A RESEARCH OF MULTIDISCIPLINARY DESIGN OPTIMIZATION ALGORITHM FOR FIGHT VEHICLE DESIGN

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Abstract

Aircraft system design involves many different disciplines, including lots of design variables, state variables, constraint equations and interrelationship. It is believed as a kind of typical complex system. To improve design quality and integrated performance of aircraft, a multidisciplinary design optimization（MDO）was presented. this method exploits synergy among the disciplines, and gets the optimal solution from the optimal angle of the whole system. The core of MDO is to construct the algorithm for multidisciplinary collaborative design. This paper discusses three of the most typical and popular algorithms, i.e. Multidisciplinary Feasible (MDF), Collaborative Optimization (CO) and Concurrent Subspace Optimization (CSSO). First, it introduces basic ideas, algorithm structures and optimization frameworks of those methods, then constructs optimization frameworks of those algorithms, and finally, with multidisciplinary optimization of the gear reducer as an example, makes a comparative analysis of those methods in the aspects of computational efficiency, computational accuracy and applicability, and accordingly concludes their application scope and selection criterion.

1 General Introduction

With regards to the limitation of the traditional overall design method, Sobieski first proposed the concept of Multidisciplinary Design Optimization (MDO for short) in 1980s[1]. MDO, as a methodology fully exploring and utilizing the collaborative mechanism of interaction in an engineering system to design a complex system or subsystem, is an effective way widely applied to the design of complex systems and products such as airplanes [2], launchers [3], satellites [4] and automobiles [5]. As tight coupling existing among different disciplines renders complex the computation and information exchange, MDO decomposes a complex system into multiple subsystems and coordinates optimization of the subsystems in different ways, thus saving computing resource and obtaining the optimal solution to the system under the premise that the accuracy is ensured to the greatest extent. Currently, MDO falls into single-stage optimization and double-stage optimization according to the hierarchical relation of optimization. Single-stage optimization methods include Multidisciplinary Feasible (MDF for short), Individual Discipline Feasible (IDF) and All-At-Once (AAO) while double-stage optimization methods mainly refer to Concurrent Subspace Optimization (CSSO), Collaborative Optimization (CO) and Bi-level Integrated System Synthesis (BLISS). As there is no specific selection criterion and application scope for these methods mentioned above, designers always have to depend on their engineering experience to select a proper method, which is a waste of both computing resource and labor cost. Therefore, it is obviously of great practical significance to define the selection criterion and application scope with engineering examples for these methods based on comparative analysis of their properties and characteristics.

Among all the above methods, MDF is a typical single-stage optimization method which mainly features integration of disciplinary analysis and disciplinary optimization and requires plenty of disciplinary analysis and system analysis during the whole optimization process with the main idea to integrate and realize disciplinary coupling analysis in system analysis; CO, with the idea of concurrent disciplinary optimization, divides engineering problems into ones related to the system and to each discipline, thus granting high autonomy to the discipline for optimization; CSSO is a decomposition optimization method to realize concurrent optimization which replaces the disciplines except the objective one with similar models in the optimization process so as to evaluate the influence of design variables of the objective discipline on system constraints and objectives, then uses similar response functions during disciplinary optimization to indicate the influence of other disciplines on status variables of this discipline and finally obtains the optimal solution through real-time update of the response surface. These three methods which adopt different ideas and strategies in MDO of engineering cases, present different characteristics in the optimization process and get different optimization results. This paper first makes a further analysis of inner structures and optimization frameworks of these methods, then uses the multidisciplinary optimization tool iSIGHT to construct an optimization platform for the three methods with multidisciplinary optimization of the gear reducer as an example to make a comparative analysis of their properties and characteristics in the aspects of computing efficiency, computing accuracy and engineering applicability, and finally, in combination with the characteristics of the methods and the actual situation of engineering cases, concludes the selection criterion and application scope for these methods.

2 Mathematic Model of MDO

As for MDO, nevertheless, the non-hierarchic system is primarily studied.Usually, three types of variables are defined in the non-hierarchic system, i.e. the global or shared variable X needed for computation of the whole system level, the local variable X_i needed by subsystems, and the status or behavioral variable Y as the output value of the subsystem level and the input parameter of other subsystems. In the problem-solving process of the non-hierarchic system, iterative analysis is required among the subsystem levels to converge and produce a feasible solution to the design problem under the premise that all status variables are consistent. A typical analysis for three subsystems is shown in Fig. 1 below.

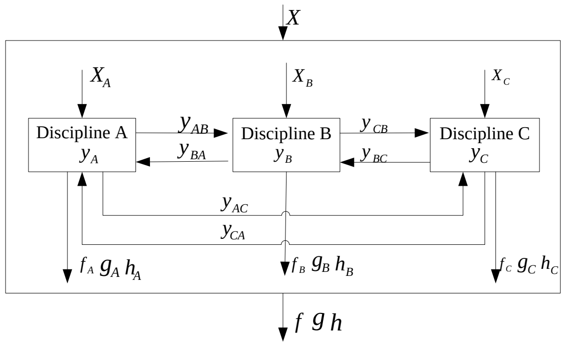

Fig.1 Non-hierarchic system of MDO

In Fig. 1, X refers to the design variable, including the system design variable X and the discipline design variables X_A, X_B and X_C; Y refers to the status variable, including the system status variable Y, the discipline status variables y_A, y_B and y_C, and coupling status variables y_{AB}, y_{BA}, y_{AC}, y_{CA}, y_{BC} and y_{CB}; g and h are constraint conditions for inequality and equality respectively; and f is the objective function.

The non-hierarchic system problem of MDO can be expressed in a mathematical form as follows:

$$\min \quad f(x,y)$$
$$s.t.\begin{cases} g_i(x,y) < 0 \\ hi(x,y) = 0 \end{cases} \qquad i = 1,2,\cdots n$$

3 Solution Strategy and Optimization Framework of MDO

In the problem-solving process of MDO above, the MDO problem model can be transformed so that different ideas and strategies can be adopted for solution. This paper introduces solution strategies and optimization frameworks of MDF, CO and CSSO.

3.1 MDF

MDF is a traditional design optimization method of MDO which uses all design variables and optimization objectives of the disciplines as those of the system. As shown in Fig.3, its optimization framework is that the system analysis module gets a design variable X from the optimization module, then makes a complete multidisciplinary analysis to get the output variable Y(X), and finally uses X and Y(X) to compute the objective function F (X, Y(X)) and the constraint function g_k (X, Y(X)).

The mathematical problem of MDF can be expressed as follows:

$$\begin{aligned} &\min \ \ \mathrm{F}(\mathrm{X}, \mathrm{Y}(\mathrm{X})) \\ &\mathrm{s.t.} \ \ g_k(\mathrm{X}, \mathrm{Y}(\mathrm{X})) \leq 0 \qquad (\mathrm{k} = 1, 2, \cdots, \mathrm{n}) \end{aligned}$$

Where F refers to the objective function, g , the constraint function and k, the number of constraints.

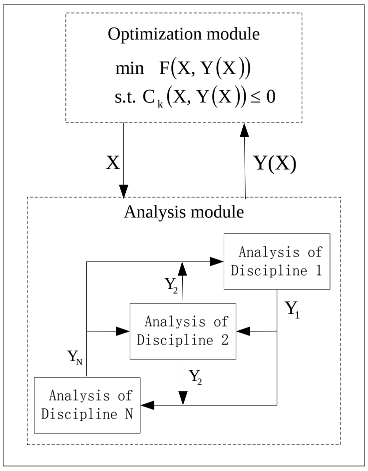

Fig.2 MDF optimization framework

3.2 CO

CO divides the optimization design problem into two levels, i.e. the level for a single system and that for multiple disciplines. The system level distributes the objective values of its variables to each discipline level and the objective function of each discipline level should minimize the gap between coupling variables among disciplines and the distributed objective values under the condition that the discipline level meets the constraints on its own. After discipline level optimization, each objective function will be passed back to the system level and form a consistency constraint on the system level, thus solving the inconsistency problem of coupling variables among different disciplines. Multiple iterations between the system level optimization and the subsystem level optimization will finally bring out the optimal system design scheme which meets disciplinary consistency. The optimization framework shown in Fig.3.

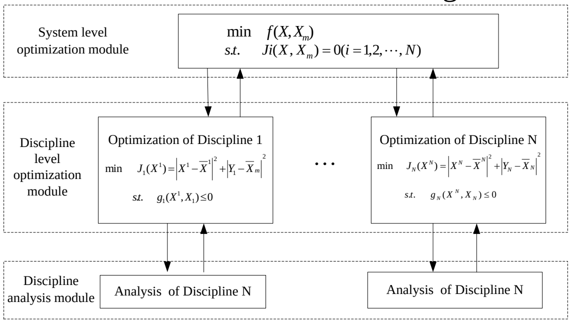

Fig.3 CO optimization framework

3.3 CSSO

CSSO adopts an approximate simplification of the design problem, decomposing the problem into discipline level ones for experts of various disciplines to conduct optimization design with a method suitable for them, and finds out the influence of one discipline on other ones through an approximate model. In the solving process, CSSO first gives out several initial values of design variables and then gets the approximate status variable values of the response surface through system analysis to form an approximate analysis model for the response surface of status variables. In the optimization process of design variables of the discipline level, an accurate analysis is used for status variables of one discipline while approximate models are used as optimization models required for other disciplines; besides, system analysis of optimal solution of each discipline is carried out for a second time and the acquired status variables are used to update the response surface. In the system level optimization process, all status variables are also obtained by the response surface, and system analysis of the optimal solution acquired through system optimization is made for a second time to update the response surface. With repeated disciplinary optimization and system optimization as well as the proceeding of the iteration process, the response surface gets more and more accurate and in this way the optimal solution can be converged.

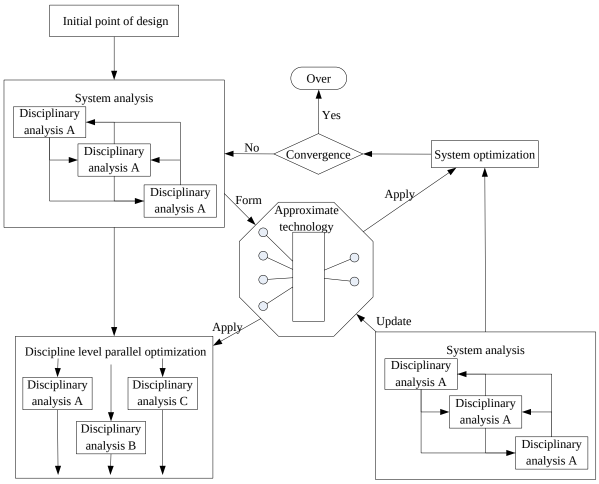

Fig.4 CSSO optimization framework

4 Optimization Implementation and Method Comparison

4.1 Description

This paper takes gear reducer as an example which is the standard algorithm example adopted by NASA to evaluate MDO. This algorithm example features computational complexity and disciplinary coupling as existing in the design of multidisciplinary optimization. This optimization problem describes the design optimization of a gear reducer, with 7 design variables. The optimization objective is to minimize the volume (weight) of the gear reducer under the premise that each design variable meets the numerous constraints on it. The above optimization process is implemented by virtue of the MDO tool, iSIGHT 5.7.

The mathematical model of this algorithm example is shown as follows:

min f（x）$=0.7854x_1x_2^2(3.3333x_3^2+14.9334x_3-43.0934)-1.5079x_1(x_6^2+x_7^2)+7.477(x_6^3+x_7^3)+0.7854(x_4x_6^2+x_5x_7^2)$

s.t. $g_1=27/(x_1x_2^2x_3)\le 1.0$;

$g_2=397.5/(x_1x_2^2x_3^2)\le 1.0$;

$g_3=1.93x_4^3/(x_2x_3x_6^4)\le 1.0$;

$g_4=1.93*x_5^3/(x_2x_3x_7^4)\le 1.0$;

$g_5=\sqrt{(\frac{745x_4}{x_2x_3})^2+16.9\times 10^6}\Big/110x_6^3\le 1.0$;

$g_6=\sqrt{(\frac{745x_5}{x_2x_3})^2+157.5\times 10^6}\Big/85x_7^3\le 1.0$;

$g_7=x_2x_3/40\le 1.0$;

$g_8=5x_2/x_1\le 1.0$;

$g_9=x_1/(12x_2)\le 1.0$;

$g_{10}=(1.5x_6+1.9)/x_4\le 1.0$;

$g_{11}=(1.1x_7+1.9)/x_5\le 1.0$;

Where the value range of each design variable is respectively given below:

$2.6\le x_1\le 3.6$ $0.7\le x_2\le 0.8$ $17\le x_3\le 28$ $7.3\le x_4\le 8.3$
$7.3\le x_5\le 8.3$ $2.9\le x_6\le 3.9$ $5.0\le x_7\le 5.5$

4.2 Computed results

MDF optimization platform is constructed in iSIGHT. Since the MDF optimization framework is simple for only system level optimization is involved, Sequential Quadratic Programming (NLPQL) in iSIGHT will be adopted, with the initial value (3.5，0.7，20，7.3，7.7，3.0，5.0), the optimal point after optimization (3.5，0.7，17，7.3，7.715，3.350，5.287), the objective value f=2994.216, the number of iterations of 44 and the iteration time of 5s. shown in Fig. 5.

CO optimization platform is constructed in iSIGHT. CO falls into system level optimization and discipline level optimization and introduces the concurrency constraint ε, which is taken as ε =0.001 in this paper. In the whole optimization process, MMDF and Sequential Quadratic Programming (NLPQL) are selected respectively in the system level optimization and the discipline level optimization, with the initial value (3.5，0.7，20，7.3，7.7，3.0，5.0), the optimal point after optimization (3.492，0.701，17，7.3，7.716，3.450，5.214), the objective value f=2996.403, the number of iterations of 25 and 1632 respectively for system and discipline level optimization, and the operation time of 186s. shown in Fig. 6.

CSSO platform is constructed in iSIGHT as shown in Fig. 10. In this optimization module, Sequential Quadratic Programming (NLPQL) is adopted with the initial value (3.5，0.7，20，7.3，7.7，3.0，5.0), the optimal point after optimization (3.54，0.7，17，7.303，8.165，3.366，5.291), the objective value f=3026.6, the number of iterations of 37 and 263 respectively for system and discipline level optimization, and the whole operation time of 252s,shown in Fig. 7.

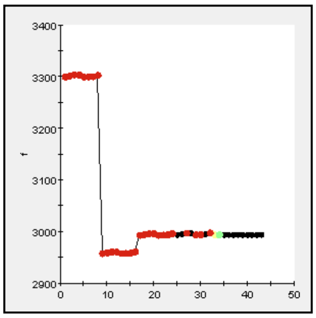

Fig.5 Optimizing curve of *f* in MDF

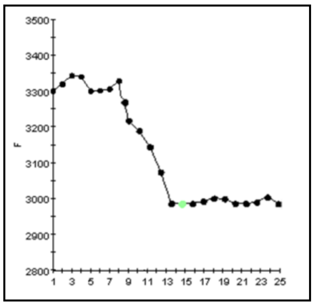

Fig.6 Optimizing curve of *f* in CO

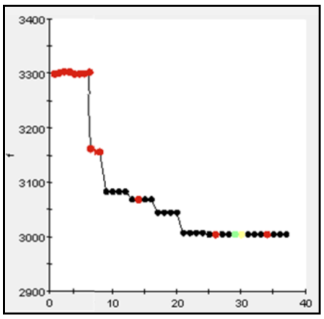

Fig.7 Optimizing curve of f in CSSO

4.3 Result analysis and comparison

Based on the implementation of the above three MDO methods in iSIGHT and their specific application to multidisciplinary optimization of the gear reducer, a comparison is made among the optimization objective, the number of iterations and the optimization time of the three methods as shown in Table 1.

Algorithm	Initial value	Optimization objective	Number of iterations		Time (s)
			System level	Discipline level	
MDF	3.5，0.7，20，7.3，7.7，3.0，5.0	2994.216	44	/	5
CO		2996.403	25	1632	186
CSSO		3026.6	37	263	252

Three methods are compared in the aspects of computational efficiency, computational accuracy and applicability:

(1) As for computational accuracy, MDF is superior to CO and CO is superior to CSSO. The main reason is that MDF makes little change to the original problem model, while CO treats the original problem with less strict consistency constraints so as to accelerate convergence, while CSSO conducts an approximate treatment to the original problem with the response surface method, thus getting an optimization result inferior to those of the other two methods.

(2)As for the computational efficiency, MDF is the best of the three for it involves only system level optimization in the whole process with a moderate number of design variables and less complicated disciplinary analysis process in the above-mentioned example, thus requiring the least time and iterations; CO involves both system level and discipline level optimization with a larger number of times of discipline level analysis and optimization, which requires more time and iterations and thus is less effective than MDF; CSSO, also involving double-level optimization, sharply reduces the number of times of optimization but is still the least effective method due to its need for not only an experiment design in initial design but an update for each response surface introduced to transform the disciplinary analysis to a mathematical solving problem which is fairly time-consuming.

(3) As for the application scope, which cannot be directly acquired in the optimization process of the algorithm example, the recommendation is given in the following according to the main idea and inner structure analysis of the example: MDF is recommended for a less complex system with uncomplicated status variables, objective functions and constraint computation,

a small number of design variables, and a small amount of disciplinary analysis and computation; CO is able to implement a parallel optimization in case of a system with a large number of system level variables and loose coupling among disciplines, especially when the system is decomposed into different organizational forms and design softwares, so it is applicable for the optimization of a large-scale system with loose coupling; for a system with a large number of system variables, tight disciplinary coupling and complicated disciplinary analysis, CSSO is recommended to reduce the complicacy of the optimization process. In the solving process for a specific engineering problem, a proper method should be selected with an overall consideration of its computational efficiency, computational accuracy, etc. and according to the characteristics of the problem and the requirements of the design, or the above-mentioned methods should be applied in combination to different stages of the problem-solving process.

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