COUPLED AERO-STRUCTURAL SYSTEM DESIGN WITH EFFICIENT MULTIOBJECTIVE OPTIMIZATION ALGORITHMS

THIẾT KẾ HỆ THỐNG KẾT NỐI KHÍ – KẾT CẤU VỚI NHỮNG THUẬT TOÁN TỐI ƯU HÓA ĐA MỤC TIÊU HIỆU QUẢ

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TÓM TẮT

Bài báo phát triển và thực hiện một khung mới và có tính ứng dụng cao cho việc tính toán tối ưu hóa thiết kế kết nối khí – kết cấu. Bài toán tối ưu hóa thiết kế khí – kết cấu đa ngành được thực hiện và xác nhận tính hiệu lực cho một cánh máy bay thử nghiệm và có thể được mở rộng một cách dễ dàng cho những bài toán phức tạp và thực tế. Về cơ bản, nghiên cứu đã sử dụng một bề mặt chung lưu chất/kết cấu có độ tin cậy cao và những thuật toán tối ưu hóa mạnh cho việc xác định chính xác của thiết kế với những sự thực hiện tốt nhất. Những đo lường sự thực hiện khí động lực và kết cấu, bao gồm hệ số lực nâng, hệ số lực cản, ứng suất Von-Mises và trọng lượng của cánh, được tính toán một cách chính xác thông qua những phân tích khí đàn hồi tĩnh của những ứng viên cánh khác nhau. Dựa trên những thực hiện được tính toán này, hệ thống thiết kế có thể được xấp xỉ hóa bằng cách sử dụng mô hình nội suy Kriging và được cải tiến tại tất cả các ngành bằng cách sử dụng những thuật toán tối ưu hóa đa mục tiêu. Thiết kế khí – kết cấu đa ngành vì thế mà trở nên đáng ao ước và thiết thực.

ABSTRACT

The paper develops and implements a new and highly applicable framework for the computation of coupled Aero-Structural Design Optimization. The Multidisciplinary Aero-Structural Design Optimization is carried out and validated for a tested wing and can be easily extended for complex and practical design problems. Basically, the study utilized a high-fidelity Fluid/Structure Interface and robust optimization algorithms for an accurate determination of the design with the best performances. The aerodynamic and structural performance measures, including the lift coefficient, the drag coefficient, the Von-Mises stress and the weight of wing, are precisely computed through the static aeroelastic analyses of various candidate wings. Based on these calculated performances, the design system can be approximated by using a Kriging interpolative model and improved at all disciplines by using Multi-objective Optimization Algorithms. The Multidisciplinary Aero-Structural Design is, therefore, desirable and practical.

Keywords: *Fluid/Structure Interface (FSI); Global Optimization; Multi-objective Optimization; Kriging Model.*

I. INTRODUCTION

Multidisciplinary Design Optimization (MDO) [1-13] has received considerable attention in the aircraft industry. MDO encompasses an extensive research area that includes the implementation of high-fidelity analysis tools in both aerodynamic and structural fields, investigations of robust interfacing algorithms for coupling these tools and improvement of the optimization algorithms so as to predict the best performances quickly. Scientists in this area have focused attention on three main categories, embracing the accuracy, robustness and expensiveness of the proposed algorithms for application to realistic design problems effectively.

Kamakoti [14] and Guruswamy [15] conducted a statistical analysis of Fluid/Structure Interaction algorithms. A remarkable amount of interfacing techniques was enumerated correlative to their grades in application.

The improvement of optimization algorithms is also an active research area in aerospace design. Many scientists have considered imitating the design problem as a virtual problem. Imitating the design problem as a virtual problem implies approximating the problem to be designed by a set of basic equations that can accurately simulate the system responses. Thus far, there have been several efficient approximation methods, such as the Response Surface Method (RSM) [5-7, 16], the Artificial Neural Networks (ANN) [17-19], the Kriging Method (KM) [20-26], etc, that can successfully be applied for design optimization.

In general, MDO has become an increasingly interesting research area in aerospace science. The development of computational design methods reduces the overall design costs and turn-around time for the development of aerospace technology. The use of high-fidelity tools also brings more confidence to the design. On the scope of this paper, good-fidelity analysis tools were employed to validate and improve the MDO system. The commercial Computational Fluid Dynamics (CFD) code FLUENT [27] and the 3D Finite Element Analysis (FEA) code were coupled to execute the static aero elasticity and optimization process. High-fidelity interfacing algorithms were also investigated. Volume Spline Interpolation (VSI) [28], defined relying on the 3D biharmonic equation which adapts to the conservation of virtual work, is used as a load transfer module that maps the aerodynamic pressure onto structural mesh. The deflections obtained from structural analysis can be transmitted onto the CFD grid using reversed VSI. The new CFD grid can be regenerated by using a robust grid deformation algorithm. This deforming algorithm is a combination of the expensive spring analogy [29] and inexpensive transfinite interpolation [30-33]. The CSM mesh can be managed by using a CSM mesh generator. Moreover, the research has utilized Kriging Method [20-26] as an approximation model to imitate the system responses precisely. The design system is then optimized using state-of-the-art Multi-objective Optimization algorithms. Several elitist Evolutionary Multi-objective Optimization algorithms have been considered, involving Non-dominated Sorting Genetic Algorithm (NSGA) [34, 35], Strength Pareto Evolutionary Algorithm (SPEA) [36, 37], Pareto-Archived Evolution Strategy (PAES) [38] and Pareto Envelope-based Selection Algorithm (PESA) [39, 40]. The best algorithms have been consequently selected to improve the design system.

II. FLUID/STRUCTURE INTERFACE

The aerodynamic and structural performances of aerodynamic bodies are tightly coupled. Structural deformation will change the distribution of the aerodynamic force on the body surface. In contrary, this alternative force makes a reverse influence on the structural deformation. Therefore, the efficient Fluid/Structure Interface (FSI) [14, 15, 41, 42] should be developed in an effort to predict the system responses accurately. The FSI can be classified broadly under three major categories: fully coupled, loosely coupled and closely coupled analyses. As the fully coupled FSI is a very expensive approach, many scientists prefer employing the loose or close coupling to resolve static and dynamic aero elastic phenomena. The typical loose Fluid/Structure coupling is shown in detail in the flow diagram of Figure 1.

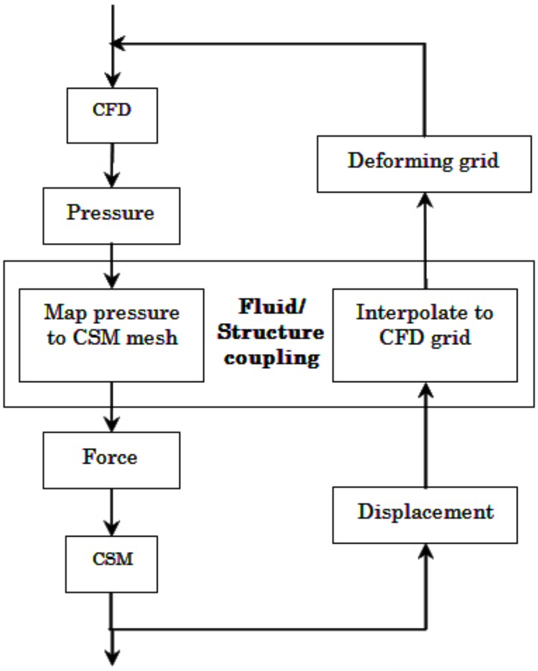

Figure 1. Fluid/Structure Interface.

The Fluid/Structure Interface is an iterative process that connects five principal modules together, involving Computational Fluid Dynamics (CFD), Computational Structural Mechanics (CSM), CFD grid generation or deformation, CSM mesh generator and data transfer (implying load and displacement transfer) modules. For each of iteration, it is necessary to map the surface loads from the CFD grid system onto the structural grid to obtain the forces on the CSM mesh system, which are then used to obtain the displacements on the CSM mesh. These displacements need to be interpolated onto the CFD surface grid to obtain a new CFD grid. This repetitive process is repeated until the convergent criterion is satisfied. The stopping condition is merely fulfilled if no considerable changes of the structural mesh are created.

1. Aerodynamic analysis

The aerodynamic analysis package used in this paper is the commercial CFD code FLUENT [27]. FLUENT is a high-fidelity and relatively-automatic flow solver, based on Finite Volume Method [43, 44], that integrates many viscous and turbulence modelings while resolving Navier-Stokes equation. It can completely be considered as an effective fluid flow analysis module for executing coupled Aero-Structural Design Optimization. In this paper, the Spalart-Allmaras viscous modeling is integrated in the design process in order to precisely predict the aerodynamic performance. The initial multiblock structured CFD grid is generated using the Gridgen [45] package. This CFD grid can be altered using a robust grid deforming algorithm.

2. Structural analysis

The process of structural analysis can be executed by a high-fidelity, fully-automatic and robust structural analysis code ADFEAP, which is developed from the original research code of Professor O. C. Zienkiewicz and Professor R. L. Taylor. The package is a structured Finite Element Method [46-50] solver that incorporates several element types, embracing truss and quadrilateral shell elements. The code can be effectively employed for usual structural analysis as well as investigating and verifying the novel structural algorithms. The CSM mesh is automatically created using the GiD [51] mesh generator.

3. Grid deformation algorithm

The grid deformation code used in this paper is based on the combination of a typical algebraic (spring analogy [29]) and iterative (transfinite interpolation [30-33]) method. The displacement of the vertices and edges is computed by the expensive spring analogy, while the displacement of the remaining grid points is specified by the inexpensive transfinite interpolation (TFI).

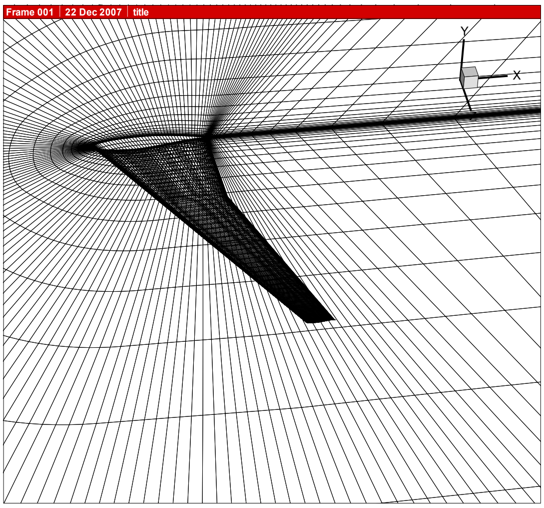

Figure 2. Original wing-only grid.

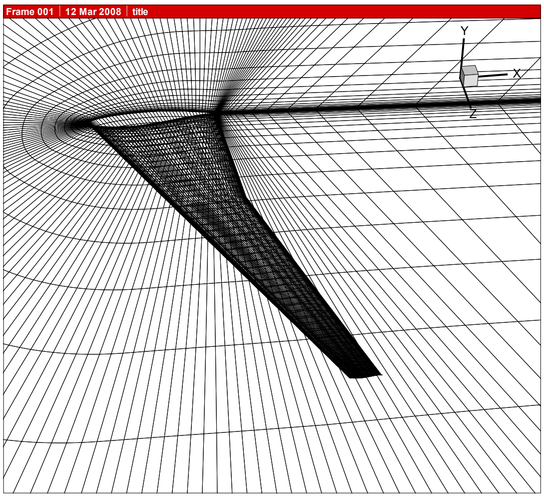

Figure 3. Deformed wing-only grid.

4. Data transfer

In coupled aero-structural analyses, the information has to be exchanged between elastomechanical and unsteady aerodynamic simulation programs. The information concerns the structural deformation connected to the elastomechanical grid and aerodynamic forces connected to the aerodynamic grid. As aerodynamic and elastomechanical models are based on grids with different structures, interpolation procedures which transfer aerodynamic and elastomechanical data between the elastomechanical and aerodynamic surface grids must be developed. It is of fundamental importance that no energy is lost in this transfer. The Volume Spline Interpolation (VSI) [28] is a very simple method which does not require any additional logic and can be applied straightforwardly to any 3D data set, without drifting so far away from the original data even the original data is non-smooth.

III. APPROXIMATION ALGORITHM

1. Kriging model

The Kriging [20-26] model postulates a combination of a global trend function $P(x)$ and a local deviated function $Z(x)$ of the following form [20-24, 26]

$$\hat{y}(x) = P(x) + Z(x) \qquad (13)$$

where $\hat{y}(x)$ is the unknown function of interest, $P(x)$ is a known polynomial (normally constant, linear or quadratic) function of the p-dimensional-variable x and $Z(x)$ is the realization of a normally distributed stochastic process in which the covariance structure of Z relates to the smoothness of the response. While $P(x)$ globally approximates the design space, $Z(x)$ creates localized deviations so that the Kriging model interpolates the n sampled data points.

2. Design of experiments

Latin hypercube sampling: The Latin hypercube [20, 25] is a matrix of n_s rows and m columns where n_s is the number of sampled points and m is the number of design variables. Each of the k columns contains the level $1,2,...,n_s$ randomly permuted and the k columns are matched at random to form the Latin hypercube. Latin hypercube sampling (LHS) offers flexible sizes while ensuring stratified sampling, i.e., each of the input variables is sampled at n_s levels. These designs can have relatively small variance when measuring output variance.

IV. STATE-OF-THE-ART EVOLUTIONARY MULTIOBJECTIVE OPTIMIZATION

Evolutionary Optimization Algorithms (EOA) are popularly used in various problem solving tasks involving nonlinearities, non-differentiable functions, non-convexity, multiple optima, multiple objectives, uncertainties in decision and problem parameter, large computational overheads, etc. Some universal EOA are Genetic Algorithm (GA) [53-56], Simulated Annealing (SA) [57-60], etc. Recently, the Evolutionary Multiobjective Optimization (EMO) has been judged as one of the three fastest growing field of research and application among all computational intelligence topics. Many excellent achievements and algorithms have been proposed and applied for the world of computer science. On the scope of this paper, the authors only mention and summarize the progresses of Multiobjective Optimization Genetic Algorithm (MOGA). The best MOGA algorithm is finally utilized for improving the coupled Aero-Structural Design Optimization System. The structure of this section is disposed by the orders: the first is an overview of Genetic Algorithm; the next steps can be employed to introduce some MOGA such as Non-dominated Sorting Genetic Algorithm (NSGA) [34, 35], Strength Pareto Evolutionary Algorithm (SPEA) [36, 37], Pareto-Archived Evolution Strategy (PAES) [38] and Pareto Envelope-based Selection Algorithm (PESA) [39, 40]; a briefly comparative study of these MOGA is also realized.

In conclusion, SPEA2 and NSGA-II proved to be the state-of-the-art MOGA. MOGA research and application seem to be in its peak at the current time.

V. WING DESIGN CASE STUDY

A tested eight-variable wing design problem was executed to validate the MDO system. The five aerodynamic variables are the break chord (C_B), tip chord ( ), sweepback angle (Λ), break semi-span (S_B) and semi-span (S_S); note that the wing has 1 m root chord length. On the other hand, the wing structure has to incorporate the lowest weight and sufficient strength. In this study, only three structural variables are included, involving the upper skin thickness (t_{us}), the lower skin thickness (t_{ls}) and the sparcabs cross-sectional area (A_{sc}). Finally, there are eight design variables in total and the ranges of these variables are summarized in Table 1. After selecting feasible design variables, the multiple objectives are then adopted to improve the wing performance. These objectives can be classified to aerodynamic objectives that are correlative to Lift/Drag L/D and structural objectives that are correlative to the weight of the wing. A summary of the design objectives and flight condition is given in Table 2.

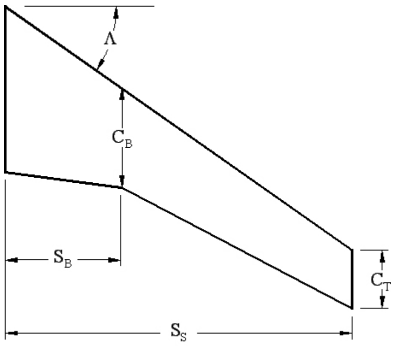

Figure 4. Wing design variables.

Table 1. Ranges of design variables.

Variables	Minimum	Baseline	Maximum	Unit
C_B	0.60	0.75	0.90	m
C_T	0.20	0.35	0.50	m
Λ	30.0	35.0	40.0	deg
S_B	0.40	0.70	1.00	m
S_S	1.80	2.10	2.40	m
t_{us}	0.0015	0.00225	0.0030	m
t_{ls}	0.0015	0.00225	0.0030	m
A_{sc}	0.000153937	0.000430398	0.000706858	m^2

Table 2. *Design objectives and flight condition*

Condition	Status	Unit
Mach number M	0.84 (cruising)	none
Angle of Attack (AOA)	3	deg
Aerodynamic objective	Maximize $(\mathrm{L/D})$	none
Structural objective	Minimize (Weight)	kg

The multiobjective function and constraints used for the coupled aero-structural design optimization are defined as

Minimize (Weight) and Maximize $(\mathrm{L/D})$

Subjected to:

$$
\begin{aligned}
&C_L > C_{L_{base}} \\
&C_D < C_{D_{base}} \\
&\sigma < [\sigma_y] \qquad (18)
\end{aligned}
$$

C_L is lift coefficient, C_D is drag coefficient, σ is maximum Von-Mises stress, and $[\sigma_y]$ is the yield stress of material. The wing is made from Aluminum alloy Al 2024-T3. The subscript *base* is utilized to symbolize the baseline calculation. The above constraints ensure that the optimized wing outperforms the baseline wing. For instance, aerodynamic constraints are imposed on the lift and drag to meet the goal that the aerodynamic performance of the designed wing should be at least as good as that of the baseline wing.

VI. MDO PROCEDURE

The MDO system begins with the selection of the design variables, constraints and objective functions. Eight variables are ultimately adopted to enhance the performance of the wing in terms of its aerodynamic and structural performance measures. To reduce the computational time, the Kriging meta model is employed to approximate the design system. The candidate points for the eight-variable design problem were successfully retrieved using the MATLAB [61] *Latin hypercube design* function to produce an accurate Kriging approximation at last. The coupled aerodynamic and structural responses are in turn computed through the process of the aeroelastic analysis.

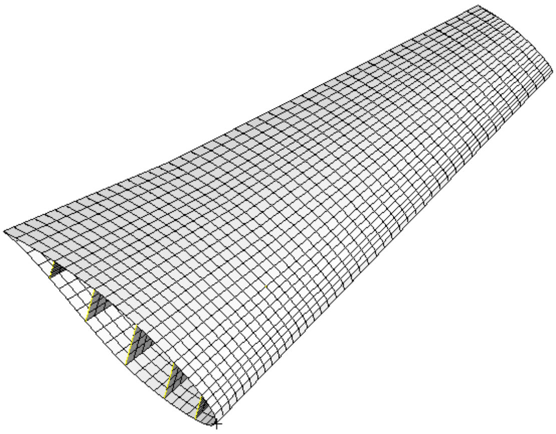

Figure 5. Wing finite element model.

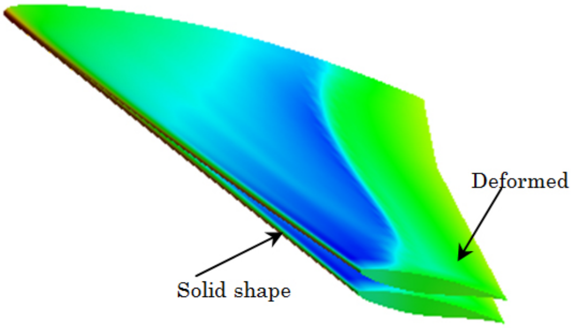

Figure 6. Static aeroelasticity.

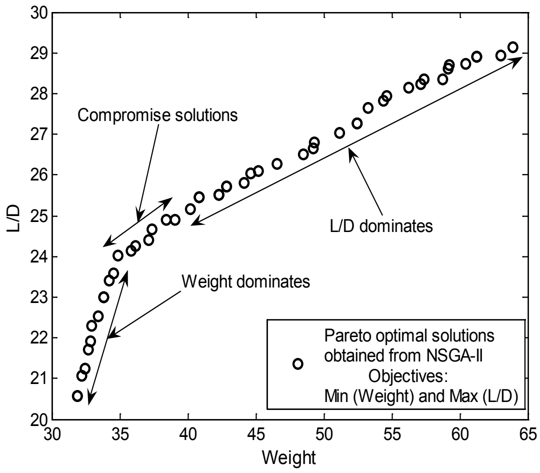

Figure 7. Non-dominated solutions with NSGA-II.

The approximate models are enhanced and optimized by using NSGA-II Multiobjective Optimization algorithm. A set of Pareto optimal solutions is successfully retrieved. Few of preferred solutions are then chosen based on interactive decision-making.

VII. CONCLUSIONS

This research is motivated by our interest in developing and improving computational capability of MDO system. Considerable MDO work was successfully performed for a tested wing to validate several suggested algorithms that can be easily applied for more complex and practical problems. The high-fidelity structural analysis code was coupled with the commercial CFD code and robust Fluid/Structure coupling to realize the aeroelastic analyses. The aerodynamic and structural meshes were well-managed by using a robust grid deformation algorithm and a CSM mesh generator. The design system was subsequently approximated by utilizing a robust Kriging interpolative model. The design system is then optimized using state-of-the-art Multiobjective Optimization algorithms. Several elitist Evolutionary Multiobjective Optimization algorithms have been considered, involving Non-dominated Sorting Genetic Algorithm (NSGA), Strength Pareto Evolutionary Algorithm (SPEA), Pareto-Archived Evolution Strategy (PAES) and Pareto Envelope-based Selection Algorithm (PESA). In general, SPEA2 and NSGA-II proved to be the most robust Evolutionary Multiobjective Optimization algorithms. Consequently, NSGA-II is employed to improve the design system at all disciplines. The Multidisciplinary Aero-Structural Design is, therefore, desirable and practical.

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