

Type II Robust Design (Flexible Specifications)

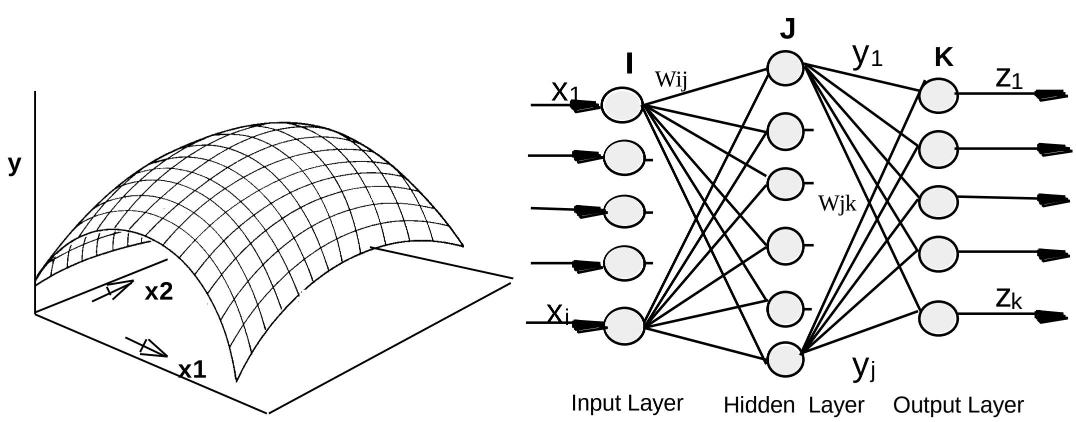
Given
- Model $f(x)$

Find
- A range of control factors x, Δx (top-level specifications)

Satisfy
- System constraints
- Goals
  - Bring the mean μ_y on target
  - Minimize the variance σ_y

Minimize
- Deviation Functions

Figure 2. Two Types of Robust Design



$$y = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j$$

(A) 2nd Order Response Surface Model **(B) ANN Architecture**

Figure 3. RSM and ANN

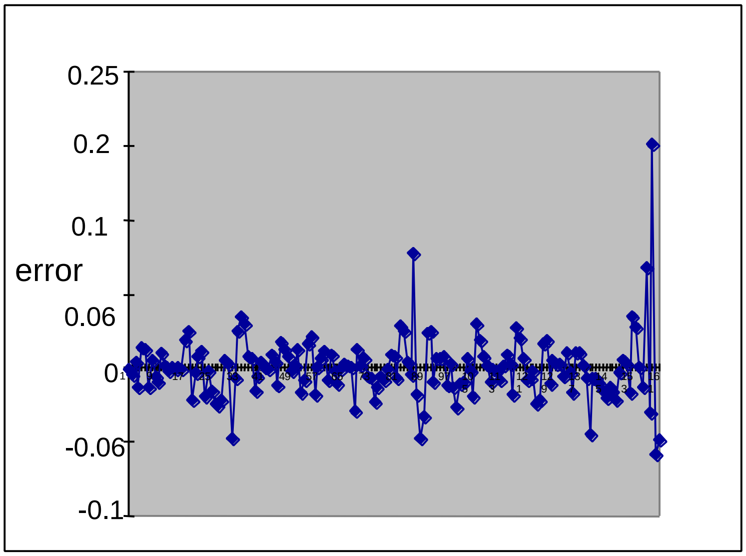


Figure 4. A Typical Error Function, e, between the Actual Model and the Predicted RSM (121 Sample Points)

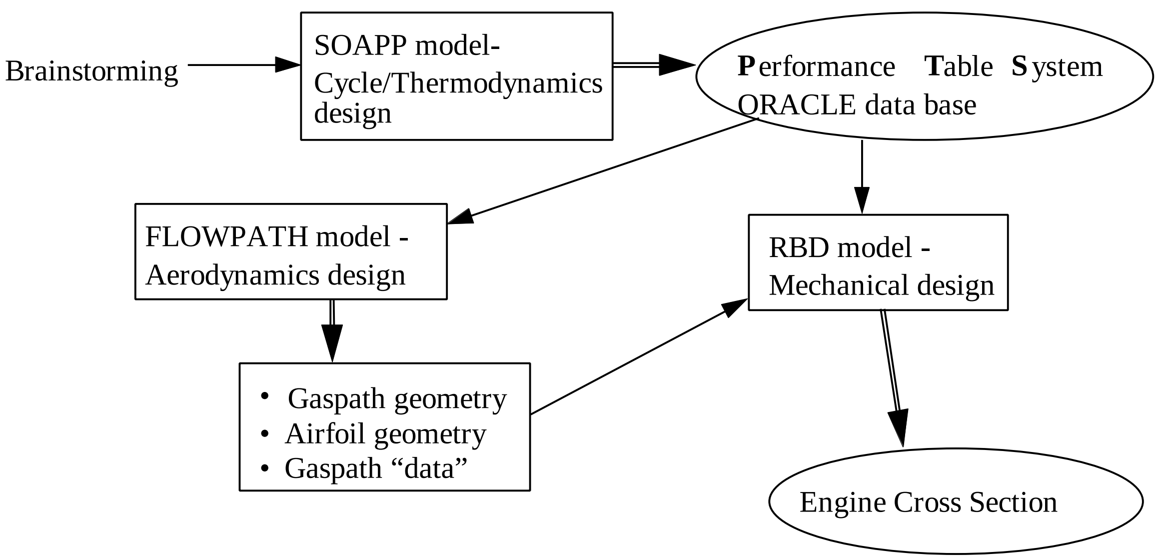


Figure 5. Traditional Top-down Approach to Engine Design (Conceptual Stage)

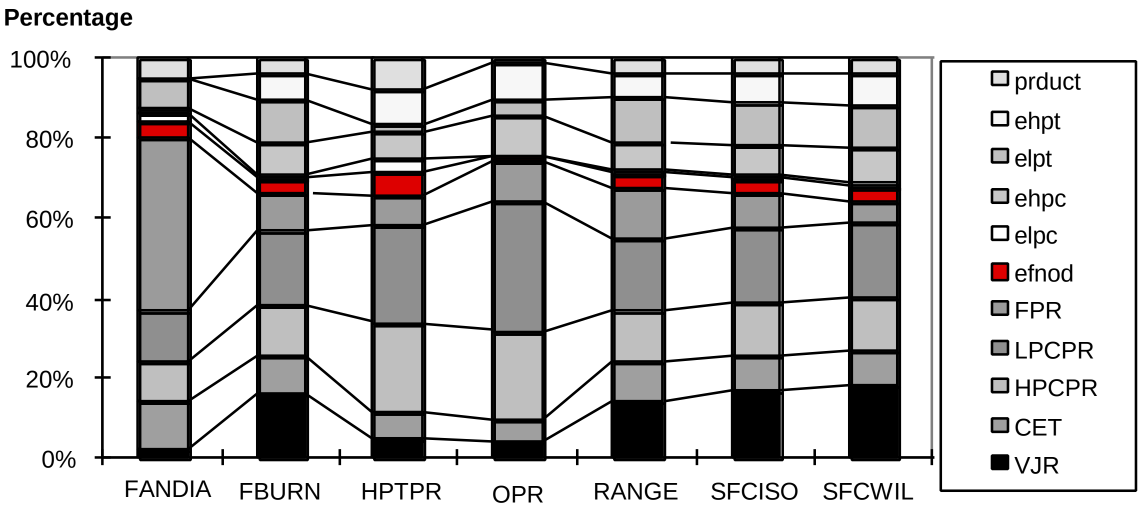
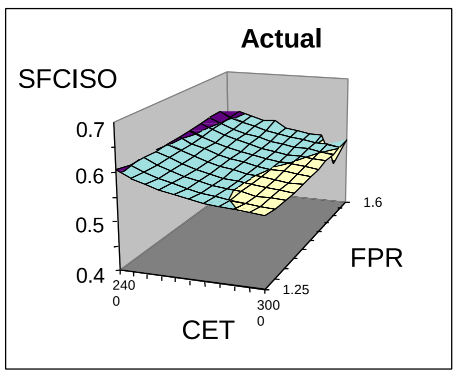
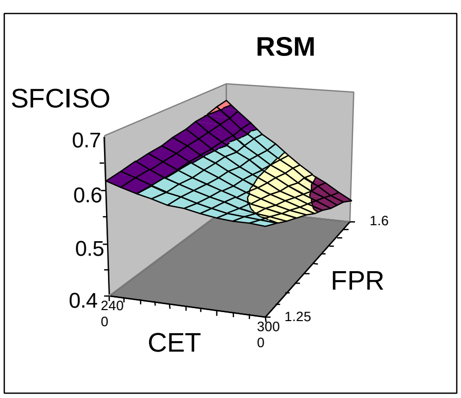


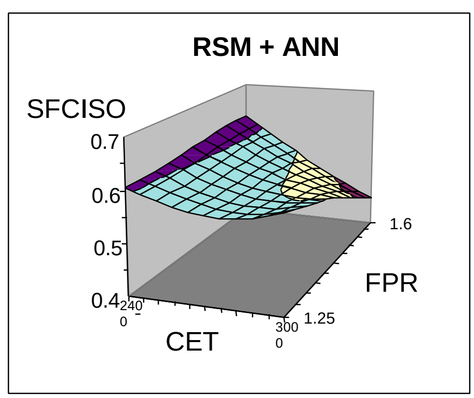
Figure 6. Main Factor Effects Including Noise Factors



(A) SFCISO - Based on the Actual Model



(B) SFCISO - Based on RSM



(C) SFCISO - Based on ANN+RSM

Figure 7. Grid Plots for SFCISO

Given:

- Approximation Models of OPR, FANDIA, HPTPR, RANGE, SFCWIL, SFCISO, and FBURN
- Engine type (ADP)
- Engine Cycle module configuration
- Noise Factors fan efficiency, low pressure compressor efficiency, and fan duct loss at their mid levels

Find: *Robust Engine Design Specifications:*

- Exhaust Jet Velocity Ratio, VJR
- Fan Pressure Ratio, FPR
- Turbine Inlet Temperature, CET
- High Compressor Pressure Ratio, HPCPR
- Low Compressor Pressure Ratio, LPCPR

Satisfy:

- The system constraints

  Overall Pressure Ratio, OPR_M + (3*OPR_DEV) $\leq$ 50

  Fan Diameter, FANDIA_M + (3*FANDIA_DEV) $\leq$ 90 inches

  High Turbine Pressure Ratio, HPTPR_M + (3*HPTPR_DEV) $\leq$ 6

- The system goals for bringing mean on target

  Minimize the mean of:

  Streamtube TSFC: SFCWIL_M/0.45 + $d_1^- - d_1^+ = 1.0$

  Isolated Pod TSFC: SFCISO_M/0.45 + $d_2^- - d_2^+ = 1.0$

  Fuel Burnt: FBURN/7500 + $d_3^- - d_3^+ = 1.0$

  Maximize the mean of:

  Aircraft Range: RANGE/3000 + $d_4^- - d_4^+ = 1.0$

- The system goals for minimizing standard deviation

  Streamtube TSFC: SFCWIL_DEV + $d_5^- - d_5^+ = 0$

  Isolated Pod TSFC: SFCISO_DEV + $d_6^- - d_6^+ = 0$

  Fuel Burnt: FBURN_DEV + $d_7^- - d_7^+ = 0$

  Aircraft Range: RANGE_DEV + $d_8^- - d_8^+ = 0$

- The bounds on the system variables (unnormalized):

  $1.25 \leq$ FPR ≤ 1.6

  $0.6 \leq$ VJR ≤ 0.9

  $2400 \leq$ CET ≤ 3000

  $10.2 \leq$ HPCPR ≤ 25

  $1.15 \leq$ LPCPR ≤ 4.9

Minimize:

- The sum of the deviation variables associated with the mean and std. Deviation of each response

  Streamtube TSFC, SFCWIL: d_1^+ and d_5^+

  Isolated Pod TSFC, SFCISO: d_2^+ and d_6^+

  Fuel Burnt, FBURN: d_3^+ and d_7^+

  Aircraft Range, RANGE: d_4^- and d_8^+

Figure 8. Compromise DSP for Type I Robust Design

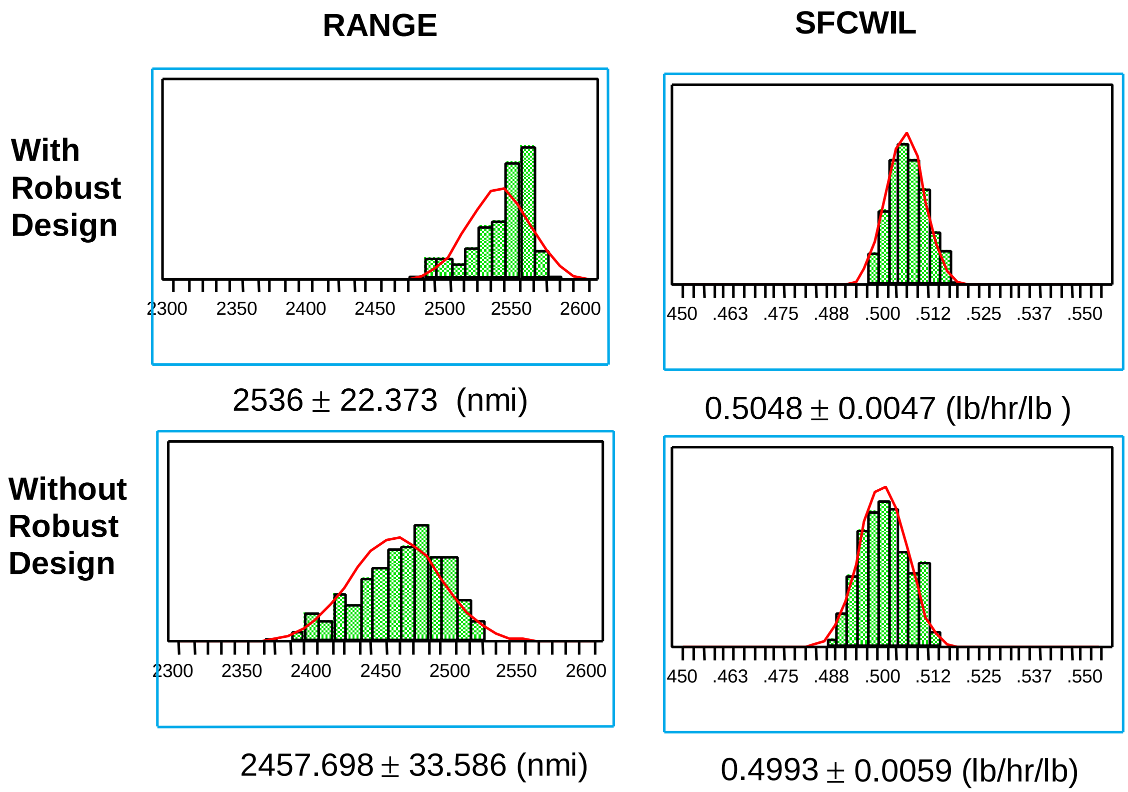


Figure 9. Comparison of the variations - Type II

Table 1. Problem Identification and Classification of Parameters

Table 1a Top-Level Design Specifications of the Propulsion System Design

Design Parameters	Lower Bound	Upper Bound	Baseline
Fan Pressure Ratio (FPR)	1.25	1.6	1.32
Exhaust Jet Velocity Ratio (VJR)	0.6	0.9	0.85
Turbine Inlet Temperature (CET) [R]	2400	3000	2750
High Compressor Pr. Ratio (HPCPR)	10.2	25	10.2
Low Compressor + Fan Root Pressure Ratio (LPCPR)	1.15	4.9	2.14
Engine Type	TurboFan, Geared TurboFan and ADP		GTF

Table 1b Engine Design – Constraints and Objectives

Constraints	Limits	Baseline
Overall Pressure Ratio (OPR)	=50	21.8
Fan Diameter (FANDIA)	= 90 in.	84.3
HP Turbine Pressure Ratio (HPTPR)	= 6.0	3.156
Objectives	**Targets**	**Baseline**
MIN Streamtube TSFC (SFCWIL)	0.45 lb/hr/lb	0.533
MIN Isolated Pod TSFC (SFCISO)	0.45 lb/hr/lb	0.585
MIN Fuel Burn (FBURN)	7500 lbs	8248.1
MAX Aircraft Range (RANGE)	3000 nmi	2300.5

Table 2. Noise Parameters for the Engine Design

Noise Parameters	Minimum	Nominal	Maximum
Fan Efficiency, efnod	0.917	0.927	0.937
Low Compressor Efficiency, elpc	0.89	0.90	0.91
High Compressor Efficiency, ehpc	0.881	0.891	0.901
Low Turbine Efficiency, elpt	0.923	0.933	0.943
High Turbine Efficiency, ehpt	0.89	0.90	0.91
Fan Duct Loss, prduct	0.007	0.0075	0.008

Table 3. R-coefficients of the Response Surface Models

Response	*R^2*	*R^ADJ*	*R^PRESS*
FANDIA	**0.99794**	**0.99716**	**0.99625**
FBURN	0.92694	0.89923	0.67434
HPTPR	**0.99011**	**0.98636**	**0.95881**
OPR	**1.00000**	**1.00000**	**1.00000**
RANGE	0.93023	0.90376	0.68791
SFCISO	0.92911	0.91255	0.68456
SFCWIL	0.93660	0.91255	0.71996

Table 4. Comparison of the Least Squared Errors

Response	***RSM***	***ANN***	***RSM+ANN***
FBURN	430.818	**261.33**	311.788
RANGE	184.47	**90.81**	119.249
SFCWIL	0.02924	**0.0154**	0.02064
SFCISO	0.03058	0.0243	**0.01743**

Table 5. Engine Design Optimization Results Using Type I Robust Design

	Scenario I (same level)	Scenario II Level 1- Mean Level 2 – Std.Dev.	Scenario III Level 1 – Std. Dev. Level 2 –Mean.	Without Robust Design
DESIGN VARIABLES				
VJR	0.9000	0.9000	0.8087	0.744
CET	2963.3	3000.0	2817.33	2964.0
HPCPR	10.200	10.200	18.973	11.088
LPCPR	4.850	4.900	2.4610	4.1302
FPR	1.600	1.5702	1.56278	1.44257
GOALS				
SFCWIL	0.5143 ± 0.000	0.5093 ± 0.000	0.5426 ± 9.542E-08	0.49638
SFCISO	0.450 ± 6.188E-04	0.4499 ± 7.032E-03	0.5743 ± 4.387E-03	0.53135
FBURN	7447.01 ± 6.06E-04	7368.05 ± 0.000	6791.92 ± 0.000	7422.7
RANGE	2541.62 ± 4.14E-04	2524.45 ± 2.28EE-04	2619.49 ± 4.535-04	2749.52

Table 6. Optimization Results Using Type II Robust Design

	Scenario I (same level)	Scenario II Level 1- Mean Level 2 – Std.Dev.	Scenario III Level 1 – Std. Dev. Level 2 –Mean.	Without Robust Design
DESIGN VARIABLES				
VJR	0.6995 ± 2.193E-02	0.857 ± 2.662E-02	0.860 ± 2.987E-02	0.744
CET	2970.93 ± 90.54	3000.00 ±117.59	2597.97 ± 93.135	2964.0
HPCPR	22.18 ± 0.792	23.035 ±0.882	11.516 ± 0.362	11.088
LPCPR	1.589 ± 5.60E-02	1.459 ±9.624E-02	1.241 ± 3.996E-02	4.1302
FPR	1.380 ± 4.35E-02	1.539 ±7.036E-02	1.369 ± 4.112E-02	1.44257
GOALS				
SFCWIL	0.504 ± 4.72E-03	0.527 ± 1.918E-02	0.582 ± 5.35E-03	0.49638
SFCISO	0.585 ± 9.802E-03	0.543 ± 2.946E-02	0.655 ± 8.772E-03	0.53135
FBURN	7963.91 ± 96.86	7411.33 ± 295.397	8791.73 ± 233.288	7422.7
RANGE	2536.30 ± 22.3731	2566.88 ± 123.189	1891.6 ± 36.842	2749.52

Table 7. Least Squared Errors for RSM and the Combined RSM+ANN

Response	RSM	Combined RSM+ANN	ANN
P&W Propulsion System (based on CCD 273 exp.)			
SFCWIL [lbf/hr/lbm]	0.02924	0.02064	0.0154
SFCISO [lbf/hr/lbm]	0.03058	0.01743	0.0243
FBURN [lbs]	430.818	311.788	261.33
RANGE [nmi]	184.47	119.249	90.81

Table 8. Least Squared Errors for Varying Number of Hidden Nodes

Response - RANGE [nmi]		
Nodes	**pure ANN**	**Combined RSM+ANN**
40	90.81	109.021
60	131.97	105.8104
90	223.77	100.066
100	167.122	119.25
150	96.6	112.51

Table 9. Comparison of the Variations - Type I

GOAL	VARIATION	
	Without Robust Design	With Robust Design
SFCWIL	1.2399E-04	0.0000
SFCISO	1.17445E-04	6.188E-04
FBURN	1.78386	6.06E-04
RANGE	0.74516	4.14E-04