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DESIGN OPTIMIZATION OF A RBCC ENGINE/EJECTOR USING COLLABORATIVE OPTIMIZATION AND NEURAL NETWORK

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Abstract This paper presents the results of optimization of an integrated inlet/ejector system of a rocket based combined cycle (RBCC) engine. A 2-D axisymmetric model of inlet/ejector was considered for this study. Newly introduced multidisciplinary optimization (MDO) approach of collaborative optimization (CO) was used. CO is a multidisciplinary design optimization technique that allows coupled engineering design problems to be uncoupled and solved concurrently. Optimization within CO was carried out with NPSOL, a nonlinear gradient-based optimizer code. The CFD simulations of the inlet/ejector system were carried out with the commercial code STAR-CD. A response surface with four design variables and the objective function was generated from CFD simulation results. The data from the response surface was used to train a neural network using MATLAB. The neural network was used for approximating the objective function, which was used by NPSOL.

INTRODUCTION

Continued interest in achieving low cost trans-atmospheric vehicle stimulates constant efforts to develop advanced technologies for space transportation system. A primary element of this goal lies in the development of advanced propulsion system capable of meeting both the performance and mission goals. The Rocket Based Combined Cycle (RBCC) is one promising approach, which has received considerable interest throughout the last 30 years. The RBCC concept utilizes air-breathing propulsion along with rocket propulsion to take advantage of the ambient oxidizer in the initial phase of the flight trajectory. Throughout the flight path, four modes of engine operation are generally employed: rocket-ejector, ramjet, scramjet, and rocket only. The least well understood of these modes is the rocket-ejector mode, which is employed from take off until approximately Mach 2.

Inlet system is a critical component of air-breathing engines. The inlet system must provide the required airflow at all operational flight speeds, allow a realistic variable geometry system for the internal flow path downstream, and minimize the occurrence of inlet "un-start".

Ejector is a generic name for a device, where a higher speed primary jet induces the flow of an ambient secondary fluid in an enclosing duct or shroud by pumping it from a lower to higher pressure. One particular type of the ejector is the thrust augmenting ejector whose function is to enhance the thrust of a primary exhaust jet by transferring energy from the primary to speed up the secondary flow, thereby increasing the momentum of the jet. The additional thrust results from the more efficient utilization of available energy in the exhaust. The simple design of thrust augmenting ejectors and their absence of moving parts makes it easy to accommodate them to a system in a light weight, low volume manner.

The success of a rocket ejector depends on the effectiveness of the mixing. The use of a single rocket engine on the axis with a concentric outer shroud results in an inordinately long mixer. Since the mixing rate depends on the interfacial shear area between the primary and the secondary, there are numerous schemes available for obtaining enhanced mixing in shorter lengths. The simplest is to use multiple rocket engines of smaller diameter. A second approach is to sue annular nozzles. Finally, improved mixing can be attained by using jets of different cross sectional geometries, such as elliptical jets.

The objective of this study is to optimize a 2-D axisymmetry inlet/ejector system of a RBCC engine. A schematic of a RBCC engine is shown in Figure 1. Multidisciplinary optimization architecture tied with response surface and neural networks technique has been used for this purpose.

NUMERICAL APPROACH:

The CFD simulations of the inlet/ejector system of RBCC engine were performed with the commercial code STAR-CD. This code solves the Reynolds conditions. To solve the system of nonlinear partial differential equations, the code uses finite difference approximations to establish a system of liberalized algebraic equations. Several differential schemes such as central difference, second order upwind were employed to approximate the convective terms of the momentum, energy and continuity equations. A variant of predictor/corrector method with one predictor and two corrector steps were used.

For the present study the geometry is taken from [1] with some changes in dimension and location of boundaries. The geometry is divided into 7 blocks. Block 5,6 and 7 are added to the physical domain for better shock capturing and result smoothness. The inlet/ejector geometry along with the grids is shown in Figure 2.

Four geometry design variables were used to generate 64 different geometries. The solution converged in less than 1500 iterations for all different geometries. The variables and their values are shown below:

1-Inlet area (A_i), two choices, 6.5 and 7 cm
2- Throat area (A_t), four choices: 2.5,3.0,3.5,5.0 cm
3-Secondary exit area (A_s): four choices, 1.75,2.0,2.25,2.5 cm
4- Ejector exit area (A_e): two choices, 7.54 and 8.59 cm

COLLABORATIVE OPTIMIZATION

The collaborative optimization architecture, a form of multidisciplinary optimization method, is designed to promote disciplinary autonomy while achieving interdisciplinary compatibility. As sketched in Fig 3 the problem is decomposed along analyses–convenient boundaries and subspace optimizers are integrated with each analysis-block. Through subspace optimization each group is given control over its own set of local design variables and is charged with satisfying its own domain-specific constraints. Explicit knowledge of the other groups constraints or design variables are not required. The objective of each subspace optimizer is to agree upon the values of the interdisciplinary variables with the other groups. A system-level optimizer is employed to coordinate this process while minimizing the overall objective.

The fundamental idea behind the development of the collaborative optimization architecture is that disciplinary experts should participate in the design decision process while not having to fully address local changes imposed by the other groups of the system. This decentralized decision strategy is not only a practical approach to design, but may also allow for the use of existing disciplinary analyses without major modification. This is not a trivial advantage, as the practical acceptance of many MDO techniques is limited by their implementation overhead requirements. sketched in Figure 3 the system level optimizer relies on information provided by repeated subspace optimization to coordinate the various sub problem optimization. One means to convey this information, as discussed in [2] and used later in this paper, is with gradients. However, alternative methods may also be possible in which the system level optimization algorithm is not restricted to gradient-based techniques. Although beyond the scope of the present investigation, one can envision a conflict resolution strategy (analogous to an auction) in which the subspace bid for desired changes in each interdisciplinary variable [3]. Here, each subspace may have a fixed allocation of points to spend in bidding for the interdisciplinary variables at each system-level iteration. In this manner, a group's strong convictions on the proper value of a certain interdisciplinary variable would be weighted appropriately.

The collaborative optimization architecture provides a higher degree of design freedom within the subspace while reducing the interdisciplinary communication requirements.

NEURAL NETWORK

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. In this work back-propagation network was used.

Generalizing the wodrow-hoff learing rule to multiple-layer networks and nonlinear differential transfer functions created back propagation. Input vectors and the corresponding output vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you. Networks with biases, a sigmoid layer, and a linear output layer are capable or approximating any function with a number of discontinuities.

Standard back propagation is a gradient descent algorithm. The term back propagation refers to the manner in which the gradient is computed for nonlinear multi-layer networks. Present study used NN to learn a response surface from 64 CFD runs to a steady sate flow in an inlet/ejector system and later it was used for evaluating an objective function during the optimization process. A feed forward back-propagation network was used. The data was entered into the net as [4x1] matrix. In the first layer "tangsig" function from MATLAB NN toolbox was used as transfer function in four neurons. In the second layer "purelin" was used in one neuron. The neural network is shown in Figure 4.

RESULT AND DISCUSSIONS

The CFD data of 64 cases were used to generate a response surface. This response surface was used for training the neural network and this later it was used for objective function evaluation, during the optimization process.

The objective function was defined as :

$$F = \frac{1}{P_r} + \beta$$

in which P_r is the pressure recovery and β is the mass flux ratio of the primary rocket to the secondary airflow.

An inlet/ejector in a RBCC engine is a single discipline system from multidisciplinary optimization point of view. Since any change in geometry or flow condition on boundaries, will affect the whole system from entrance to the nozzle at the end. On the other hand, as problem gets bigger by including more and more variables, using a single optimizer will be more difficult even by isolating the inlet/ejector from other disciplines in the vehicle design. So it is logical to start the inlet/ejector as a multidisciplinary optimization problem.

To start we show the decomposition for a simple bounded form in which two disciplines are both limited to the domain variables. In this form the collaborative optimization will converge in first iteration because two disciplines will agree with system level suggestion. In the second run, we apply one linear constraint to each of the disciplines such that when these two disciplines receive the suggested values from the system level, they will not necessarily agree, and start sending back the new suggestions as they try to decrease the discrepancy between the system level variables and their own suited variables. First decomposition is shown below. Two subsystems are the same and it is not possible to optimize one of the elements of the objective function in one subsystem and the other one in the second subsystem since the problem is unbounded. In this case each subsystem variable is a system level variable as well.

System Level

Min $F(Z)=1/P_r(Z_1,Z_2,Z_3,Z_4) + \beta\ (Z_1,Z_2,Z_3,Z_4)$

s.t.

$$g_1^* = \sum_{i=1}^{4} (Z_i - X_i^*)^2 = 0$$

$$g_2^* = \sum_{i=1}^{4} (Z_i - X_i^*)^2 = 0$$

Subsystem 1

$$\text{Min } g_1 = \sum_{i=1}^{4} (Z_i - X_i^*)^2$$

s.t. $l_i<X_i<u_i$ for i.=1,4

in which:

X_1 represents A_i, the inlet area

X_2 represents A_t, the throat area

X_3 represents A_s, the secondary airflow area

X_4 represents A_e, the ejector exit area

This system is optimized in the first iteration, and the result of this optimization is shown here:

Final nonlinear objective value=1.652109 corresponding to:

A_i=6.500

A_t=4.00

A_s=4.00

A_e=7.906

In the second run two linear constraints are added to the original problem, each of them applied to one of the disciplines. As a result of this the two constraints did not let the system level to converge to the first optima. So system level started to minimize the function subject to the system level constraints and subsystems tried to reduce the discrepancies.

Two added constraints are as follows:

1- Throat area should be less or equal to 50% of the inlet area

2- Secondary area should be equal or greater than 50% of the exit area.

Some of the optimally constraints are mentioned in [4] but the above constraint were chosen arbitrarily to show the effect of constraints existence.

System Level

Min $F(Z)=1/P_r(Z_1,Z_2,Z_3,Z_4) + \beta\ (Z_1,Z_2,Z_3,Z_4)$

s.t.

$$g_1^* = \sum_{i=1}^{4} (Z_i - X_i^*)^2 = 0$$

$$g_2^* = \sum_{i=1}^{4} (Z_i - X_i^*)^2 = 0$$

Subsystem 1:

$$\text{Min } g_1 = \sum_{i=1}^{4} (Z_i - X_i^*)^2$$

s.t. $l_i<X_i<u_i$ for i.=1,4

s.t. $2X_3 - X_4>0$

Subsystem 2:

$$\text{Min } g_2 = \sum_{i=1}^{4} (Z_i - X_i^*)^2$$

s.t. $l_i<X_i<u_i$ for i.=1,4

s.t. $2X_2 - X_1<0$

The result of this optimization is shown below:

Final nonlinear objective value=3.850653 corresponding to:
A_i=6.998
A_t=3.497
A_s=4.549
A_e=8.101

After 79 iterations, system level converged to this point. Figure 5 shows a convergence history of system level objective function and two constraints. Figure 6 shows how the value of objective function jumps from one solution domain to another one, as it tries to reduce the interdisciplinary discrepancies. Figure 7 shows how the system level constraints varied, during the iterations. The results show that the minimum value of the function always occurred when the constrains are relatively big and the iterations continue. Figure 8 shows the variation in the system level variables, which are the areas. The inlet area is constant in all the iterations but the others are reducing to the optimum point.

CONCLUSIONS

Collaborative optimization algorithm was successfully applied to an integrated inlet/ejector system of a RBCC engine. Four geometric design variables were used to optimize the chosen objective function. Commercial CFD code STAR-CD was used to generate the response surface. The data from the response surface were used to train a neural network using MATLAB. The gradient based nonlinear optimizer NPSOL was used for both system level and subsystem level optimization. One additional linear constraint for each of the disciples was applied to demonstrate the optimization process.

ACKNOWLEDGEMENT

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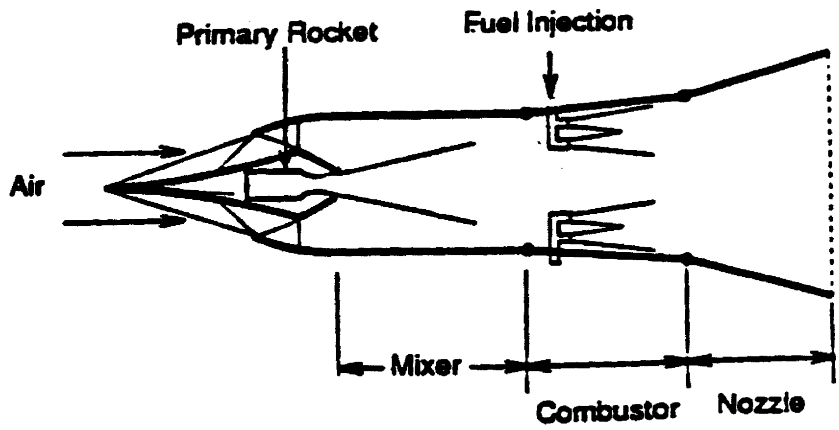

Figure 1. Components of a RBCC Engine.

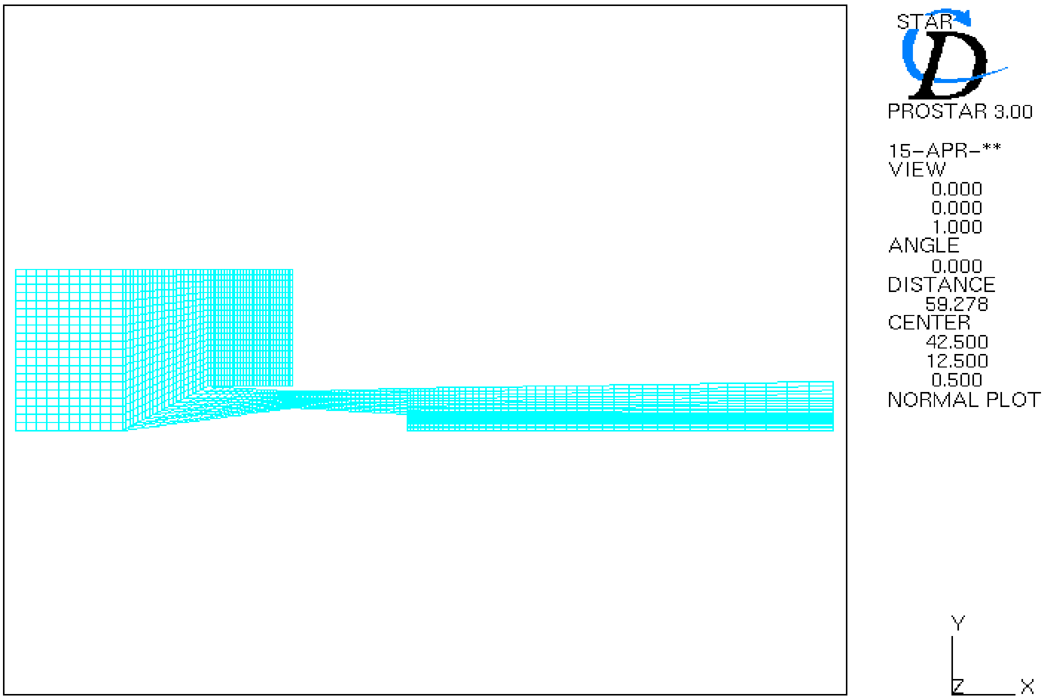

Figure 2. The Inlet/Ejector Grids.

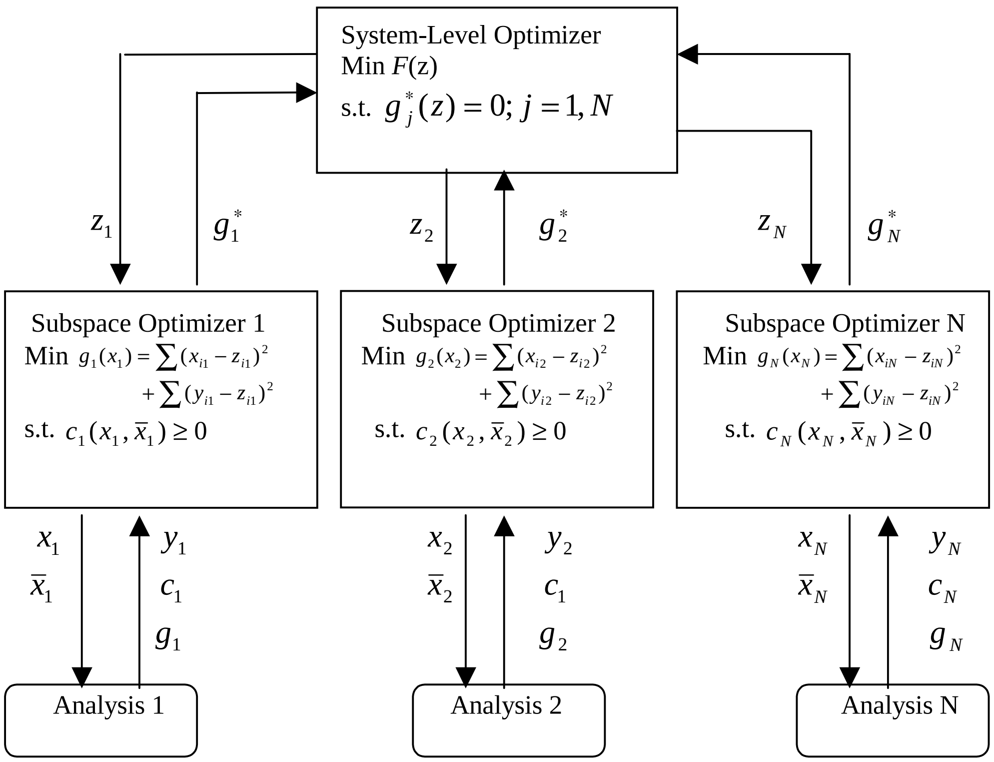

Figure 3. The Collaborative Optimization Architecture in Detail.

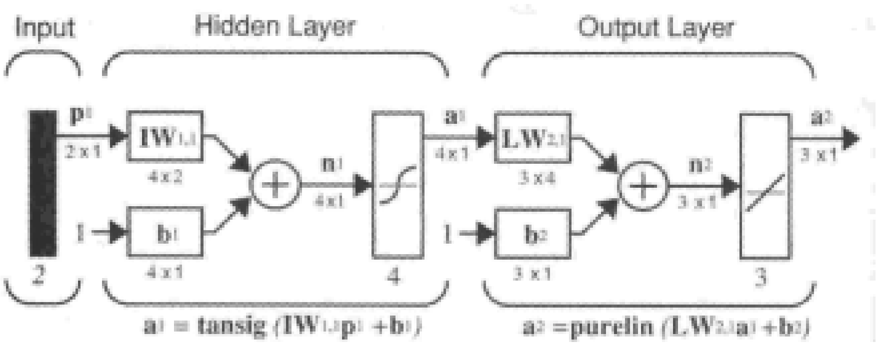

Figure 4. A Two-Layer Backpropagation Network.

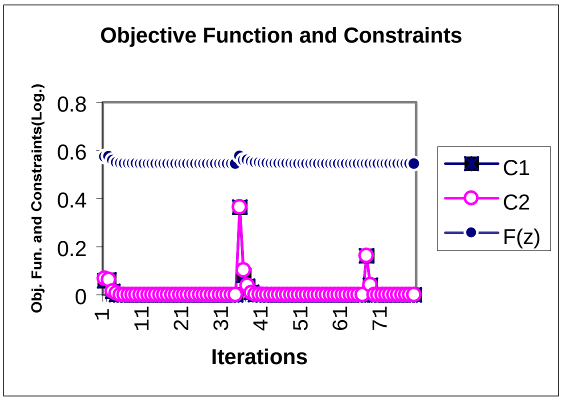

Figure 5. A History Graph of Objective Function and Constraints in System Level.

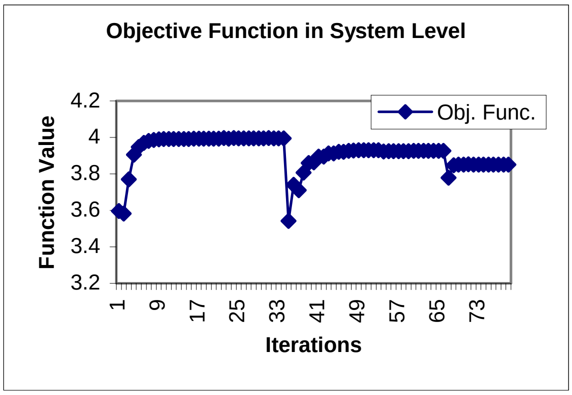

Figure 6. A History Graph of the Objective Function in the System Level.

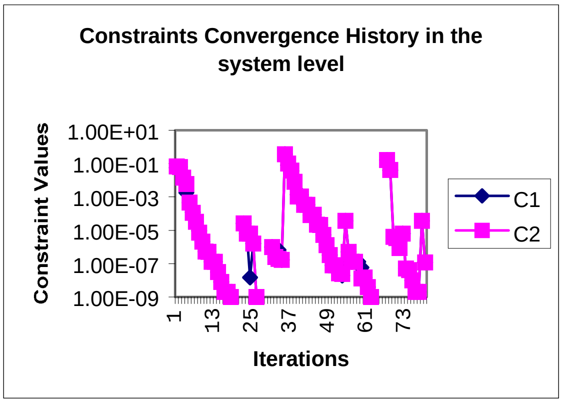

Figure 7. A History Graph of the C1 and C2 in System Level

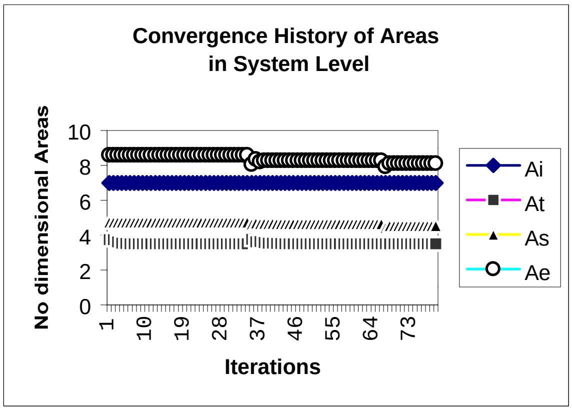

Figure 8. A History Graph of the Areas in System Level