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MULTI-OBJECTIVE DESIGN EXPLORATION USING EFFICIENT GLOBAL OPTIMIZATION

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Abstract. *Multi-Objective Design Exploration (MODE) and its application are presented. MODE reveals the structure of the design space from the trade-off information and visualizes it as a panorama for Decision Maker. As an optimizer for MODE, Efficient Global Optimization (EGO) based on the Kriging model has been extended to Multi-EGO to solve multi-objective problems, which allow using Multi-Objective Genetic Algorithms efficiently. The resulting MODE was applied to the multi-disciplinary wing design problem and revealed the detailed trade-off information about aerodynamic and structural performance successfully.*

1 INTRODUCTION

A typical Multidisciplinary Design Optimization (MDO) problem involves multiple competing objectives. 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 together.

If one can find many Pareto-optimal solutions to reveal trade-off information among different objectives, a designer will be able to choose a final design with further considerations. Evolutionary Algorithms (EAs, for example, see Ref. 1) are particularly suited for this purpose. However, because EAs are a population-based approach, they generally require a large number of function evaluations. To alleviate the computational burden, the use of the response surface method (RSM) has been introduced as a surrogate model (for example, see Ref. 2).

The surrogate model used in this study is the Kriging model.[3,4] This model, developed in the field of spatial statistics and geostatistics, predicts the probability density distribution of function values at unknown points instead of the function values themselves. From this distribution, both function values and their uncertainty at unknown points can be estimated. By using these values, a balanced local and global search is possible. The criterion 'Expected Improvement (EI)' indicates the probability being superior to the current optimum in the design space. By selecting the maximum EI point as an additional sample point of the Kriging model, the improvement of model accuracy and the exploration of global optimum can be achieved at the same time. This concept is expressed as Efficient Global Optimization (EGO).[3]

EGO has been extended to Multi-EGO[5] for MOPs. In Multi-EGO, the original MOP is converted to the MOP of maximization of EIs. MOGA finds the non-dominated solutions about EIs of the objective functions and then several points are selected from the non-dominated solutions to update the Kriging model. Multi-EGO performs a balanced local and global search for MOPs.

By incorporating Multi-EGO, the MDO system named as Multi-Objective Design Exploration (MODE)[6] can be summarized as a flowchart shown in Fig. 1. 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 a designer. One will know the reason for trade-offs from non-dominated designs, instead of receiving an optimal design without trade-off information.

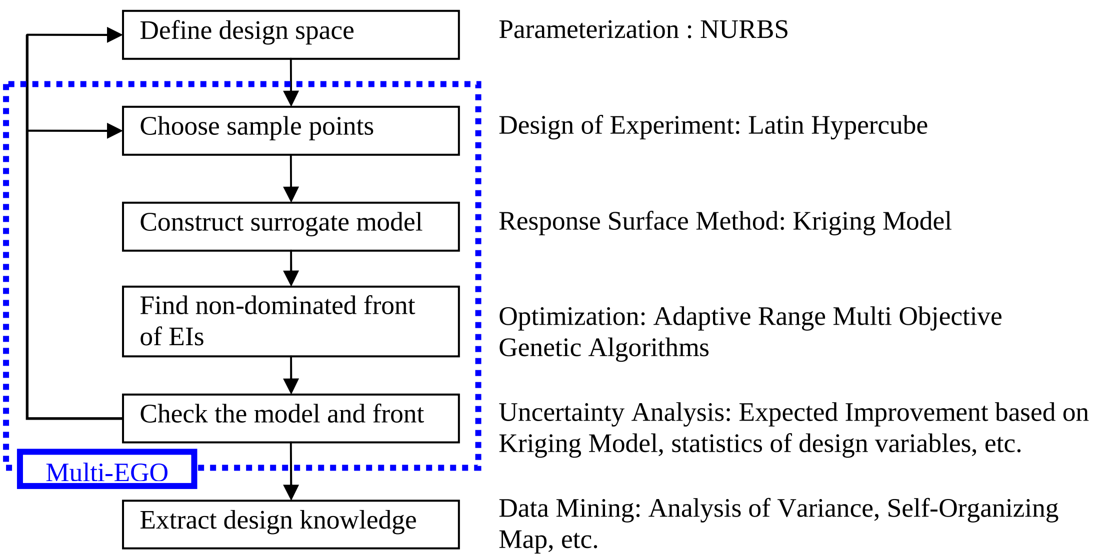


Figure 1: Flowchart of Multi-Objective Design Exploration (MODE) with component algorithms

2 AERO-STRUCTURAL WING SHAPE DESIGN OPTIMIZATION

The present aero-structural wing shape design optimization is considered as follows:

<Objective functions>

Minimize

- Drag at the cruising condition
- Drag divergence between cruising and off-design conditions
- Pitching moment at the cruising condition
- Structural weight of the main wing

<Design variables> (109 variables in total, see Ref. 7 for details)
- 26 variables (NURBS) for each airfoil definition times 4 spanwise sections ($2y/b$= 0.1, 0.35, 0.7 and 1.0)
- 5 twist angles to determine spanwise twist distribution

<Constraints>
- Rear spar heights > Required values
- Strength and flutter margin > Required values

In order to evaluate aerodynamic and structural performance, CFD and CSD modules are used as follows:

1. Full potential analyses are performed for all Kriging sample points and Euler analyses are performed for several points to validate the accuracy of the full potential analyses.
2. Using the pressure distribution obtained from FP/Euler analyses, structural and flutter analysis models are generated by FLEXCFD which is an aeroelastic-structural interface code (Fig. 2).
3. Structural optimization to minimize the wing weight that satisfies the strength and flutter requirements is conducted.

Given the wing outer mold line for each individual, the finite element model of wing box is generated automatically by the FEM generator for the structural optimization. The wing box model mainly consists of shell elements representing skin, spar and rib, and other wing components are modeled using concentrated mass elements. In the present study, MSC. NASTRAN[8] is employed for the structural and aeroelastic evaluations.

The overall flowchart of the present Multi-EGO for aero-structural wing design is given in Fig. 3. In the present optimization, the Kriging model has been updated five times. In total, 160 sample points were evaluated.

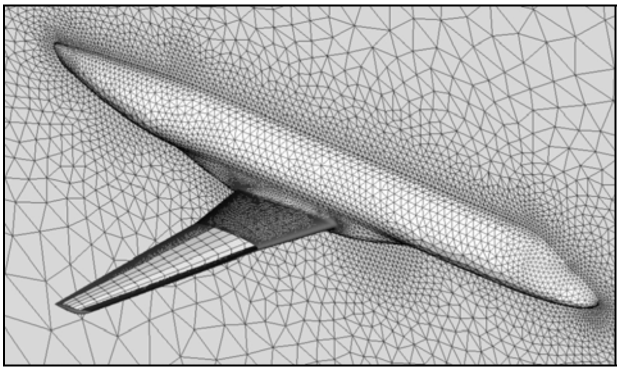


Figure 2: CFD unstructured mesh and CSD structured mesh

3 RESULTS

Figure 4 shows plots of two-dimensional trade-offs based on the performance of the baseline configuration and those of the additional sample points after every iteration step. As iteration progresses, individuals move toward the optimum direction in terms of all objective functions. It means that the additional sample points for the update were correctly selected. One of the additional sample points (Point A in Fig. 4) has improvements of 6.2 counts in drag, 0.4 counts in drag divergence, 79.4 counts in pitching moment, and 74.0 kg in wing weight compared with the baseline design.

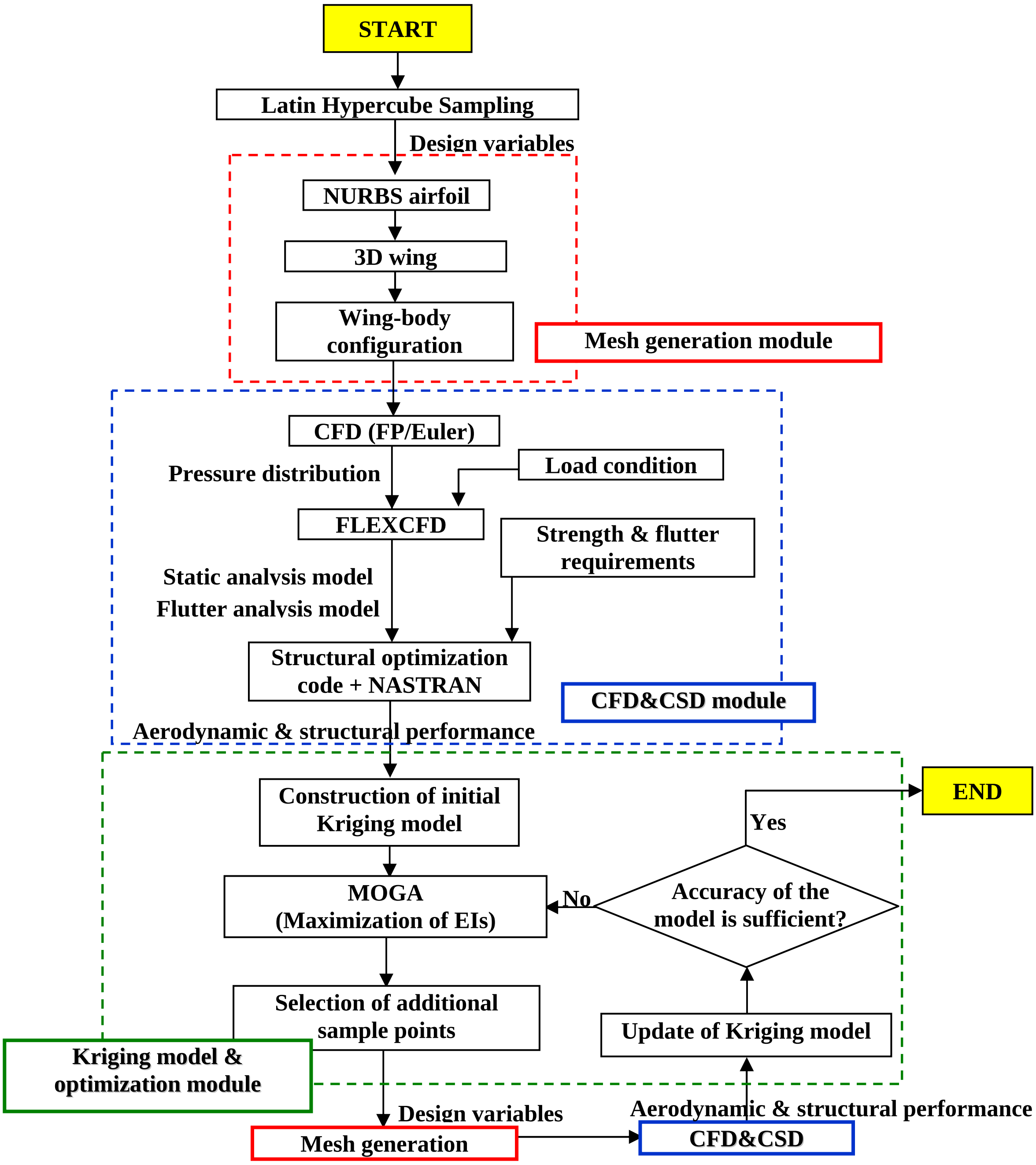
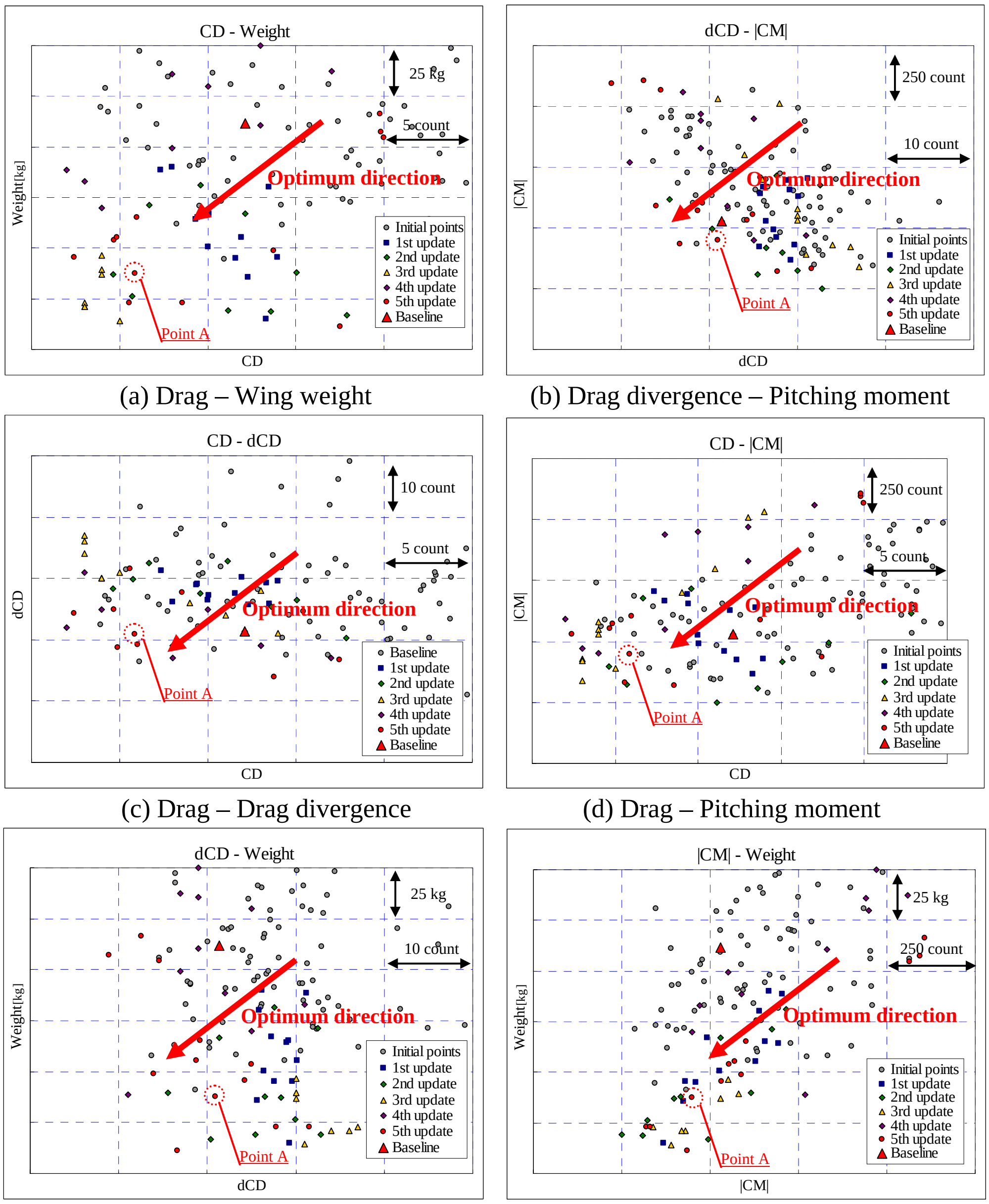


Figure 3: Flowchart of the present Multi-EGO for aero-structural wing design



(a) Drag – Wing weight (b) Drag divergence – Pitching moment

(c) Drag – Drag divergence (d) Drag – Pitching moment

(e) Drag divergence – Wing weight (f) Pitching moment – Wing weight

Figure 4: Two-dimensional trade-offs based on the full potential analysis

Because the present MDO considers four objectives, Fig. 4 requires six plots to visualize the trade-offs. To visualize the entire design space in the two-dimensional map, Self-Organizing Map (SOM)[9,10] proposed by Kohonen was applied to the solutions uniformly sampled from the design space. Figure 5 shows the resulting SOM with 13 clusters considering the four objectives. Furthermore, Fig. 6 shows the same SOMs colored by the four objectives, respectively. These color figures show that the SOM indicated in Fig. 5 can be grouped as follows:

The right edge area corresponds to the designs with low drag, low pitching moment and low wing weight. The upper right area corresponds to those with high drag divergence. The upper left corner corresponds to those with high drag and high pitching moment. The lower left corner corresponds to those with low drag divergence and high wing weight.

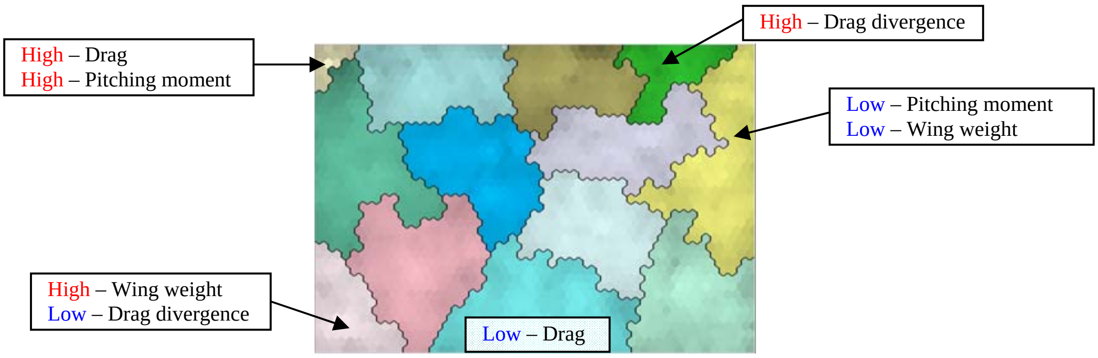
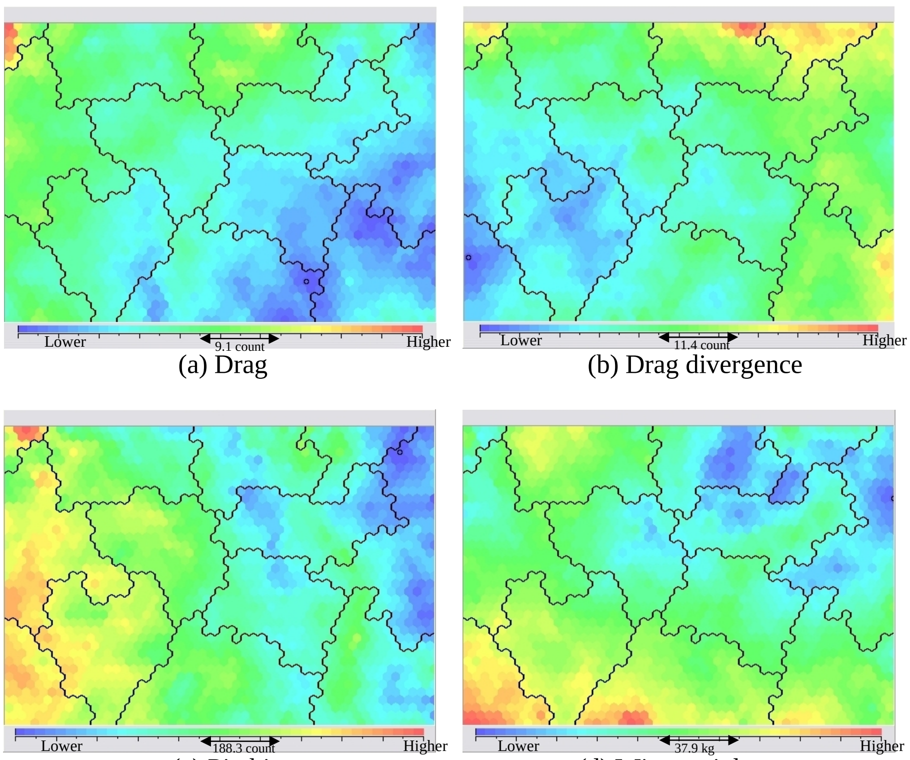


Figure 5: SOM of solutions uniformly sampled from the design space.



(a) Drag

(b) Drag divergence

(c) Pitching moment

(d) Wing weight

Figure 6: SOM of solutions uniformly sampled from the design space colored by the objective functions.

As a result, there is no sweet spot in this design space that improves all four design objectives. However, if the drag divergence is tolerable, the right edge area can be a sweet spot for design.

4 CONCLUSIONS

EGO has been extended to Multi-EGO and incorporated into MODE successfully. The resulting MODE was applied to the wing design problem that considers the aerodynamic and structural performance simultaneously. As a result of the present optimization, several solutions dominating the baseline configuration were generated with 160 function evaluations, which was a drastic reduction compared with that of conventional EAs. One of them has improvements of 6.2 counts in drag, 0.4 counts in drag divergence, 79.4 counts in pitching moment, and 74.0 kg in wing weight compared with the baseline design.

Visual data mining for the design space was performed using SOM. SOM obtained from the solutions uniformly sampled from the design space revealed that the sweet spot could exist if the drag divergence was tolerable. The use of data mining will provide more knowledge about the design space and extract more information from the optimization process.

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