AIAA 98- 4917

An Application of Concurrent Subspace Design (CSD) to the Preliminary Design of a Low-Reynolds Number UAV

Xiong Qing Yu [†]
Marc A. Stelmack *
Stephen M. Batill **
Department of Aerospace and Mechanical Engineering
University of Notre Dame, Notre Dame, Indiana

ABSTRACT

The Concurrent Subspace Design (CSD) framework has been used to conduct a preliminary design optimization of an electric powered, unmanned air vehicle (EPUAV) operating a low Reynolds number. A multidisciplinary system analysis has been developed for this class of vehicles and includes aerodynamics, weights, propulsion, performance and stability and control. The CSD framework employs artificial neural network based response surfaces to provide approximations to the design space. This approach was applied to two design studies. In one case 29 continuous and discrete design variables were included representing the most demanding application of the CSD framework to date. In each case the CSD framework was able to identify feasible designs with significant weight reductions relative to any previously considered (i.e. initial database) designs. This was accomplished with a limited number of system analyses. The results also demonstrate the adaptive nature of this design framework to changes in design requirements.

INTRODUCTION

The purpose of this paper is to describe an MDO application of a multidisciplinary design framework, Concurrent Subspace Design, CSD, in which model-based design decisions can be applied to multidisciplinary, conceptual design. Of particular concern is the ability to implement this framework without having to extensively modify or adapt the software used for the multidisciplinary system analysis.

At the onset the authors wish to emphasize an attempt on their part to differentiate between engineering system design and mathematical optimization. Though it would be the goal of any designer to develop the global "optimum" design, in most practical situations this is generally not possible. Therefore, one is often satisfied with a design which meets the primary constraints or performance goals and is more effective by some quantifiable measure (i.e. merit function) than other designs which have been considered. It is also important that this design be identified in a reasonable amount of time. The framework used in this work represents a method for the efficient selection of a feasible design for a complex system and our purpose is to demonstrate issues of problem formulation and implementation.

The CSD framework has been used in a number of different applications ranging from simple demonstration problems to more complex engineering components[1-3]. In the current application a special class of aircraft are considered, electric powered unmanned air vehicles, EPUAVs. The design and fabrication of this class of aircraft have provided a focus for the capstone design experience at the University of Notre Dame for the past decade. This experience has provided an aircraft database as well as a number of discipline specific analyses, which have been developed to support these design studies. Due to the unique and non-traditional potential missions for EPUAVs they also provide an interesting example for design studies.

The first phase of the current work was the development of integrated system analysis software to provide the information for design decisions. This integrated system analysis includes vortex lattice aerodynamics, empirical drag and weights estimation, propeller and electric motor propulsion system computations, flight performance and stability and control assessments.

[†] Visiting Scholar, (Associate Professor, Nanjing University of Aeronautics and Astronuatics, PRC)

* Graduate Research Assistant, Member AIAA

** Professor, Associate Fellow, AIAA

This current application represents an extension of the complexity of the system analysis and an increase in the number of design variable and system states from previous CSD implementations. The paper overviews certain features of CSD, its use with the EPUAV's and highlights a number of design studies.

Terminology

In order to present the discussion in this paper a number of terms or concepts need to be developed.

Design variables,{x}: The set of independent parameters which can be "controlled" by the designer. The set of design variables completely defines the artifact at some level of abstraction. Some design variables maybe continuous(real-valued), others discrete (integers), and others may not be "numeric" at all, such as material type.

State variables, {y}: A set of parameters which are used to describe the performance or characteristics of a specific design. Design decisions are based upon state information. States are functions of design variables.

System analysis, SA: That process whereby the complete set of state variables associated with a specific set of design variables is determined by satisfying a set of state equations.

$$\{y\} = \mathbf{F}\{x\} \tag{1}$$

For multidisciplinary systems the SA involves a variety of different engineering disciplines and their associated analysis methods and corresponding models.

Consistent design: A set of design variables and associated states which satisfies all of the conditions set forth in the system analysis. Not every set of design variables may result in a consistent design (i.e. a particular aircraft design may not have enough power available to achieve steady level flight at any speed.)

Feasible design : A consistent design which satisfies a set of explicit requirements or constraints, in addition to the state equations, which are imposed on either design variables or states. In most optimization problems the constraints are functions of design variables and system states.

Optimum design: A feasible design with the best performance as quantified by some measure of merit relative to all other designs proximate to the optimum. The optimum can either be local or global and for most practical problems it occurs on constraint boundaries.

CONCURRENT SUBSPACE DESIGN

The MDO framework presented in this paper has evolved from the fundamental structure of Concurrent Subspace Optimization (CSSO) proposed by Sobieski[4] and it involves the use of neural network based response surface approximations. For additional information related to its development and implementation and a variety of other issues related to mixed continuous discrete optimization problems, the reader is referred to References 5-8.

The current approach attempts to exploit the fact that the system being designed can be decomposed in a manner which corresponds to the analysis or prediction "tools" used to provide the information required to make design decisions. This is a model or "tool-based" decomposition. As an example, the "weights" discipline is responsible for determining the weights of all of the components based upon information related to configuration, geometry, loads and materials. The "tools" used by the weights discipline can vary with the level of detail and time available to develop the information. For the framework presented herein individual technical discipline, or subspace, "experts" can each contribute to the design process by suggesting candidate designs. These designs can be developed using whatever methods or tools are best suited for the particular subspace - at the particular point in the design process.

A schematic of the basic CSD algorithm is shown in Figure 1. The process flow in the CSD algorithm begins with the selection of a group of baseline designs. A system analysis is performed on each of these designs to initially populate the design database with design variable and associated state information. The initial design database can contain a baseline design, perturbations about the baseline or information from other design studies or data sources. A set of response surface approximations is then formed using this initial set of designs. As implemented in this study CSD uses three-layer, feed-forward, sigmoid activation neural networks for response surface approximations.

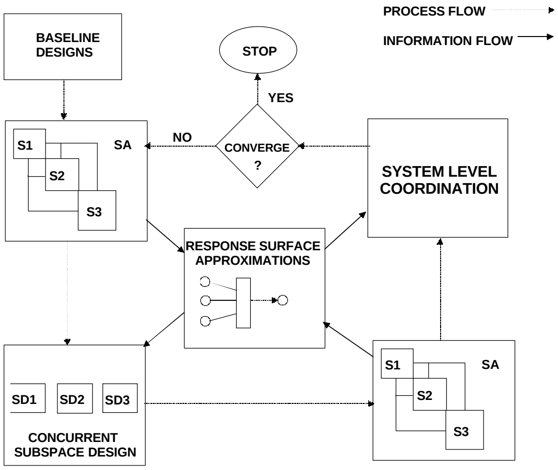


Figure 1. CSD Framework

In the next step in the process independent and concurrent design activities of the subspace experts yield additional members of the design database. This algorithm allows discipline designers to be creative in arriving at new candidate designs. The solutions obtained by discipline-level designers can be very different from the current design being considered (not restricted by move-limits) and the subspace designers can suggest as many designs as time and resources will permit. Designers at the subspace level are not required to optimize at all, but rather provide new designs by any available means.

In order to effectively participate in the design process, subspace designers are given the ability to change a subset of the system design variables. A given design variable maybe controlled by a single designer or shared by subspace designers. Designers have available to them information which can be used to approximate the impact of their decisions on non-local states at little computational expense once the response surfaces are quantified. It should be noted that not all subspaces need to develop new design candidates at each step in the process. Some subspaces may not contribute new designs. The issues related to the role of the subspace expert are also influenced by the level of “automation” desired in the process.

The result of the Concurrent Subspace Design phase of the CSD algorithm is a set of new designs. These new designs are analyzed and added to the design database from which an updated system approximation is constructed. The design database continues to expand with each iteration of the algorithm; each time a new approximation is formed using all of the available design database information.

The next step in the process is the fully approximate system coordination problem. It has the benefit of using all of the system design variables and of removing certain restrictions on the optimization algorithm. Since the cost of performing the approximate system analysis is quite small, optimization algorithms such as those associated with discrete system optimization, or hybrid approaches, can be used. An additional benefit of the global approximations is apparent when the design requirements or constraints change during the design process. Because the response surface approximations are re-formed using all available design space data and they approximate states, rather than constraints or the merit function, the rapid re-evaluation of designs, based on a change in design criteria, is possible. It is even possible to initiate the system coordination problem from multiple starting locations so that one can identify and avoid local optimum.

This framework is similar to the more traditional design methods based upon “carpet” plots. In CSD the multidimensional “carpet” plots have been parameterized in the form of neural network approximations and the most appropriate optimization strategies are used to seek the best design. The ability of this approach to provide improved or optimum designs is directly related to the accuracy of the response surface approximation used for system level coordination.

Mixed Continuous Discrete Optimization

Both continuous and discrete variables were required in the current application. This was accomplished by combining two distinct optimization strategies, one suitable for purely discrete and the other for purely continuous optimization. Since the system analysis performed at the system level is fully approximate, it provides certain flexibility in the selection of the optimization algorithm. The system level optimization was therefore initially posed as fully discrete. This was accomplished by discretizing each of the continuous variables, and using a discrete optimizer, simulated annealing, to adjust all the design variables. This enabled it to effectively explore any region of the space and helped avoid local minimum. Continuous optimization followed simulated annealing in this hybrid scheme.

A drawback of simulated annealing, as is common among all discrete optimization methods, is the large number of merit function evaluations required. Since the optimization performed at the system level is based solely upon information gained from the response surface approximations, the large number of function evaluations is not a limiting drawback. In performing constrained optimization by simulated annealing, the constraints were formulated as penalty functions and added to the objective function. The form of these penalty functions can affect the performance of the optimizer. Reference 7 details alternatives for the penalty functions and describes the methods used in CSD.

Continuous optimization in the current formulation of the CSD framework was performed using the generalized reduced gradient method[9]. It is a gradient-based technique that is suitable for constrained optimization.

User Interactive CSD

Figure 2 illustrates the CSD framework as invoked in the current study. A recently developed system analysis for EPUAVs provided the model-based design information. The goal of the current work was to use this "monolithic" analysis package and integrate it into the CSD framework with minimal new "code" development. This implied that subspace design would be performed by "experts" using experience and intuition - not optimization algorithms which would require additional software. Thus a user-interactive form of CSD is outlined below.

To initiate the process, the initial database was selected and, using that database, an initial set of response surfaces developed. A system-level, fully-approximate, mixed continuous-discrete optimization was then performed resulting in a baseline design.

At this point the subspace experts were involved. Each expert was allowed to suggest new designs to add to the database. At each iteration each expert could suggest one or more new designs but were not required to suggest any if this was appropriate at a given point in the process. The new subspace designs were based on experience or resulted from "what if" logic. The subspace "experts" had available the full system analysis tool to perform their manual subspace design studies as well as the response surface approximations to determine the impact of their decisions on "non-local" states or constraints. These experts were not limited to suggesting single designs to add to the database and at certain points in the process they actually selected multiple designs.

These candidate designs were then analyzed using the full system analysis and added to the database. The response surfaces were updated and the process continued until convergence was achieved. Convergence of this process was determined by the designers who monitored the design progression and determined when a suitable design has been achieved.

The primary framework was invoked on a Unix workstation with process control developed using TCL/TK. The system analysis was a series of FORTRAN codes which were assembled from a variety of independent analyses and integrated into a single executable.

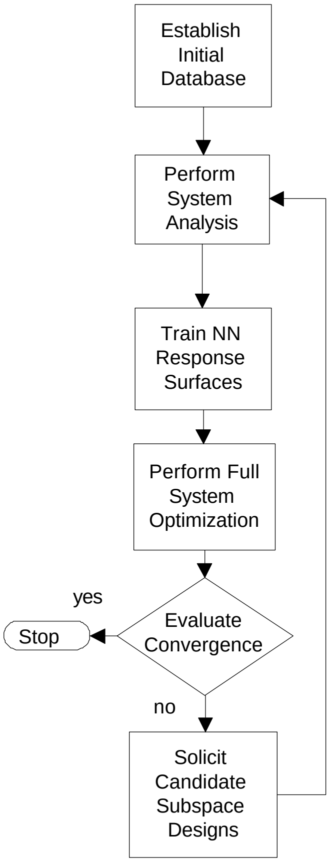


Figure 2. User Interactive CSD Framework

UAV SYSTEM ANALYSIS

The System Analysis (SA) is the source for the information used to describe system performance. It is the critical evaluation of this information that the designer uses to make decisions. The artifact designed in the current application, EPUAV, is a complex, multidisciplinary system. The system analysis for the EPUAV is shown schematically in Figure 3. In this application the disciplines of aerodynamics, weights estimation, propulsion, performance and stability and control were included. Figure 3 is referred to as a dependency or N^2 diagram and it illustrates the information exchanged between the individual disciplines. The purpose of the system analyses is to provide consistent designs, they need not be feasible. In this case this allows the system analyses to assume a hierarchic form thus not requiring information feedback. The system analysis is organized as shown in Figure 3 in a manner so that all necessary state information is "fed-forward" (i.e. appears above the diagonal). Thus the aerodynamics, weights or propulsion disciplines can be performed in any order as long as they precede the performance and stability and control disciplines.

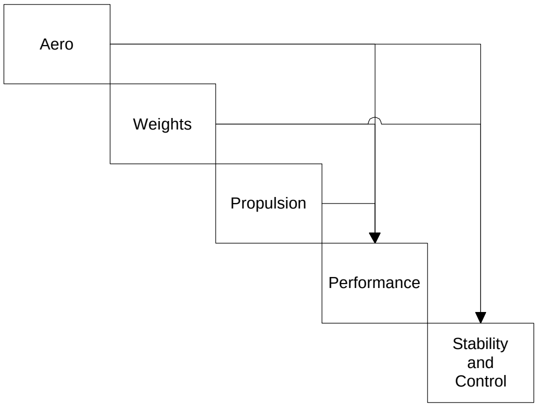


Figure 3. EPUAV System Analysis

The system analysis was developed for electric-powered, remotely or autonomously controlled, low-Reynolds-number flight vehicles. The vehicles are powered by fixed-pitch propellers driven by electric motors. Batteries are used for energy storage. The airframes are fabricated using lightweight, organic, orthotropic composites (wood) and plastics. The database used to provide the empirical models for certain parts of the system analysis contains aircraft with 6-15 ft^2 wing area, weights of 5-15 lbs with maximum flight speeds of less than 100 ft/sec. This implies that the Reynolds number based on chord for most of the lifting surfaces is less than $5x10^5$. Typical payloads are avionics systems and other instrumentation ranging from 0.5 - 5 lbs.

The system analyses for the electric powered UAV required 42 parameters to completely describe a design and associated flight condition. These included external dimensions on the wing, horizontal and vertical empennage surfaces, elevator, motor and battery type. The aircraft itself was restricted to a simple planform configuration with a nose mounted motor and propeller, single main wing and aft mounted horizontal tail. The fuselage was divided into three segments: forward, which contained the motor; mid-section, which contained any payload and avionics and support for the main wing ; aft, which supported the horizontal stabilizer. A single system analysis takes approximately 10 seconds on a Sparc Ultra1 workstation.

Discipline Analyses

The analyses associated with each of the disciplines are described below. Space does not allow for a detailed description of each.

Aerodynamics

The aerodynamics discipline is responsible for developing the "lift curve" and drag polar for the aircraft. The wing and horizontal stabilizer are modeled and analyzed using the vortex lattice method [10]. The wing and tail are modeled as non-planar, interfering surfaces and the analysis allows linear taper, sweep and twist. The paneling of the surfaces is automated in order to maintain reasonable panel aspect ratios as the lifting surface geometry changes during the design. Currently 5 different low-Reynolds number airfoils are available for use in the analysis and their selection represents a discrete design variable in the optimization phase.

The maximum lift coefficient is estimated by determining when the local section maximum lift coefficient exceeds the 2-D maximum lift coefficient for the airfoil. Drag estimation for the aircraft is based upon the component build-up method as presented by Jensen[11].

The state output from this discipline is an estimate of C_{Lmax}, C_D vs. C_L and pitching moment characteristics for the aircraft. These are internal states since they do not directly enter into the calculation of the merit function or constraints in the design optimization problem.

Weights

Weight prediction is based upon empirical models developed from a database of aircraft of this class designed and fabricated at the University of Notre Dame during the past decade. Weights are estimated for the major components: wing, fuselage, empennage surfaces and landing gear. Avionics and payload weights are fixed as user input and the motor, propeller and battery weights are determined by the selection of those individual components. This discipline analysis determines total aircraft weight and center of gravity location.

Since the merit function for the design optimization is total vehicle weight, the overall optimization results strongly depend upon the accuracy and suitability of these empirical correlations.

Propulsion

Electric propulsion represents a rather unique feature of this application. Electric motors with battery energy storage present special challenges for flight vehicle design. Batteries are heavy and system weight does not decrease during flight. Motor speed is controlled by varying the voltage applied to the motor and range and endurance depend upon current requirements and battery capacity.

This discipline analysis has two primary components. The first is a blade element propeller analysis for fixed-pitch propellers which includes induced velocities, tip loses, as well as Mach and Reynolds number corrections[12]. It computes thrust and power coefficients and propeller efficiency. The propeller is then matched with a permanent magnet electric motor to determine thrust and power available as well as current draw which are the output states for this discipline. These too are internal states since they only indirectly influence the constraints and the merit function.

Performance

The flight performance estimates are based upon the internal states provided by the aerodynamics and propulsion disciplines. The output states are maximum and minimum level flight speeds, maximum steady rate of climb, take-off distance and maximum range. A number of the flight performance calculations were adapted from code developed by Smetana[13] and the take-off estimate is a numerical integration ground roll prediction. These calculations are performed at a fixed altitude.

Many of the states determined in this discipline are included as constraints in the design optimization.

Stability and Control

This discipline involves an assessment of basic longitudinal stability and control. The static margin is estimated base upon the information provided by the aerodynamics discipline and the center of gravity provided by the weights discipline.

The landing gear are placed on the aircraft (tricycle configuration) so that a fixed percent of the total weight is on the main gear. Then for a fixed maximum elevator deflection, the speed at which the nose gear can be lifted from the ground is determined. The static margin and rotation speed are used as constraints in the optimization problem.

This newly developed system analysis for EPUAVs provides a useful tool to the designer. Though extensive evaluation of the complete analysis is ongoing, a simple “trade study” is used to illustrate certain characteristics. Figure 4 presents a carpet plot for an example in which payload and wing aspect ratio are varied (all other design variables fixed) and takeoff weight and maximum range determined. It illustrates the monotonic and nonlinear variation in particular states for this complex coupled system analysis.

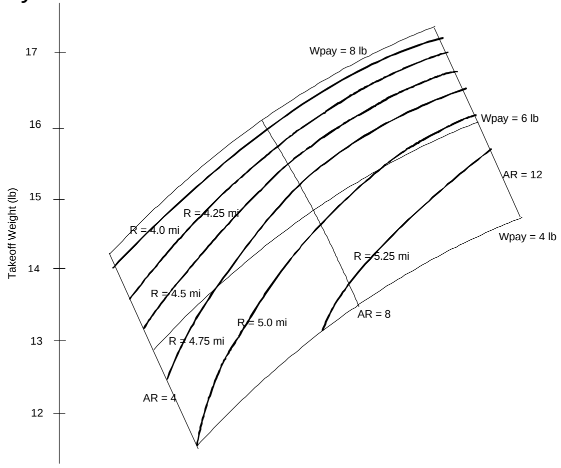


Figure 4. Sample Result from System Analysis

EPUAV APPLICATION OF CSD

The system analysis described above provided the foundation for the design-optimization study. Two design problems will be presented. In the first, twelve design variables were identified. This fairly small number of design variables (all continuous) was selected to allow for a comparison of the CSD framework with a gradient-based NAND (Nested ANalysis/Design) optimization[14]. The merit function and constraints for this first problem were similar to the second problem and since the second application was the primary focus of this study, it will be presented in some detail below. Results for this smaller, benchmark application follow later in this paper.

In the second application the design problem was posed using 29 design variables which are listed in Table 1. Four were discrete (airfoil profile, number of batteries, battery type and motor type) and the remainder continuous. To give some idea of the scope of this design problem, if each of these 29 design variables were used in a two-level, full-factorial exhaustive search, it would take 340 years based on the assumption that each system analysis takes 10 seconds.

The SA produces a significant amount of information but for this study selected design variables and eight system states were used to compute the design merit function and the constraints for the optimization. The design/optimization problem for the CSD formulation can be stated as:

Minimize: Takeoff Weight (Wto)
Subject to Inequality Constraints on:

a. Maximum Range (R)
b. Maximum and minimum level flight speed (Vmax and Vmin)
c. Maximum steady rate of climb (ROC)
d. Takeoff ground roll distance (Sto)
e. Longitudinal static margin (S.M.)
f. Takeoff rotation speed (Vrot)
g. Geometry constraint on wing-tail spacing
h. Geometry constraint on wing root chord and fuselage centerbody relative sizes

and upper and lower bounds on all continuous design variables.

In order to determine the state vs. design variable dependencies, and thus the appropriate forms for the response surface approximations to the states, a series of system analyses were performed. This was accomplished by “manually” varying each design variable across its allowable range while all the others were fixed at their nominal values. Approximately 4 values were selected across the range of each design variable. The resulting 113 designs formed one of the databases used in the design studies and were used to develop the information in Table 1. This Table illustrates the states and the design variables on which they depend. Thus the neural network response surface for Wto was a 13xNx1 network where the number of hidden layers, N, was determined using the techniques outlined in References 7 and 8. Significant care must be exercised in identifying these dependencies and space does not permit detailing the methods invoked to insure appropriate design variable allocation.

The subspace optimization allows for the concurrent design of the system by allowing designers to suggest alternative designs at the subspace level. The design variable allocation for each of the subspace design (optimization) problems were defined as shown in Table 1. Four subspaces were identified.

SS1 - Weights
SS2 - Aerodynamics and Performance
SS3 - Propulsion
SS4 - Stability and Control

Each subspace “expert” was responsible for a subset of the system design variables. This allocation resulted in both shared and discipline-unique design variables for the subspace design problems. Each subspace design problem takes the same form as above and were performed in a “quasi-heuristic” fashion using both the SA and response approximations to provide design guidance.

RESULTS

A series of studies was performed to provide a preliminary evaluation of the formulation of the design problem and the performance of CSD. As indicated above a number of “initial” databases were developed. Each database contained a baseline design, usually near the “center” of the design space and perturbations of single design variables from this baseline. Table 2 summarizes the four databases considered. Those containing 25 and 49 designs were used for the 12 DV study and each contained a single feasible design and the average and minimum weight of all the designs are indicated in Table 2.

Those containing 58 and 113 designs were used for the 29 DV study and none of the designs in these initial databases were feasible.

Variable Name (Type)	Wto	Vmax	Vmin	ROC	Sto	R	S.M.	Vrot	SS1	SS2	SS3	SS4
Wing Aspect Ratio (C)	x	x	x	x	x	x	x	x	x	x		x
Wing Area (C)	x	x	x	x	x	x	x	x	x	x		
Wing Taper Ratio (C)		x	x	x	x	x	x	x		x		
Wing Sweep (C)		x	x	x	x	x	x	x				x
Wing Washout (C)		x	x	x	x	x	x	x		x		
Wing Incidence (C)		x	x	x	x	x		x		x		
Airfoil Section (D)	x	x	x	x	x	x	x	x	x	x		x
Horizontal Tail AR (C)		x	x	x	x	x	x	x				x
HT Area (C)	x	x	x	x	x	x	x	x	x			x
HT Taper (C)		x	x	x	x	x	x	x				x
HT Sweep (C)		x	x	x	x	x	x	x				x
HT Incidence (C)		x	x	x	x	x		x				x
HT Thickness Ratio (C)		x	x	x	x	x				x		
Elevator Chord Ratio (C)								x				x
Fuselage Width - Center Section (C)	x	x	x	x	x	x	x	x	x	x		
Fuselage Height - Center Section (C)	x	x	x	x	x	x	x	x	x	x		
Fuselage Length - Center Section (C)	x	x	x	x	x	x	x	x	x	x		x
Fuselage Length - Aft Section (C)	x	x	x	x	x	x	x	x	x	x		x
Fuselage Length - Forward Section (C)	x	x	x	x	x	x	x	x	x	x		x
Wing Longitudinal Position (C)		x	x	x	x	x	x	x				x
Battery Type (D)	x	x	x	x	x	x	x	x	x		x	
Number of Batteries (D)	x	x	x	x	x	x	x	x	x		x	
Battery Position (C)							x	x				x
Motor Type (D)	x	x	x	x	x	x	x	x	x		x	
Motor Position (C)							x	x				x
Propeller Diameter (C)	x	x	x	x	x	x	x	x	x		x	
Propeller Pitch (C)		x	x	x	x	x					x	
Avionics Position (C)							x	x				x
Payload Position (C)							x	x				x

Table 1. Design Variables, Types, State Dependency and Subspace Allocation

The first study was the gradient based NAND approach using 12 design variables. The results of three cases (1-3) are shown in Table 3. Each optimization was begun from a different starting location. Case 1 was begun at the center of the space and Cases 2 and 3 at arbitrarily selected points with the space. Cases 2 and 3 converged to similar designs while Case 1 appeared to converge to another local minimum. There was significant variation in the number of iterations (system analyses) required for each case and this appeared to depend upon the starting location.

Total Number of Designs	Average Weight (lb)	Number Feasible	Least Weight Feasible (lb)	Least Weight (lb) [# of Violated Constraints]
25	6.432	1	6.45	6.125 [1]
49	6.258	1	6.25	5.960 [1]
58	6.050	0	-	5.767 [2]
113	6.052	0	-	5.767 [2]

Table 2. Database Summary Information

Case	Method	Number of D.V.	Size of Initial Database	Final Weight (lb)	# of SA's (design)	Total # of SA's
1	NAND	12	-	5.905	887	887
2	NAND	12	-	5.732	190	190
3	NAND	12	-	5.735	271	271
4	CSD	12	49	5.709	52	101
5	CSD	12	49	5.708	34	83
6	CSD	12	25	5.706	57	82
7	CSD	29	113	5.582	41	154
8	CSD	29	113	5.461	51	164
9	CSD	29	58	5.407	46	104
10 *	CSD	29	113	5.541	31	144
11 *	CSD	29	113	5.246	71	184
12 *	CSD	29	113	5.237	96	209
13 **	CSD	29	158	5.744	22	22

(* - modified simulated annealing parameters, ** - revised constraints)

Table 3: Design Case Studies: Summary Information

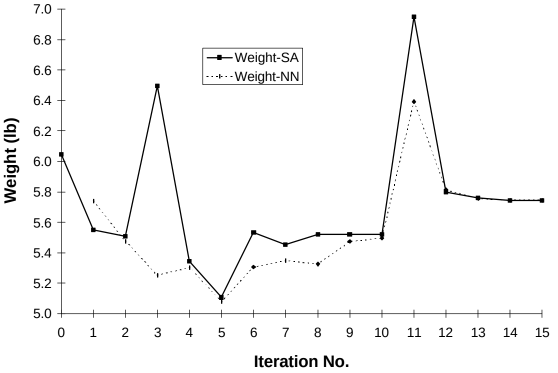
The CSD framework was applied to the same 12 DV problem discussed above (Cases 4-6) Cases 4 and 5 started with the same initial database (49 designs) and Case 6 started with a database about ½ the size (25 designs). All three cases converged to similar designs. All three designs were feasible and each weighed less than any of the NAND designs. The total number of system analyses (design iterations plus initial database) were similar for all three cases and where anywhere from 50% to an order of magnitude less than that required for the NAND approach. The 12 DV cases involved only continuous design variables and thus did not fully exercise the capabilities of the hybrid, mixed approach but did serve to benchmark the CSD performance.

Cases 7-13 in Table 3 summarize the results achieved for the 29 DV problem. They involved the use of different sized initial databases and a brief study related to the control parameters for simulated annealing. No comparative results similar to the NAND approach for the 12 DV problem were available since this is a true mixed optimization problem and gradient-based optimizers cannot address this problem. All of the resulting designs were feasible and provided a 3.2% to 9.2% reduction in weight over the least weight design in the entire database (which was infeasible). This was accomplished with a total number of system analyses (initial database plus design iterations) in a range of 150 to 200. This is a marked improvement in comparison with even the NAND results on the smaller 12 DV problem.

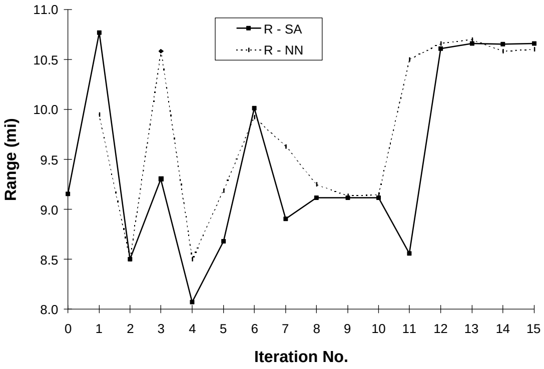
Limited space does not allow detailing all the final designs for this study. It is not possible at this time to state that any of these designs are more than local optimum. In Cases 10-12 various cooling schedules for the simulated annealing step in the hybrid, mixed optimization algorithm were invoked. These three cases resulted in different final designs with Case 12 providing the least weight design achieved to date. For this design 9 of the design variables were at side constraints, and none of the constraints were exactly satisfied with only the range requirement near active. It is not unreasonable to expect that this would occur since a number of important propulsion system design variables are discrete and changes in these discrete variables to achieve feasibility may not allow the design to reside on constraint surfaces.

The most interesting of these cases is Case 13 for which some additional details are provided. In Case 13 ten iterations of CSD were performed using the same constraints as Cases 7-12. After ten iteration, the database had grown to 158 designs. At this point, as is the case in many actual design studies, the "requirements" were changed. The maximum and minimum level flight speeds, maximum steady rate of climb, maximum range and takeoff distance constraints were all modified to be more "demanding". Figure 5 represents the convergence history for this case and presents the weight, range, maximum speed and takeoff distance versus iteration. Note iteration 10 is when the constraints were changed. The solid lines indicate the actual system states as determined by the system analysis and the dashed lines the neural network response surface approximations at that design step. One notes that as the design converges the approximations improve as additional training data is added in the vicinity of the final design.

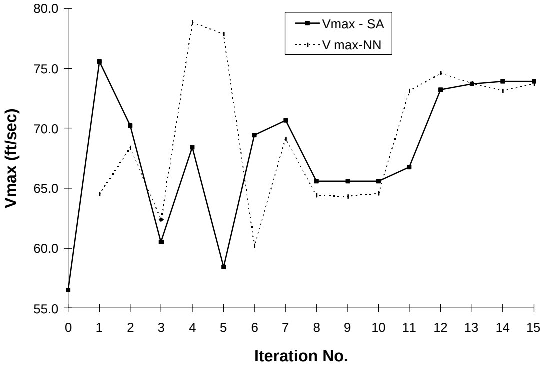
It is of particular interest to realize that it only required 22 additional system analyses to achieve this new feasible, optimal design. By being able to exploit the information developed during the "earlier studies" CSD was able to significantly reduce the computational requirements for this multidisciplinary system.



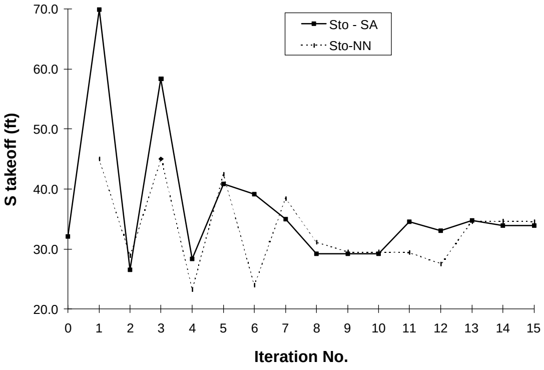
a. Takeoff Weight



b. Maximum range



c. Maximum level flight speed



d. Takeoff ground roll

Figure 5. Case 13 Design History

CONCLUSIONS

A fairly demanding implementation of the CSD framework has been demonstrated using a complex, multidisciplinary system. This was accomplished through the development of a coupled, system analysis for this special class of flight vehicles, EPUAVs, and an adaptation of the basic CSD algorithm to allow for optimization of systems which are mixed, thus containing both continuous and discrete design variables.

Two series of studies were presented containing 12 and 29 design variables respectively. In each case the CSD framework was able to identify feasible designs with significant weight reductions relative to any “previously considered” (i.e. initial database) designs. This was accomplished with a practical number of system analyses.

One final aspect of the current work was associated with the manner in which the software was developed. The SA was developed independently of the CSD framework and could function as a “stand-alone” code. Its adaptation to the CSD framework was performed by engineers who had not been involved in the development of the CSD framework code and was done with a relatively small amount of training and documentation.

Future efforts will focus on the performance of this hybrid optimization algorithm and evaluation of the character of the response surface approximations to this complex, discontinuous design space.

ACKNOWLEDGEMENTS

This work was supported in part by the National Aeronautics and Space Administration, Langley Research Center, Grant NAG-1-1561. Dr. J. Sobieski, Project Monitor. The authors would also like to recognize the support provided by the China Scholarship Council for X.Q. Yu during his stay as a Visiting Scholar at the University of Notre Dame.

REFERENCES

1. Batill, S.M., Stelmack, M.A. and Sellar, R.S., “Framework for Multidisciplinary Design Based upon Reponse-Surface Approximations,” AIAA Journal of Aircraft, In-press.
2. Stelmack, R.S., Batill, S.M., Beck, B.C. and Flask, D.J., “Application of the Concurrent Subspace Design Framework to Aircraft Brake Component Design Optimization,” Paper 98-2033, AIAA/ASME/ASCE/AHS/ASC 39nd Structures, Structural Dynamics and Materials Conf., Long Beach, CA, April 1998.
3. Sellar, R.S., “Multidisciplinary Design Using Artificial Neural Networks for Discipline Coordination and System Optimization,” PhD Dissertation, University of Notre Dame, Notre Dame, IN, April 1997.
4. Sobieszczanski-Sobieski, J., “ On the Sensitivity of Complex, Internally Coupled Systems,” NASA TM-107622, Jan. 1988.
5. Sellar, R.S., Batill, S.M., and Renaud, J.E., "Response Surface Based, Concurrent Subspace Optimization for Multidisciplinary System Design, "AIAA Paper 96-0714, AIAA Aerospace Sciences Meeting and Exhibit, Reno, Nevada, January 1996.
6. Sellar, R.S., Stelmack, M., Batill, S.M., and Renaud, J.E., "Response Surface Approximations for Discipline Coordination in Multidisciplinary Design Optimization," AIAA Paper AIAA-96-1383, AIAA/ASME/ASCE/ AHS/ASC 37th Structures, Structural Dynamics and Materials Conference, Salt Lake City, Utah, April 1996.
7. Stelmack, M. and Batill, S.M., "Concurrent Subspace Optimization of Mixed Continuous/Discrete Systems," AIAA Paper AIAA-97-1229, AIAA/ASME/ASCE /AHS/ASC 38th Structures, Structural Dynamics and Materials Conf., Kissimmee, Florida, April 1997.
8. Stelmack, M. and Batill, S.M., “Neural Network Approximations of Mixed Continuous/Discrete Systems in Multidisciplinary Design,” AIAA Paper 98-0916, AIAA Aerospace Sciences Meeting and Exhibit, Reno, Nevada, January 1998.
9. Gabriele, G., Beltracchi, T., “OPT3.2: A FORTRAN Implementation of the Generalized Reduced Gradient Method, User’s Manual,” Department of Mechanical and Aerospace Engineering and Mechanics, Rensselaer Polytechnic University, New York, 1988.
10. Magason, R.J., and Lamar, J.E., “Vortex-Lattice FORTRAN Program for Estimating Subsonic Aerodynamic Characteristics of Complex Planforms,” NASA TN D-6142, Feb. 1972.
11. Jensen, D.T.,”A Drag Prediction Methodology for Low Reynolds Number Flight Vehicles,” M.S. Thesis, University of Notre Dame, Notre Dame, IN, Feb. 1990.
12. Young,B., ”Propeller Performance Analysis for Small Computers,” M.S. Thesis, University of Notre Dame, Notre Dame, IN, May 1984.
13. Smetana, F.O., Computer Assisted Analysis of Aircraft Performance, Stability and Control, McGraw-Hill, New York, 1984.
14. Yu, J. and Zhou, J., “Constrained Variable Metric (CVM) Method - User’s Manual,” Huazhong University of Science and Technology, PRC, Dec. 1986.