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# Multidisciplinary Aerospace Systems Optimization—Computational AeroSciences (CAS) Project

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September 2001

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# Multidisciplinary Aerospace Systems Optimization
# (NASA Computational Aerosciences Project)

**Srinivas Kodiyalam**

## 1.0 Introduction:

Multidisciplinary Design Optimization (MDO) embodies a set of methodologies which provide a means of coordinating efforts and possibly conflicting recommendations of various disciplinary design teams with well-established analytical tools and expertise [1,2]. MDO involves multiple disciplines, engineering, business and program management, often with multiple, competing objectives. These disciplines may just be an analysis code which contains a body of physical principles or in addition, they may possess some intelligent decision-making capabilities. In an attempt to address the issues involved with the MDO process, formal methods have been derived, making use of consistent mathematical concepts, unique organizational structures, and alternative system representation techniques. While the architecture of some of these MDO methods which we will use may not be entirely intuitive, their solution approach provides for a more practical and efficient path to reaching an optimal solution or at least an improved solution over the conventional sequential, all-in-one approaches.

Optimal design of complex systems, more specifically, aerospace systems, is increasingly becoming a geographically distributed activity involving multiple decision teams and heterogeneous computing environments. Hence within this environment, MDO processes will need to be executed necessitating, in addition to a range of design space exploration functions such as formal MDO methods, numerical search strategies, approximation methods, sensitivity methods, and trade-off studies, a flexible MDO environment that would support:

1. Meta-computing consisting of a collection of high performance machines that can provide the aggregate computing powers necessary for solving large-scale, multidisciplinary optimization problems.
2. The ability to easily access remote analysis tools as well as easily bringing together multiple analysis tools into an integrated system analysis while hiding the details of data management from the user. This includes visually linking data between different analysis components on different platforms.
3. Tool interfaces based on standards such as CORBA and COM to increase the usefulness and reuse of each disciplinary analysis tool in the distributed MDO environment.
4. Make MDO easy to use.

Today, the simulation based design process relies heavily on complex computer analysis and simulation codes such as finite element analysis and computational fluid dynamic analyses to improve the product design. These time consuming and expensive analyses are repeatedly invoked during optimization making the design exploration and multidisciplinary design optimization time significantly long, if not prohibitive. Two solutions are possible to make these problem solution times tractable:
(i) Use of Approximation Models (also referred to as Surrogate Models) for the design objectives and constraints in conjunction with the numerical search process. Since these approximate models are

inexpensive to evaluate for a new set of data or values assigned to design variables, we can afford to evaluate approximate responses many more times without having to worry about the computational resources. Consequently, a number of different types of studies including design optimization using high fidelity analysis become possible. The purpose of these studies must be extraction of data that are directly useful for the design decisions.
(ii) Use of High Performance Computing (HPC) servers with a large number of processors to enable multiple levels of parallelism (coarse and fine grained parallelism) for higher throughput computing and faster solution turn around times.

In this project, the following technical aspects of MDO has been implemented and investigated on certain realistic aerospace design problems.

- Design space sampling strategies in conjunction with concurrent processing on Origin 2000 HPC server;
- Design space approximation using Kriging metamodeling procedure and subsequently optimization with Kriging models
- Design space Pareto trade-off analyses using Kriging models
- Design process integration using commercial-off-the-shelf (COTS) integration framework, Model Center.

The applications include:

- Air Borne Laser (ABL) Optical Bench MDO for structures, thermal and optical line of sight disciplines;
- Conceptual design of a supersonic business aircraft involving Aerodynamics, Structures and Propulsion disciplines.

## 2.0 Description of Technical Methodology:

### 2.1 Design Space Sampling Strategies:

The two sampling methods proposed below are variations of Design of Experiment (DOE) procedures for using a fixed number of processors and operating concurrently [3]. The goal of these proposed methods is to have a reasonably uniform coverage of the design space to maximize the information gathered about the design space characteristics. A Monte Carlo simulation with a uniform probability distribution and a fixed number of points would be analogous to the proposed methods. In addition, similar to the DOE methods, these methods have been motivated by the inability to handle the computational cost involved with the analysis of the full factorial number of design points.

#### 2.1.1 Method 1 - Uniform Dispersal of Design Points:

Assume that there are N variables, $X_i$, i=1,N to define the N-D space, and, NP processors available for concurrent execution. Li and Ui define the lower and upper bounds on the variables.
NDP is the number of design points to be generated and is usually equal to the number of available processors (NP).

Introduce a non-dimensional variable, Vi, such that:

Xi = Li + (Ui – Li)*Vi

Now we have replaced the X space with the V space in which all the V variables vary from 0 to 1.

Assume that the design space volume contains $D^N$ little cubes, each cube having the side length of S = 1/D, assuming that we have normalized the interval of interest along each of the N-D axis to length 1, and allowed D levels. The sampling of each little cube is at the cube centers.

The number of design points, NDP, in a factorial pattern is

$NDP = D^N$

Inversion of the above provides for D as follows:

$D = (NDP)^{1/N}$

The mesh density, S, measured from a point to its nearest neighbor is

S = 1/D (assuming that the normalization to 1 of the interval length).

Now, the algorithmic steps for generating an approximately uniform dispersal of NDP points in the N-D space is defined as follows:

1) Set counter i = 1;

2) Roll electronic die of uniform probability distribution to generate point Vi

3) Update, i = i+1, Repeat #3, and evaluate dik = (Vi-Vk)^1/2, where i designates the new point, and k refers to the previously generated points.

Now, apply this filter:

If dik > = S, proceed to the next Vk;
If dik < S, reject Vi and return to #3.

4) Transform from V space to X space using equation above.

It appears that this simple algorithm would have the effect of generating an approximately uniform dispersal of NP points in the N-dimensional space owing to the use of uniform distribution in step 2, and with accidental bunching of points prevented by step 3. The MC with a uniform probability distribution and a fixed number of points should come close to meeting the criterion.

2.1.2 Method 2 - Hypersphere Method:

1. Assume:

N variables Xi in vector X to define an N-dimensional design space.
NP processors available for a simultaneous execution. .
Li and Ui define the lower and upper bounds on the variables.
NDP is the number of design points to be generated and is usually equal to the number of available processors (NP).

2. Select the "exploration interval" bounded by Ai and Bi, Ai < Bi, and centered on the initial "best guess" value of Xi = Xio, where

Xio = (Ai + Bi)/2;
Ai > Li; and,
Bi < Ui.

3. Introduce a non-dimensional variable Vi such that

Xi = Xio + (Bi-Ai)/2 Vi = (Ai+Bi)/2 + (Bi-Ai)/2 Vi

4. Next, construct a hypersphere in space V.

Now we have replaced the space X with the space V, in which all Vi variables vary from -1 at Ai, through 0 at the center, to +1 at Bi. The passage from V to X is provided by eq. 1.

We will now construct a hypersphere in the space V. The hypersphere is defined by a radius vector R that originates at Xio, or Vio=0, and a set of angles, Hi, that vector forms with the axis Vi, i = 1, N-1. Note that R and N-1 angles, not N angles define a point on the "surface" of the N-dimensional hypersphere.

It is also important to point out that the hypershpere is not to be thought of as having a surface like a 3-D sphere has. The notion of a surface does not carry from 3D to higher dimensions. It should be thought of as a sub-domain whose dimensionality is N-1, just as the surface of a sphere in 3D is a 2D sub-domain. It is the N-1 dimensionality reduction that carries to higher dimension by virtue of having to satisfy only a single equation that relates R to Vi on the sphere surface:

R = SQRT(Σ Vi^2); (1)

To handle the hypersphere construction let us establish that

$V_i = R \cos H_i$   (2)

Considering that Vi was normalized to vary from -1 to 1, R must be:

$R = 1$   (3)

to keep the hypersphere center at the mid-point of the (Ai,Bi) interval. We use eq.4.2&3 above to express one Vj in terms of R, Hi, and other Vi's:

Vj = SQRT (1 - (Σ Vi^2), i=1,N, and i <> j)

In the above, the index j may be selected from the set i=1,N randomly (it could also be chosen judgmentally although it is hard to think of a good reason why to do it that way).

In equation 4.4 there is no safeguard against (Σ Vi^2)>1, and that might cause a SQRT run-time error. In N dimensions, after we have selected j in eq. 4.4, it is necessary to check the satisfaction of the following condition:

Vp^2 + Vk^2 <= 1; p=1,N; k=1,N; p <> j;   (5)

Even this condition, however, does not guarantee that the sum is less than 1.

A procedure to generate a design point on the surface of an N-D hypersphere R= 1 may now be written to place NPP points over the hypersphere "surface". NPP = (NP-1)/2 where NP is the number of processors, because we reserve one processor for the point at the center of the sphere and one half of the remaining points are to become the nadirs to the points randomly generated.

We place the points by rolling an electronic die (using a random uniform distribution) on the angles Hi taking advantage of the spherical symmetry. Observe that the interval (Ai,Bi) defined above corresponds to the diameter of the hypersphere coinciding with the coordinate Vi, hence when the angle Hi varies from 0 through $\pi$, or 0 through 180 deg., the radius R traces a semi-circle arc that spans the interval.

Specifically, we repeat the following steps for each Hi, except Hj, where the j- index identifies Vj that was made dependent by eq.4.4:

-1. Initialize all Hi = 90deg, not 0 deg. This sets all cosines to 0.;

0. Roll electronic die (all dice here is uniform distribution) to pick index j in eq.4.4

1. Roll electronic die to pick index i
    -- if i <> j accept i and proceed

--if i = j reject I and repeat from 1 to pick a different value

2. Roll electronic die (uniform distribution) to select a value Hi in the 0,180 deg. interval.

3. Compute Vi per eq.4.2;

4. Check all permutations of eq. 4.5
   -- if all satisfied, then proceed
   -- when the first instance of eq. 4.5 violated is found, reject Hi and return to step 2 to pick a different Hi.

5. Repeat from 1 until all (N-1) Hi values are generated, while satisfying all the eq. 4.5 constraints.

6. Compute Vj from eq. 4.4.

7. Compute Hj = arccos (Vj) assuming that R=1. This completes generation of N angles Hi.

8. Repeat from (1) until all NPP design points (NPP sets of angles Hi) are generated.

We have now placed (NP-1)/2 points over the hypersphere. We have one point in the hypersphere center. To complete the operation and bring the number of points up to the number of processors NP, we reflect each of the (NP-1)/2 points to their nadirs by a simple sign change in the transformation from space V to space X.

X = Xo + (B-A)/2 (-1) Vi = (A+B)/2 + (B-A)/2 (-1) V

This completes placement of NP points in the X space on a surface of the hypersphere centered on the best guess and whose radius captures the interval of initial interest. The points are nearly uniformly distributed over the hypersphere owing to the use of a uniform distribution in generation of Hi. The X vectors constitute input to the analysis.

The uniform distribution maximizes the amount of information extracted from the design space using a fixed number of processors.

2.2 Kriging Metamodel based Design Space approximation

The mathematics of Kriging includes a combination of a global model of the design space as well as local deviations so that the Kriging interpolates the sampled data points [4]. Specifically, it is given by:

$$y(x) = \sum_{l=1}^{k} f_l(x) + Z(x)$$

where, the first term f(x) represents the global model characterized by a standard polynomial response surface model or an artificial neural network and the second term Z(x) is the localized deviations and the departure from the standard polynomial RSM. Z(x) represents the realization of a stochastic process with a mean zero, variance $\sigma^2$ and a non-zero covariance. The covariance of Z(x) that dictates the local deviations is given by:

$$Cov\left[Z\left(x^i\right), Z\left(x^j\right)\right] = s^2 R(x^i, x^j)$$

In the above equation, R is the correlation matrix, and $R(x^i, x^j)$ is the correlation function between any two of the $n_s$ sampled data points $x^i$ and $x^j$. R is a ($n_s$ x $n_s$) symmetric, positive definite matrix with ones along the diagonal. The correlation function could be an exponential, gaussian, cubic or such kind of an approximation function. For a gaussian correlation function, R is given by:

$$R\left(x^i, x^j\right) = \exp\left[-\sum_{k=1}^{ndv} w_k \left|x_k^i - x_k^j\right|^2\right]$$

where, ndv is the number of design variables and $w_k$ are the unknown correlation parameters used to fit the model and $x^i$ and $x^j$ are the $k^{th}$ components of the sample points. The best values for the correlation parameters ($w_k$ ) are obtained by solving a k-dimensional unconstrained optimization problem of the following form:

$$\underset{w_k > 0}{Max} - \left[\frac{n_s \ln\left(\hat{s}^2\right) + \ln|R|}{2}\right]$$

In this phase, we have to calculate determinant of a covariant matrix repeatedly during unconstrained function minimization. The size of this square matrix, R, as mentioned previously is the number of sampled data points. The number of variables ($w_k$) of this fitting optimization problem is the same as the number of design variables of the design problem. In some cases, using a single correlation parameter gives sufficiently accurate approximations.

The approximation to output y(x) at untried values of x is given by:

$$\tilde{y}(x) = \tilde{b} + r^T(x) R^{-1}\left( y - f\,\tilde{b} \right)$$

where, f is column vector of length $n_s$ which is filled with ones when f(x) is taken as a constant and,

$$\tilde{b} = \left( f^T R^{-1} f \right)^{-1} f^T R^{-1} y$$

$$r^T(x) = \left[ R\left(x, x^1\right), R\left(x, x^2\right), \ldots, R\left(x, x^{n_s}\right) \right]^T$$

A flow diagram of the Kriging surrogate models based optimization procedure is shown below.

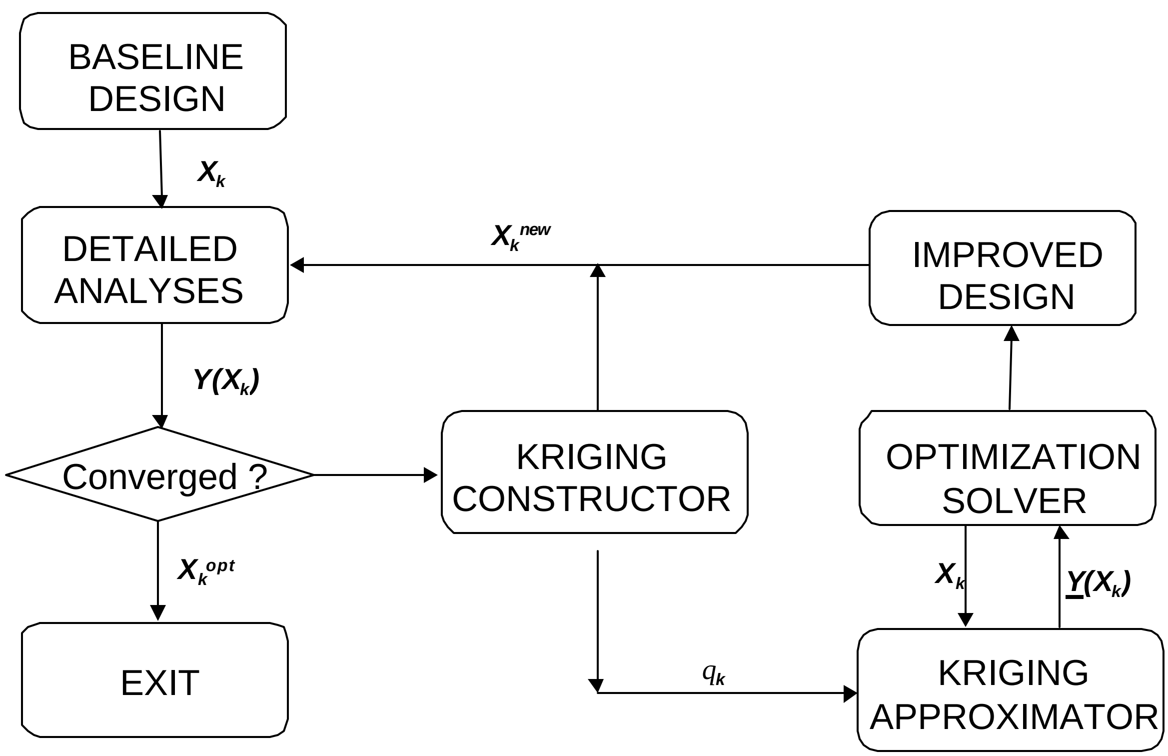


Figure 1: Flow diagram of Kriging approximation concepts based Optimization

2.3 Pareto Multicriterion Trade-Offs:

Typically, in an engineering system optimization many different criteria are involved and the designers and disciplinary experts would like to have trade-off information available for deciding how best to balance the various criteria to arrive at the most desirable design. It is common industry practice to perform trade-off analysis among the specified design criteria. Trade-off analysis is the study of the relationship between multiple competing design requirements/constraints in order to define more *balanced* targets for the optimization. Trade-off analysis is used in constructing Pareto curves (in 2D) and surfaces (in 3D), that separate the feasible region from the infeasible region. Balanced targets for design requirements/constraints are identified from these Pareto curves/surfaces. However, trade-off curves themselves should not be viewed as a unique relation between the design requirements/constraints.

Pareto trade-off curves generation will involve performing several optimizations by gradually varying the bounds on one design constraint at a time while keeping the other constraint targets fixed and plotting the change in the design objective. With the understanding that the Pareto optimal surface/curve generation could be a costly process involving several optimization analyses, Kriging approximation models will be exploited to achieve the desired computational efficiency.

2.4 Design Process Integration – Model Center COTS framework:

A COTS process integration framework called ModelCenter [5] for integrating the different tools/component (including spreadsheets) is used to in this project for integrating all the analysis codes and performing the Kriging approximations based MDO problem solution. ModelCenter based on JAVA provides a highly visual environment to link applications and map key data from one analysis tool to another. ModelCenter also facilitates linking application tools residing on different computers within a network. Once the data is linked, a driver component (such as Optimizer, DOE or Parametric Trade Study) can iterate with the linked simulation model to optimize the variables.

A JAVA based optimization driver is used with ModelCenter framework for the MDO solution. The core optimization solver is ADS, a numerical optimization code that includes several continuous optimization algorithms [6]. The JAVA driver also incorporates the Kriging metamodel for approximations, described in Section 2.2. The optimization driver developed within ModelCenter is generic and can be used with or without the Kriging metamodel based approximations concept.

A flow diagram of the sequence of steps in the MDO process is shown in Figure 2. It includes the sampling strategies described in Section 2.1 for generating the design points, followed by concurrent multidisciplinary analysis of the design points on SGI Origin 2000, 256 processor machine at NASA Ames facility. The results are processed and used for constructing the Kriging approximation model. The MDO problem is then solved using the Kriging approximation model for design objectives and constraints evaluation. After convergence (satisfaction of Kuhn-Tucker conditions) with respect to the approximation model, a detailed analysis is performed is verify the satisfaction of constraints and the

relative change in the objectives between successive cycles. At this stage the human engineers can also review the results and make changes as necessary.
Then the complete process is repeated till a satisfactory design is obtained.

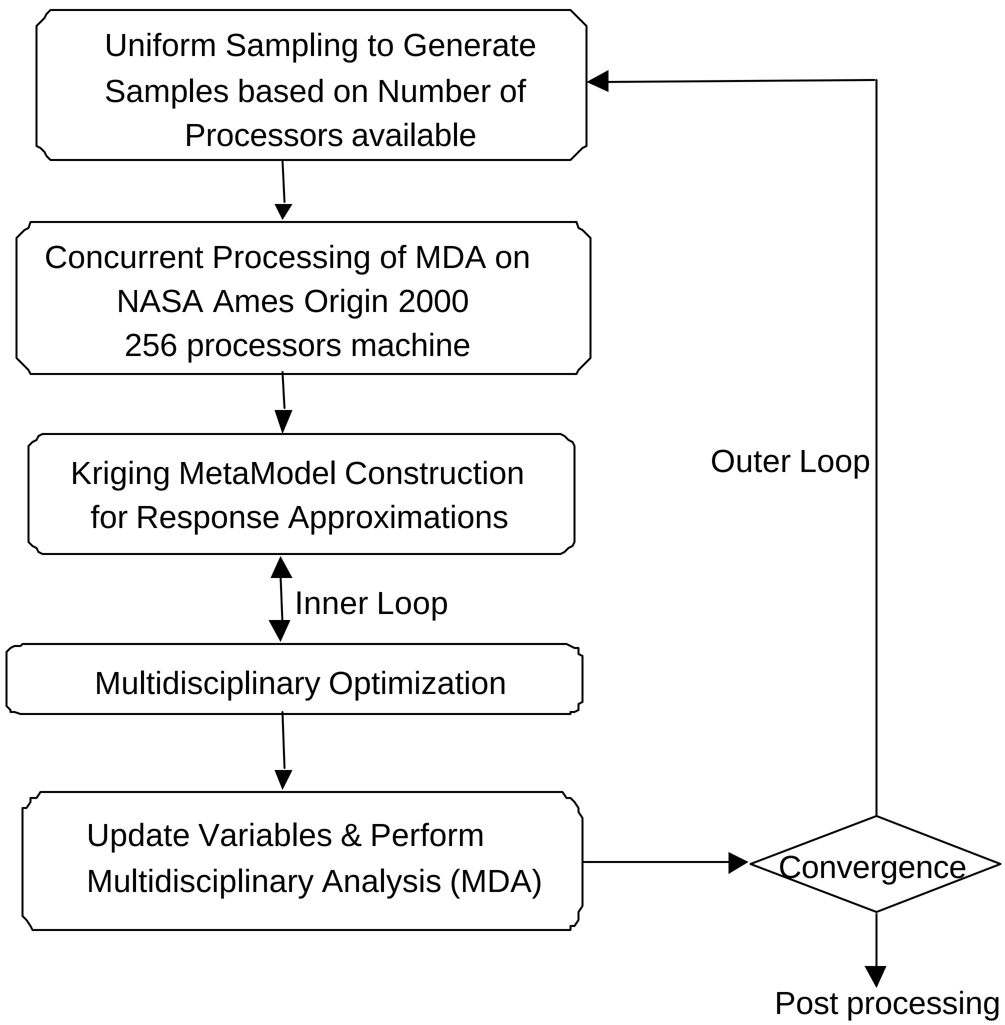


Figure 2: MDO methodology in a High Performance Computing environment

## 3.0 Application Problems and Solutions

Two design examples are considered:

- Air Borne Laser (ABL) Optical Bench MDO for structures, thermal and optical line of sight disciplines (detailed composites ply layup design).
- Conceptual design of a supersonic business aircraft MDO involving Aerodynamics, Structures and Propulsion disciplines.

3.1 Air Borne Laser (ABL) Optical Bench MDO:

ABL is a laser weapon system, carried on a 747-400F aircraft, designed to autonomously detect, track and destroy hostile theater ballistic missiles in the boost phase. Team ABL includes the USAF, Boeing, TRW and Missiles & Space. ABL will operate above the clouds, where it will detect and track missiles as they are launched using an onboard surveillance system. The Beam Control/Fire Control system will acquire the target, then accurately point and fire the laser with sufficient energy to destroy a missile while it is still in the highly vulnerable boost phase of flight-before separation of its warheads. The Beam Control/Fire Control system includes the Beam Transfer, Fire Control, and Turret Assemblies.

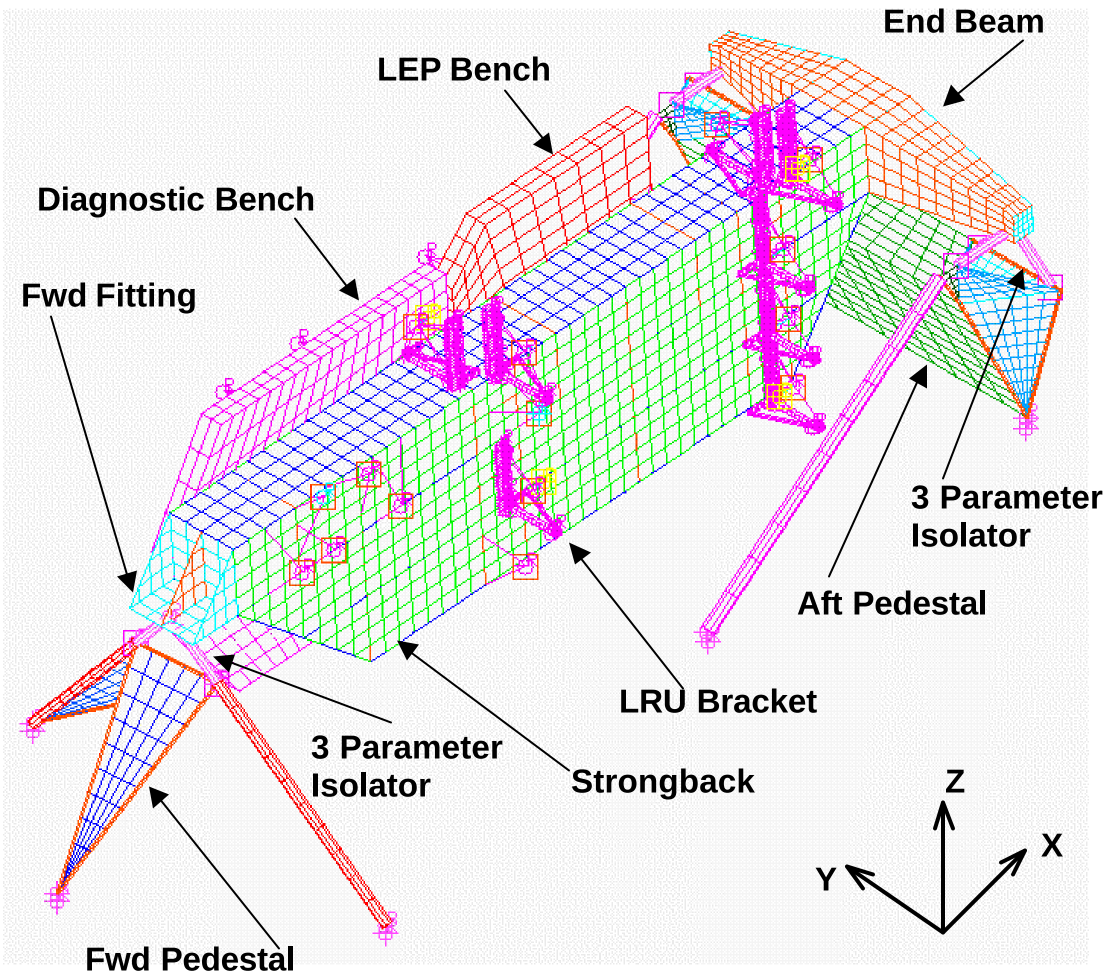


Figure 3: FEM of ABL Optical Bench

The Wavefront Control Subsystem of the ABL compensates for local and atmospheric disturbances by measuring wavefronts of outgoing and return beams with the Wavefront Sensor (WFS), then processing the measurements to provide actuator commands to the deformable mirrors (DM) and then the

actuators warp the surface of the DMs to correct the wavefront error.
The WFS misregistration is the misalignment between DM actuators and WFS sub-apertures caused by initial alignment errors, mechanical vibration, acoustics, thermal loads, etc.

The WFS and DMs are located on the main optical bench. Hence it is important that the main optical bench structure be sufficiently stiff to reduce the WFS Misregistration while being within a weight budget. The optical bench design is a composite design with ply layup being a critical driver in the structural stiffness and strength characteristics as well as thermal deformations. A finite element model of the optical bench is shown in Figure 3.

WFS Misregistration = (Optical Bench Structural Response)*(Optical Line-Of-Site Coefficients)
where:
Structural Response = 6 degrees-of-freedom displacements (translation & rotation) of the 8 optics between the WFS and ACDM due to vibration loads or thermal loads; and,
Line-Of-Site (LOS) coefficients = misregistration per unit displacement of each optic.

For Structural and Thermal analysis, the MSC.Software (MSC/NASTRAN v70.7) is used and a Lockheed Martin in-house code called GALPRO is used for the Optical LOS analysis.

The ABL Optical Bench MDO problem, that is a focus of this work, is formulated as follows:

Optimize the Composites Bench Ply Layup thickness, to:

| | |
|---|---|
| Minimize: | WFS Misregistration |
| Subject to constraints on: | Bench Structural Weight < allowable value; |
| | Bench Mode Frequency < allowable value; |
| | Thermal deformations at each optic < allowable value; |
| | Bounds on the ply layup thickness. |

A total of 10 design variables are considered.

The MDO process integration is performed using ModelCenter and is shown in Figure 4. The MSC/NASTRAN analyses for Weights, Thermal and Modal Frequency responses are performed on the SGI origin 2000, 256 processor machine at NASA Ames, California while the Optical LOS computations are performed on SGI Origin machine at Lockheed Martin Aeronautics in Denver, Colorado. The MSC/NASTRAN analyses on the sampling algorithm generated design points are performed concurrently on the Ames multiprocessor machine for higher throughput. The modal frequency response analysis, which is the time consuming analysis among all the disciplinary analyses, is performed using the Distributed Memory Parallel (dmp) capability in MSC/NASTRAN v70.7 for faster turn around in analysis computer times. Benchmark computer times for this DMP based modal frequency response analysis using different number of processors are provided in Table 2.

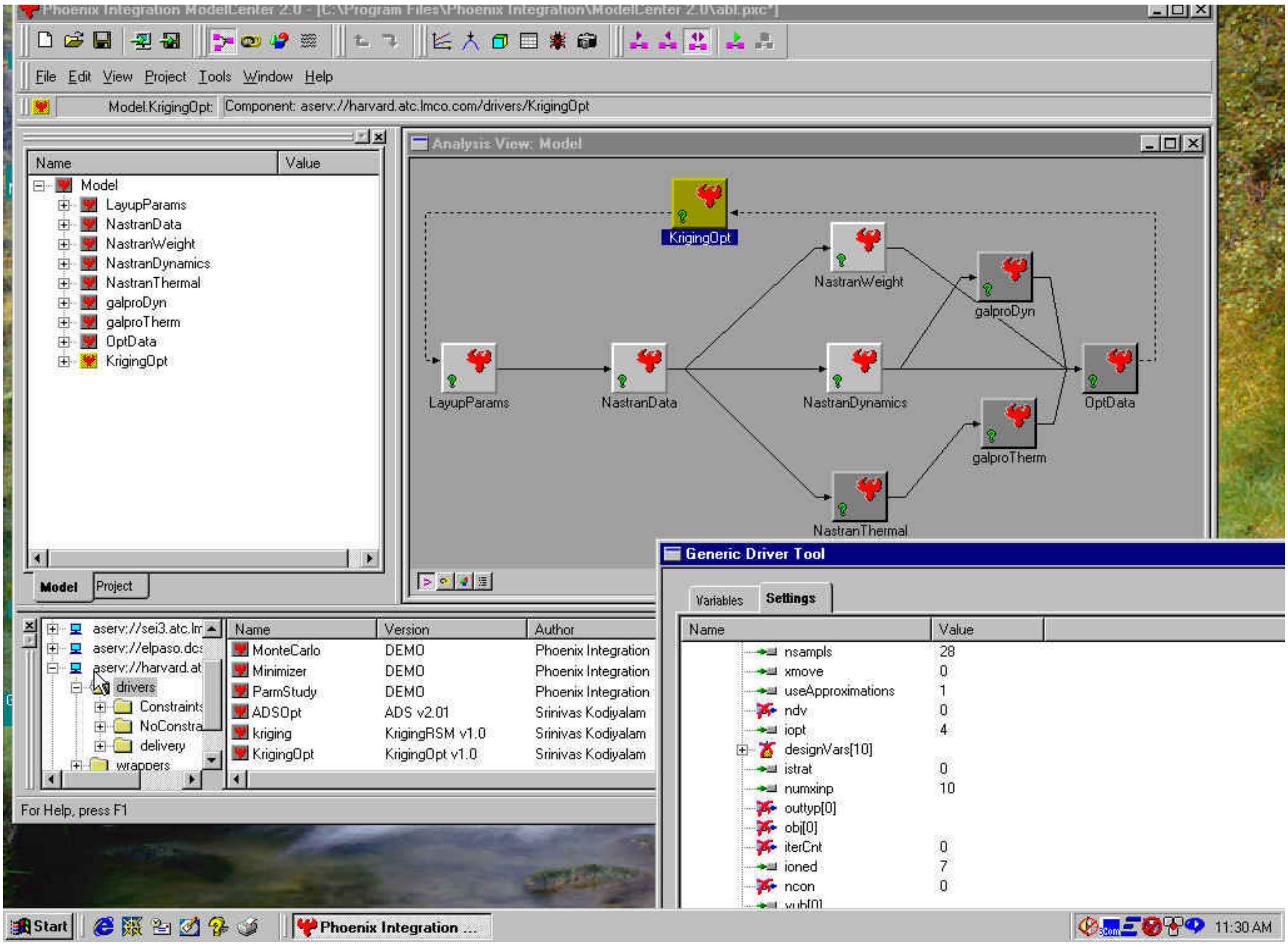


Figure 4: ABL MDO Process Integration with ModelCenter

| Design Variables | Initial (in.) | Cycle 3 | Lower (in.) | Upper (in.) |
|---|---|---|---|---|
| pcomp1&2 (LEL & HEL panels – 4/core/4 plies) | 0.125 | 0.25 | 0.1 | 0.25 |
| pcomp3 (outer longerons – 4plies) | 0.2 | 0.2 | 0.2 | 0.5 |
| pcomp4 (inner longerons – 4 plies) | 0.1 | 0.1013 | 0.1 | 0.25 |
| pcomp5 (inner vertical shear webs – 4 plies) | 0.1 | 0.1 | 0.1 | 0.25 |
| pcomp6 (inner horizontal gussets – 4 plies) | 0.1 | 0.1023 | 0.1 | 0.25 |
| pcomp7 (outer vertical end plates – 4 plies) | 0.25 | 0.3071 | 0.25 | 0.5 |
| pcomp14 (LEL bench facesheets – 4 plies) | 0.125 | 0.101 | 0.1 | 0.25 |
| pcomp16 (Diag bench facesheets – 4 plies) | 0.125 | 0.1 | 0.1 | 0.25 |
| pcomp22 (3PT End Beam – 4 plies) | 0.125 | 0.1443 | 0.125 | 0.25 |
| pcomp23 (3PT End Beam – 4 plies) | 0.25 | 0.25 | 0.25 | 0.5 |

| Responses | Initial | Final |
|---|---|---|
| WFS Dynamic Misregistration (% of subaperture) | 3.148 | 1.98 (Approx. 1.98)<br>**37% Reduction** |
| Weight (lbs-mass) | 5413 | 5517.4 (Approx. 5517)<br>**2% Increase** |
| Bench Mode (Hz) | 39.96 | 43. (Approx. 43.8) |
| WFS Thermal Misregistration (%) | 1.143 | 1.124 (Approx. 1.12) |

Table 1: ABL MDO Problem Results

| Number of Processors | 1 | 2 | 4 | 8 |
|---|---|---|---|---|
| Elapsed Time (mins) | 96.3 | 60.9 | 43.8 | 32.5 |

Table 2: Elapsed computing times for a single MSC.Nastran SOL111 run on a SGI Origin 2000, 256 processor, 250 MHz machine

The following provides a step by step comparison of the elapsed computer times involved in the sequential MDO process and the massively parallel processing based MDO process.

Case 1: On a single processor of SGI Origin 2000:

1. Baseline analyses (3 MSC/NASTRAN solutions and 2 GALPRO computations): 115 min
2. Cycle 1 - analyses of 32 samples: 115 * 32 = 3680 min
3. Approximate model construction: < 15 min
4. Optimization based on approximate model: < 3 min
5. Cycle 1 - optimum point analyses: 115 min
6. Cycle 2 - analyses of 32 samples: 115 * 32 = 3680 min
7. Update Approximate model with new samples: < 20 min
8. Optimization based on approximate model: < 3 min
9. Cycle 2 - optimum point analyses: 115 min
10. 5 additional analysis for Pareto point solutions: 5 * 115 = 575 min

The total elapsed time on single processor: 8320 minutes or 139 hours

Case 2: Massively parallel processing with SGI Origin 2000:

In this case we use 4 processors for each MSC/NASTRAN dynamics analysis (fine-grained parallelism) and further use all of the remaining 256 processors of SGI Origin 2000 for concurrent processing of MSC/NASTRAN runs for different design inputs (coarse-grained parallelism). The elapsed times provided below are an estimate based on the benchmark runs shown in Table 2.

1. Baseline analyses (3 MSC.N solutions and 2 GALPRO computations): 49 min
2. Cycle 1 - analyses of 32 samples concurrently: 49 min
3. Approximate model construction: < 15 min
4. Optimization based on approximate model: < 3 min
5. Cycle 1 - optimum point analyses: 49 min
6. Cycle 2 - analyses of 32 samples concurrently: 49 min
7. Update Approximate model with new samples: < 20 min
8. Optimization based on approximate model: < 3 min
9. Cycle 2 - optimum point analyses: 49 min
10. 5 additional analysis for Pareto point solutions: 5 * 49 = 245 min

The total elapsed time for the massively parallel approach is 530 minutes or 8.8 hours. The elapsed time reduction is 16X compared to serial solution.

Figure 5 shows the Pareto trade off curve between design objective (Misregistration) and the active constraint (Weight). Each point in this curve is generated based on an MDO solution using the Kriging approximation model, with the active constraint upper bound relaxed by a certain %. In this Pareto study, the upper bound on Weight constraint I varied from the baseline of 54.2 to 55 to 55.2 to 55.7 to 56 to 56.2.

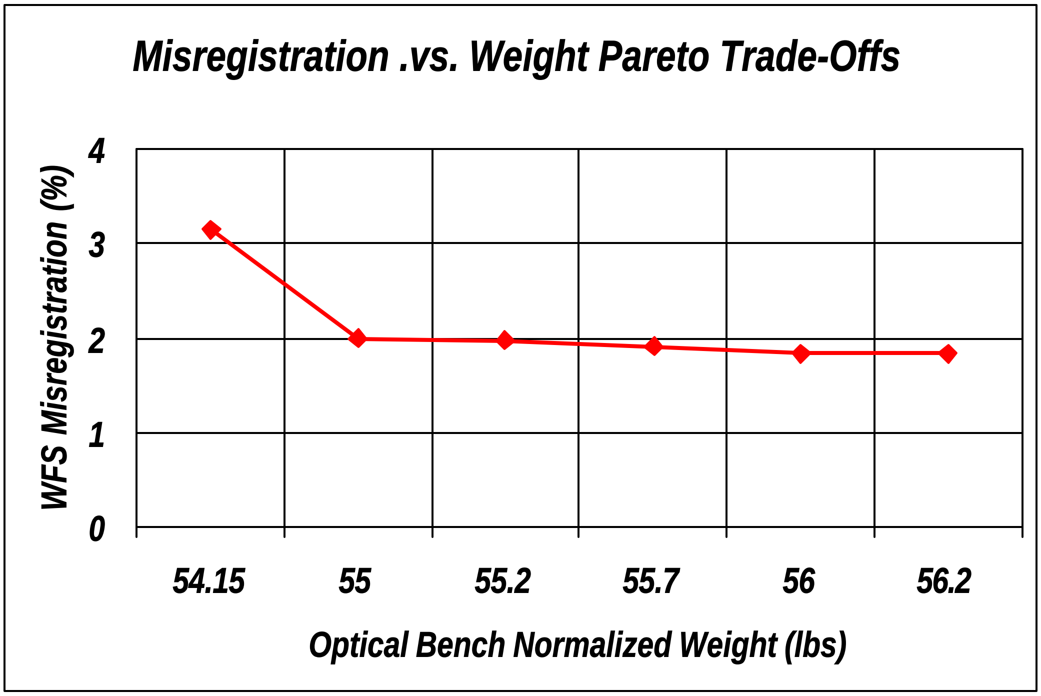


Figure 5: Pareto Optimal Trade-Off curve for Misregistration versus Weight

By relaxing weight in step 1 from 54.2 to 55, two of the design variables doubled in value (100% change) from the baseline and this reduced the design objective, Misregistration, by about 30%. The two variables correspond to those of HEL (high-energy laser) and LEL (low energy laser) panel thickness. These 2 parameters have the largest effect on Misregistration. Relaxing the weight constraint further in successive Pareto steps did not bring down the Misregistration that dramatically, since the remaining 8 design variables did not influence Misregistration to such an extent. More significant reductions in Misregistration can only be obtained by increasing the upper bound on the 2 critical (HEL & LEL panel) thickness but the ABL design engineer did not want those panels to be further increased in thickness. Hence, after Pareto step 1, further significant reduction in Misregistration is not possible.

3.2 Aircraft Optimization

In this example, a supersonic business jet modeled as a coupled system of structures (BB1), aerodynamics (BB2), propulsion (BB3), and aircraft range (BB4) is used. This problem is identical to the one used in Reference [7], and complete details of the problem can be obtained from the same reference. A data flow diagram of the coupled system analysis is shown in Figure 6.

The mathematical formulation of the MDO problem is as follows:

Maximize: Aircraft Range (F(**X**))

Subject to constraints on:

Stress on wing < 1.09; ($G_j$(**X**), j=1,5)

0.96 < Wing twist < 1.04; ($G_j$(**X**), j=6,7)

Pressure gradient < 1.04; ($G_j$(**X**), j=8)

0.5 < Engine Scale factor < 1.5; ($G_j$(**X**), j=9,10)

Engine Temperature < 1.02; ($G_j$(**X**), j=11)

Throttle setting < $T_{UA}$; ($G_j$(**X**), j=12)

There are a total of 10 design variables, **X**, including, thickness/chord ratio, altitude, Mach number, aspect ratio, wing sweep, wing surface area, taper ratio, wingbox cross-section, skin friction coefficient, and throttle.

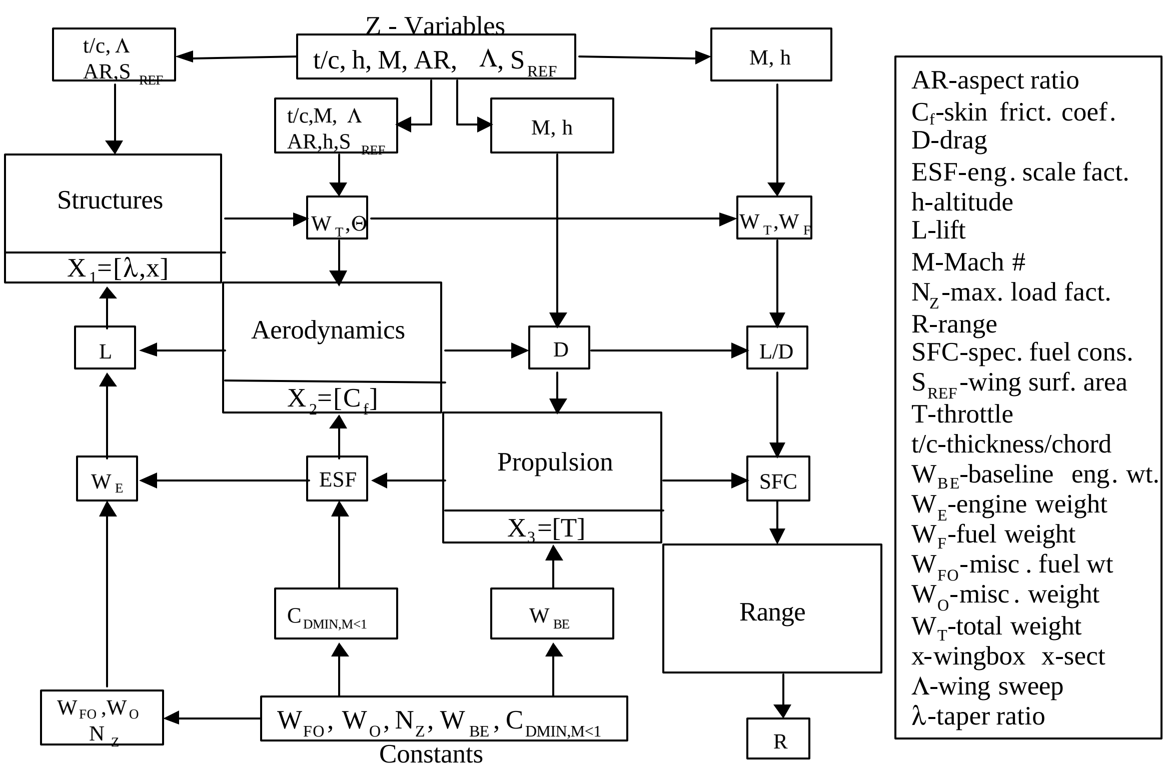


Figure 6: Data flow diagram for Aircraft MDO problem

The following MDO procedure is used with this aircraft problem.

1) Generate using the Hypersphere method (outlined in Section 2.1.2), NDP number of design points with the center of the hypersphere located at the baseline design point. Here NDP is equal to 128.
2) Perform concurrent analyses of the NDP design points using the NASA Ames SGI Origin 2000, 256 processor machine. Compute the design objectives and constraints as stated in the above MDO problem.
3) Identify the "best" design point in terms of usability and feasibility from the set of NDP design points.
4) Construct an approximation model using the Kriging method (outlined in Section 2.2) using the NDP design points inputs and outputs.
5) Perform MDO problem solution based on the approximation model of Step 4.
6) Perform verification analysis on the optimal design obtained in Step 5. Check for satisfaction of constraints and relative changes in the objective function.
7) Perform any necessary modifications to the model, optimization problem formulation, etc… based on the interpretation of solution from Step 6.
8) If not converged, revise the design move-limits and generate a new set of NDP design points that is now centered at optimal point of Step 6. Go to Step 2 and repeat the process till convergence.

| Cycle Number | Hypersphere DOE Sampling – Best design point from the sample set of 128 points | | Hypersphere DOE Sampling followed by Kriging Approximation based Optimization using the 128 design points | |
|---|---|---|---|---|
| | Objective | Max Constraint | Objective | Max Constraint |
| Baseline | 535.78 | +0.16 (violated) | 535.78 | +0.16 (violated) |
| Cycle 1 | 1201.72 | +0.01 (violated) | 1548.3 | +0.007 (active) |
| Cycle 2 | 2062.40 | +0.009 | 2879.4 | +0.003 (feasible) |
| Cycle 3 | 2359.5 | +0.007 | 3015.5 | +0.008 |
| Cycle 4 | 2765.8 | +0.009 | 3061.1 | +0.003 |

Table 3: Aircraft MDO problem results.

The results shown in the above Table 3 provide a comparison of the best points obtained purely from the sampling algorithm versus an approximation model based optimization using the sample points. The successive cycles start with the best point found in the previous cycle (either from sample set points or from optimization solution). If constraints are more violated than the previous cycle and if the design is infeasible then sampling space is shrunk by a reduction factor of 50%. It is important to note that the optimization solution is significantly better than the hypersphere sampling based best point. It is also important to note that the approximation model based optimization is not computationally intensive.

## 4.0 Summary

In this work, the following methods have been investigated for MDO solution of realistic aerospace design problems in a multi-processor, high performance computing environment.

- Design space sampling strategies in conjunction with concurrent processing on a SGI Origin 2000 HPC server;
- Design space approximation using Kriging procedure and subsequently optimization with Kriging models; and,
- Design space Pareto trade-off analyses using Kriging models.

In addition, a commercial-off-the-shelf (COTS) design process integration framework, Model Center, is used with the MDO study. ModelCenter facilitates integration across a meta computing environment involving a cluster of PCs, workstations and HPC servers with multiple processors.

The applications used in this work include:

- MDO of a Air Borne Laser (ABL) Composites Optical Bench for structures, thermal and optical line of sight disciplines;
- Conceptual design of a supersonic business aircraft involving Aerodynamics, Structures and Propulsion disciplines.

The present approach to MDO investigated in this work is comparatively simpler than the existing approaches, involving a design space sampling strategy that exploits concurrent processing, an approximation method for constructing approximations to the design objectives and constraints, and, an optimizer. Based on the trends in massively parallel processing and HPC (High Performance Computing), it is expected that the MDO methods will become simpler as well as easier to understand and use with complex design problems. The HPC environment operating concurrently with a large number of processors will offset the computational cost/time required for performing the required number of system and local disciplinary analyses.

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The report describes a method for performing optimization of a system whose analysis is so expensive that it is impractical to let the optimization code invoke it directly because excessive computational cost and elapsed time might result. In such situation it is imperative to have user control the number of times the analysis is invoked. The reported method achieves that by two techniques in the Design of Experiment category: a uniform dispersal of the trial design points over a n-dimensional hypersphere and a response surface fitting, and the technique of krigging. Analyses of all the trial designs whose number may be set by the user are performed before activation of the optimization code and the results are stored as a data base. That code is then executed and referred to the above data base. Two applications, one of the airborne laser system, and one of an aircraft optimization illustrate the method application.

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