Multi-Objective Design Exploration for Multidisciplinary Design Optimization Problems

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Abstract. *A new approach, Multi-Objective Design Exploration (MODE), is presented to address Multidisciplinary Design Optimization (MDO) problems by CFD-CSD coupling. MODE reveals the structure of the design space from the trade-off information and visualizes it as a panorama for Decision Maker. The present form of MODE consists of Kriging Model, Adaptive Range Multi Objective Genetic Algorithms, Analysis of Variance and Self-Organizing Map. The main emphasis of this approach is visual data mining. An MDO system using high fidelity simulation codes, Navier-Stokes solver and NASTRAN, has been developed and applied to a regional-jet wing design. Because the optimization system becomes very computationally expensive, only brief exploration of the design space has been performed. However, data mining result demonstrates that design knowledge can produce a good design even from the brief design exploration.*

Key words: Multi-Objective Design, Multidisciplinary Design Optimization, Evolutionary Computation, Self-Organizing Map, CFD.

1 INTRODUCTION

This paper discusses a new approach for Multidisciplinary Design Optimization (MDO) by CFD-CSD coupling. MDO has been a rapidly growing area of research[19,21]. Typical MDO problem involves competing objectives, for example in the aircraft design, minimization of aerodynamic drag, minimization of structural weight, etc. While single objective problems may have a unique optimal solution, multi-objective problems (MOPs) have a set of compromised solutions, largely known as the trade-off surface, *Pareto-optimal* solutions or *non-dominated* solutions. These solutions are optimal in the sense that no other solutions in the search space are superior to them when all objectives are considered (Fig. 1).

Traditional optimization methods such as the gradient-based methods[22] are single objective optimization methods that optimize only one objective. These methods usually start with a single baseline design and use local gradient information of the objective function with respect to changes in the design variables to calculate a search direction. When these methods are applied to a MOP, the problem is transformed into a single objective optimization problem by combining multiple objectives into a single objective typically using a weighted sum method. For example, to minimize competing functions f_1 and f_2, these objective functions are combined into a scalar function F as

$$F = w_1 \cdot f_1 + w_2 \cdot f_2 \tag{1}$$

This approach, however, can find only one of the Pareto-optimal solutions corresponding to each set of the weights w_1 and w_2. Therefore, one must run many optimizations by trial and error adjusting the weights to get Pareto-optimal solutions uniformly over the potential Pareto-front. This is considerably time consuming in terms of human time. What is more, there is no guarantee that uniform Pareto-optimal solutions can be obtained. For example, when this approach is applied to a MOP that has concave trade-off surface, it converges to two extreme optimums without showing any trade-off information between the objectives (Fig. 2). To overcome these difficulties, Normal-Boundary Intersection Method[3] and Aspiration Level Method[14] were developed.

An alternative approach to solve MOP is to find as many Pareto-optimal solutions as possible to reveal trade-off information among different objectives. Once such solutions are obtained, Decision Maker (DM) will be able to choose a final design with further considerations. Evolutionary Algorithms (EAs, for example, see [2] and [4]) are particularly suited for this purpose.

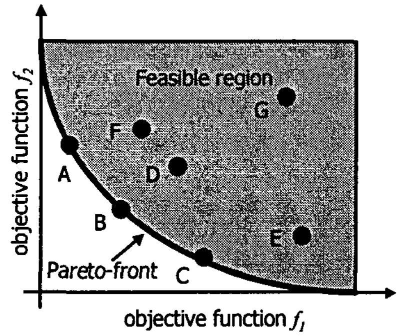


Figure 1 The concept of Pareto-optimality

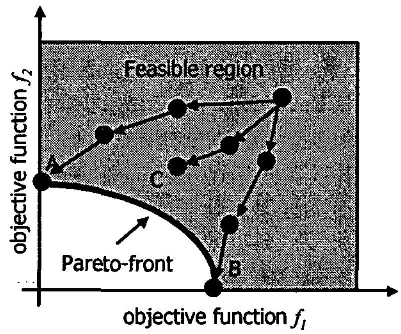


Figure 2 Weighted-sum method applied to a MOP having a convex Pareto-front

EAs have been extended successfully to solve MO problems[6,7]. EAs use a population to seek optimal solutions in parallel. This feature can be extended to seek Pareto solutions in parallel without specifying weights between the objective functions. Because of this characteristic, EAs can find Pareto solutions for various problems having convex, concave and discontinuous Pareto front. The resultant Pareto solutions represent global trade-offs. In addition, EAs have other advantages such as robustness and suitability for parallel computing. Due to these advantages, EAs have been applied to MOPs very actively (EMO proceedings). EAs have been also applied to single objective and multi-objective aerospace design optimization problems[1, 8, 16, 18, 20].

This approach of finding many Pareto solutions works fine as it is, however, only when the number of objectives remains small (usually two, three at most, as shown in Fig. 3). To reveal trade-off information from the resultant Pareto front for real-world problems with many objectives, visualization of the Pareto front becomes an issue. Several techniques have been considered, such as parallel coordinates[6], box plot[17], and Self-Organizing Map (SOM)[15]. Because such visualization is a tool for data mining, data mining is found very important in this approach.

To support data mining activities, response surfaces are found versatile. Once the surface is constructed, it can be used for statistical analysis, for example, analysis of variance (ANOVA)[10]. ANOVA shows the effect of each design variables on objective functions quantitatively while SOM shows the information qualitatively. When the response surface method (RSM) is introduced for data mining as post-process of optimization, it can be applied to pre-process of optimization as a surrogate model,[9,12,23] too. Pre-process has been an important aspect of introduction of surrogate models because it would reduce the computational expense greatly, while it would produce rich non-dominated solutions efficiently. In this paper, surrogate models are introduced for both pre- and post-processes. However, it should be noted that RSM is needed for post-process primarily. EAs may be applied from the beginning in parallel to building the surrogate model. If function evaluations are very cheap, EAs may also be applied directly.

As a result, the new approach for MDO named as Multi-Objective Design Exploration (MODE) can be summarized as a flowchart shown in Fig. 4. MODE is not intended to give an *optimal* solution. MODE reveals the structure of the design space from the trade-off information and visualizes it as a panorama for DM. DM will know the reason for trade-offs from non-dominated designs, instead of receiving an *optimal* design without trade-off information.

A preliminary form of MODE without RSM has been applied to a MDO problem for a regional-jet wing (Fig. 5) in cooperation with Mitsubishi Heavy Industries, Ltd. under the small jet aircraft R&D project sponsored by the New Energy Development Organization of Japan (NEDO). The present MDO system employs a Navier-Stokes code coupled with NASTRAN. Because the resulting optimization system becomes very computationally expensive, only brief exploration of the design space has been performed. This paper reports the results of the visual data mining. A full version of MODE is currently applied to obtain further improvements.

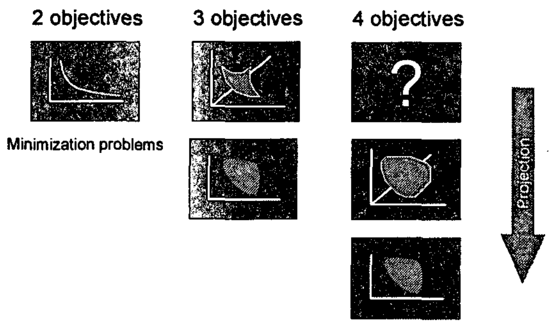


Figure 3 Visualization of Pareto front

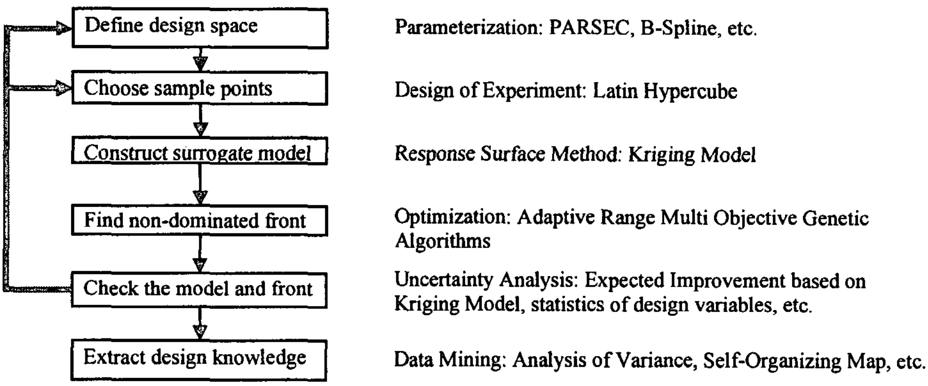


Figure 4 Flowchart of Multi-Objective Design Exploration (MODE) with component algorithms

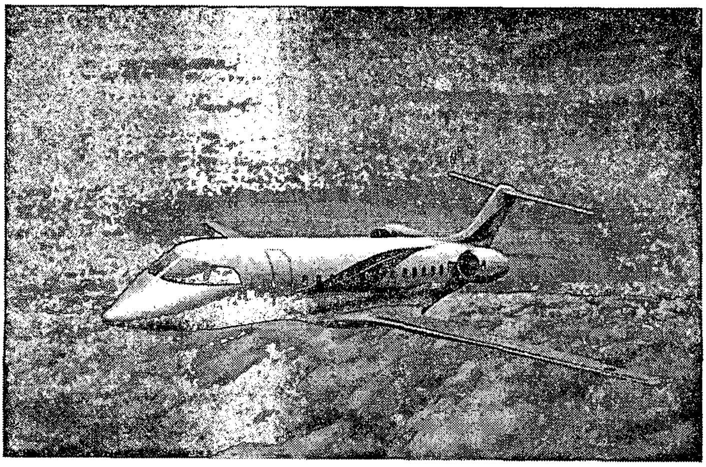


Figure 5 Artist view of regional jet (courtesy of Mitsubishi Heavy Industries, Ltd.)

2 MULTIDISCIPLINARY WING DESIGN

2.1 Objective Functions

In this optimization, minimization of the block fuel at a required target range derived from aerodynamics and structures is considered as the primary objective function. In addition, two more objective functions are considered: minimization of the maximum takeoff weight and minimization of the drag divergence between transonic and subsonic conditions. See [1] for details.

2.2 Geometry Definition

The design variables describe airfoil, twist, and wing dihedral. The airfoil was defined at three spanwise cross-sections using the modified PARSEC with nine design variables (x_{up}, z_{up}, z_{xxup}, x_{lo}, z_{lo}, z_{xxlo}, α_{TE}, β_{TE}, and r_{LElo}/r_{LEup}) for each cross-section as shown in Fig. 6. The twists were defined at six spanwise locations, and then wing dihedrals are defined at kink and tip locations. The entire wing shape was thus defined using 35 design variables.

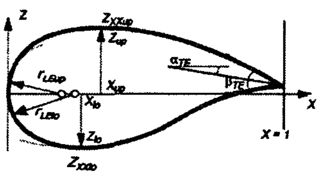


Figure 6: Illustration of the modified PARSEC airfoil definition

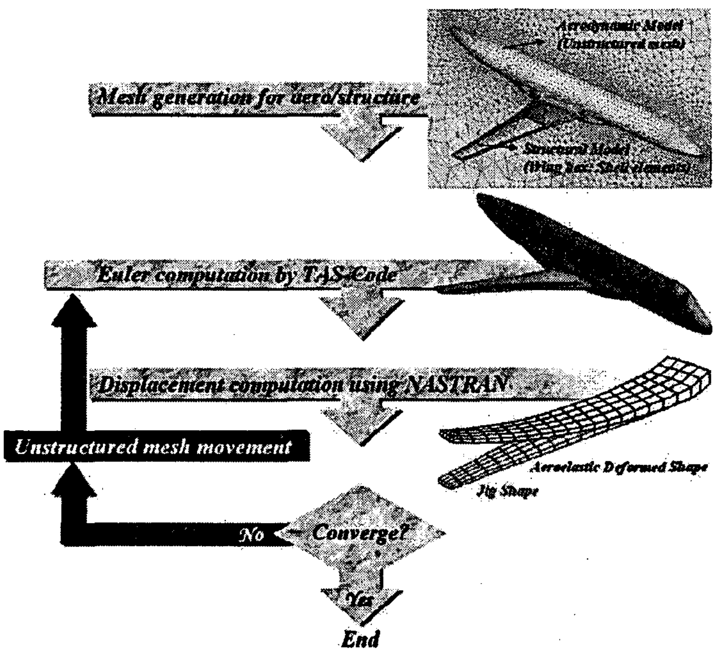


Figure 7: Flowchart for static aeroelastic analysis

2.3 Evaluation Method

The present ARMOGA generates eight individuals per generation, and evaluates aerodynamic and structural properties of each design candidate as follows:

1. Structural optimization is performed to jig shape to realize minimum wing weight with constraints of strength and flutter requirements using NASTRAN. And then, weights of wing box and carried fuel are calculated.
2. Static aeroelastic analysis is performed at three flight conditions to determine the aeroelastic deformed shapes (1G shape) using Euler solver and NASTRAN (Fig. 7).
3. Aerodynamic evaluations are performed for the 1G shapes using a N-S solver.
4. Flight envelope analysis is performed using the properties obtained as above to evaluate the objective functions. Using the objective functions, the optimizer generates new individuals for the next generation via genetic operations, such as selection, crossover, and mutation.

The entire flowchart is given in Fig. 8.

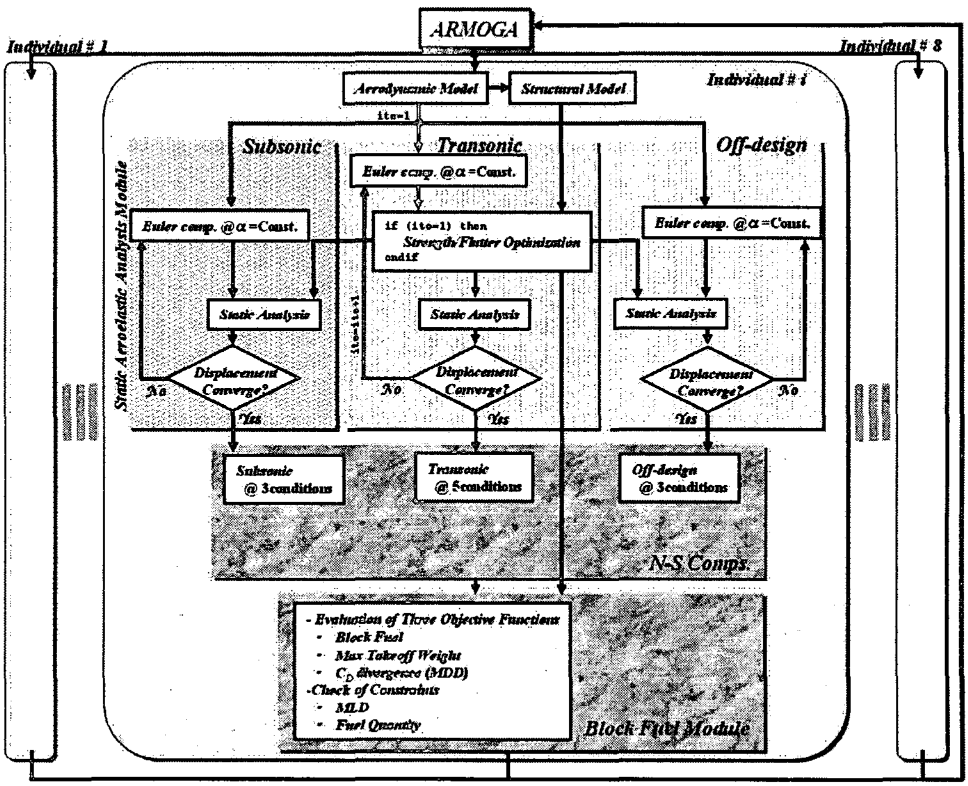


Figure 8: Flowchart of the present MDO system for regional-jet wing

3 DATA MINING RESULTS

In this design, instead of searching for the *optimal* solution, we have applied ARMOGA to explore the design space briefly. The optimization process was stopped when improvements were observed in *all* objectives. Then, SOM was applied to visualize the design space by using all the solutions computed so far. SOM is an unsupervised learning, nonlinear projection algorithm[13] from high to low-dimensional space. This projection is based on self-organization of a low-dimensional array of neurons. In the projection algorithm, the weights between the input vector and the array of neurons are adjusted to represent features of the high dimensional data on the low-dimensional map. Present SOMs are generated by using commercial software Viscovery® SOMine plus 4.0 produced by Eudaptics GmbH [5].

Based on the observation, a new wing design has been suggested and the resulting wing has been confirmed to outperform the other computed solutions. This illustrates the importance of the present approach because design knowledge can produce a better design even from the brief exploration of the design space.

3.1 Optimization Results

The population size was set to eight, and then roughly 70 Euler and 90 N-S computations were performed in one generation. It took roughly one and nine hours of CPU time on NEC SX-5 and SX-7 per PE for single Euler and N-S computations, respectively. The population was re-initialized every five generations for the range adaptation. A total evolutionary computation of 19 generations was carried out. The evolution did not converge yet. However, the results are satisfactory because several non-dominated solutions have achieved significant improvements over the initial design. Furthermore, a sufficient number of solutions are searched so that the sensitivity of the design space around the initial design can be analyzed.

Figure 9 shows all solutions projected on a two-dimensional plane between two objectives, the block fuel and the drag divergence. The non-dominated front is formed, indicating the trade-off between the block fuel and the drag divergence. All solutions projected on two-dimensional planes between other combinations are shown in Figs. 10, and 11. As the non-dominated solutions did not comprise a front, these figures indicate that there are no global trade-offs between these combinations of the objective functions.

The comparison between initial and optimized geometries is investigated. Although the wing box weight tends to increase as compared with that of the initial geometry, the block fuel can be reduced. Thus, the aerodynamic performance can redeem the penalty due to the structural weight. An individual on the non-dominated front shown in Fig. 9 is selected, indicated as 'optimized', and then the optimized geometry is compared with the initial geometry.

Although the drag minimization is not considered here, C_D is reduced. By comparison of the polar curves at constant C_L for the cruising condition, C_D of the optimized geometry is found to be reduced by 5.5 counts. Due to the improvement of the drag, the block fuel of the optimized geometry is decreased by over one percent even with its structural weight penalty.

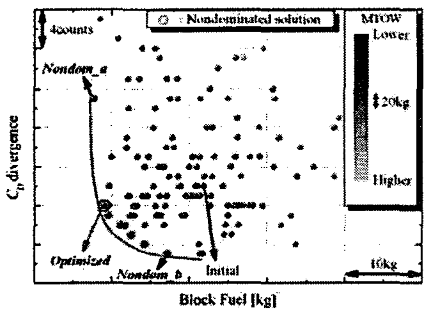


Figure 9: All solutions on two-dimensional plane between block fuel and drag divergence

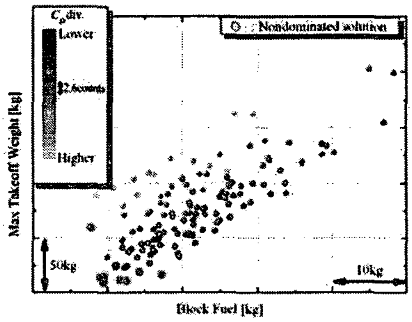


Figure 10: All solutions on two-dimensional plane between block fuel and maximum takeoff weight

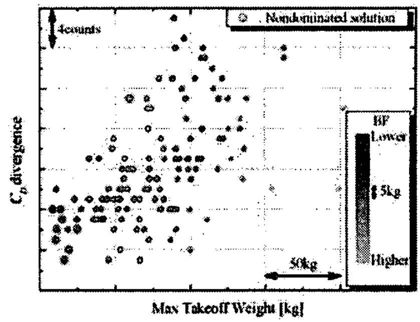
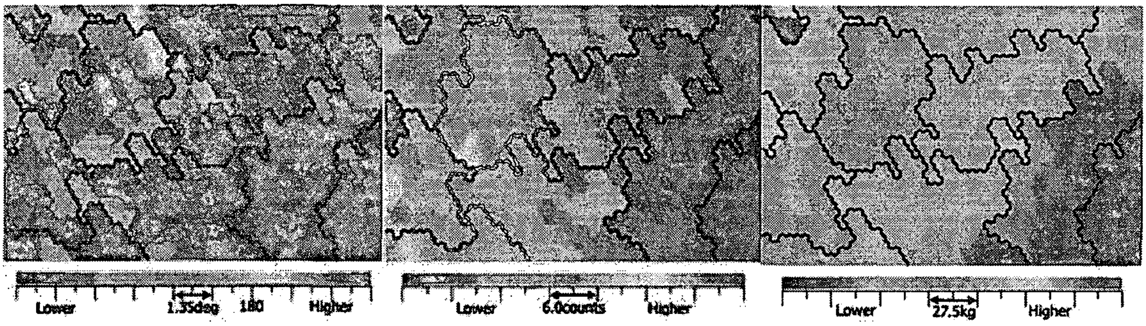


Figure 11: All solutions on two-dimensional plane between maximum takeoff weight and drag divergence

3.2 Data Mining by SOM

Detailed flow visualization for the optimized geometry indicates that the main drag reduction is achieved at the kink location. However, the optimized geometry has inverted gull at the kink. Figure 12(a) shows the SOM colored by the angle between inboard and outboard on the upper wing surface for the gull-wing at the kink location. Angles greater and less than 180 deg correspond to gull and inverted gull-wing, respectively. Higher values of this angle as shown in Fig. 12(a) correspond to higher C_D at the transonic cruising flight condition as shown in Fig. 12(b). However, at angles less than 180 deg, there is little correlation between Fig. 12(a) and 12(b). The inverted gull did not affect aerodynamic performance very much.

Furthermore, SOM also shows that higher angles shown in Fig. 12(a) correspond to higher maximum takeoff weights as shown in Fig. 12(c). The inverted gull-wing is known to have a structural weight increase, which is also observed in the present results. From the visualization of the design space by SOM, it is suggested that non-gull wings should be designed even though the optimized geometry has inverted gull.



(a) (b) (c)

Figure 12: SOM; (a) colored by the angle on upper surface expressing the gull-wing at the kink location, (b) colored by C_D under transonic cruising flight condition, (c) colored by the maximum takeoff weight.

3.3 Evaluation of the Non-Gull Geometry

The optimized wing shape has been modified to examine the non-gull wing shape (called as 'optimized_mod') can achieve better performance and to verify the design knowledge obtained by the previous data mining.

The result is shown in Figs. 13 to 15. These figures show that optimized_mod improves both block fuel and maximum takeoff weight. Moreover, by comparison of the polar curves at constant C_L for cruising condition shown in Fig. 16, C_D of optimized_mod is found to be reduced by 10.6 counts over the initial geometry. Due to the improvement of drag, the block fuel of optimized_mod is reduced by 3.6 percent.

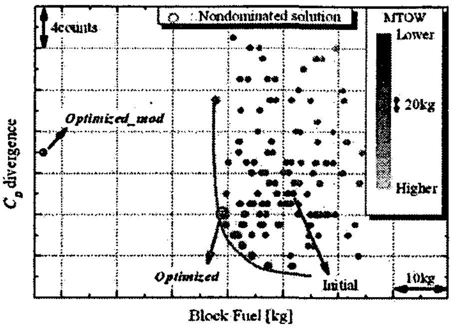


Figure 13
Comparison of *optimized_mod* and all solutions on two-dimensional plane between block fuel and C_D divergence

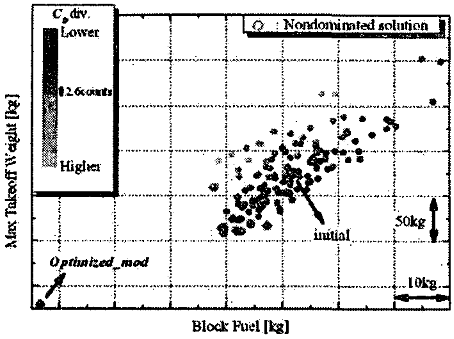


Figure 14
Comparison of *optimized_mod* and all solutions on two-dimensional plane between block fuel and maximum takeoff weight

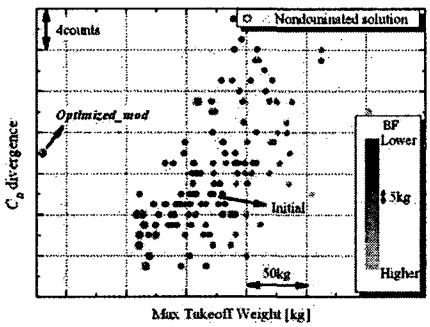


Figure: 15
Comparison of *optimized_mod* and all solutions on two-dimensional plane between maximum takeoff weight and C_D divergence

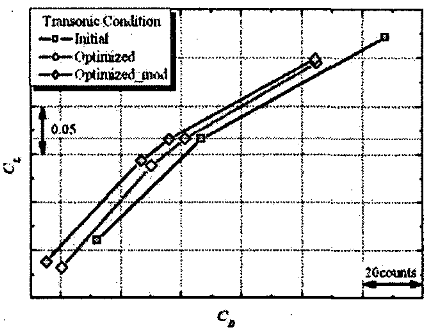


Figure: 16
Comparison of the C_L-C_D curves among three geometries as initial, *optimized*, and *optimized_mod* under transonic flight condition

The present optimization is probably incomplete because only the small number of the generations has been performed. In addition, the automatic mesh generator may clip the design space severely. In the present MDO system, surface spline function of the geometry deviation is used for the modification of the wing surface mesh, and then the volume mesh is modified accordingly by the unstructured dynamic mesh method. However, this process made the surface mesh distorted around the leading edge. This mesh generation might be the primary reason for the difficulty in finding the non-gull geometry. However, the present result demonstrates that data mining can produce a good design even from the results of the incomplete optimization.

4 CONCLUDING REMARKS

A new approach, MODE, has been presented to address MDO problems. MODE is not intended to give an optimal solution. MODE reveals the structure of the design space from the trade-off information and visualizes it as a panorama for DM. DM will know the reason for trade-offs from non-dominated designs, instead of receiving an optimal design without trade-off information.

The main emphasis of this approach is visual data mining. The data mining results are presented for the high fidelity MDO problem of a regional-jet wing. It optimizes aerodynamic performance and structural weight under aeroelastic constraints. Because the design space was large and high fidelity simulation codes were time-consuming, ARMOGA was used to explore the design space briefly. The optimization was stopped after improvements were obtained. Then, SOM was applied to visualize the design space. Based on the observation, a new, better wing design has been suggested. This illustrates the importance of the present approach because design knowledge can produce a better design even from the brief exploration of the design space.

Although it is not discussed in this paper, the flowchart of MODE shown in Fig. 4 has feedback loops. The design space can be redefined by analyzing the surrogate model[11]. Moreover, from data mining, competing objectives and active constraints can be identified. This will lead to the re-definition of the MDO problem itself. MDO often uses conceptual performance equations as design objectives. However, sensitivities of those equations to high fidelity simulation codes are not well understood. As more and more high fidelity simulation codes become available to MDO, selection of objective functions will become more crucial.

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