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An inquiry into Multi-disciplinary and multi-purpose optimization methods used in optimum design of different aerospace precision-guided projectiles

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ABSTRACT
Multidisciplinary design optimization (MDO) is a new approach in the design of complex engineering systems which over the past two decades, has seriously drawn many investigators and design centers attention around the world, especially in the field of aerospace. In MDO by assumption of original design issues and proper modeling of them, verifying of one or more generic optimization criterion, are considered. In this respect the main design issues, codifying each of their content, structure and the interaction between them, the accuracy of the modeling and optimization, have been supposed as the MDO problem main challenges and in recent years have been the basis of much researches. In this study, the conceptual multidisciplinary and multi-purpose designs have been examined and multi-purpose and multidisciplinary different design methods and factors which affecting these types of designs will be presented.
***Key words**: Conceptual design - multi-disciplinary optimization - multi-purpose optimization- precision-guided launch*

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INTRODUCTION

Multidisciplinary and multi-purpose design optimization

Multidisciplinary design optimization or multidisciplinary optimized design were considered for the first time in 1984 in the multidisciplinary design optimization conference in NASA research center [1]. Multidisciplinary design optimization (MDO) is a new approach in the design of complex engineering systems which over the past two decades, has been seriously drawn many investigators and design centers attention around the world, especially in the field of aerospace. In MDO by assumption of original Design issues and proper modeling of them, verifying of one or more generic optimization criterion, are considered. In this respect the main design issues, codifying content each of them, structure and the interaction between them, the accuracy of the modeling and optimization have been supposed as the MDO problem main challenges and in recent years have been the basis of much researches. In this paper, explanation of a variety of methods and approaches in MDO have been discussed by expressing the multidisciplinary design optimization and factors affecting this method. The conceptual and mathematical definitions referred to this type of design have been presented.

• optimized multi-disciplinary design approach

In traditional design methods, to simplify large-scale problems and multidimensional responses, each subsystem is designed separately by taking other subsystems requirements into account. Then modifications are applied to subsystems design so that the whole system performance be acceptable.

However, various subsystems goals are often opposing each other. For example, in designing an airborne vehicle, maybe something which is deemed optimal would be too costly in terms of aerodynamic structures groups or be unstable from the point view of mechanics and control. Therefore, all the issues parameters which affecting the problem of design are required to be optimized simultaneously. This work is multidisciplinary design optimization`s aim. Many MDO problems have more than one goal functions inherently because of having several different categories and usually the goal functions are in conflict with each other. These optimization issues are referred to as multidisciplinary. Many researchers try to solve these problems by using single-purpose algorithms by means of changing the definition of multidisciplinary problem to a single-purpose or by employing approximated definitions. One of these methods is the weighted sum method (Figure 1). This method is very approximate, and in fact after the weighted sum of the goal functions, new goal function is created which designing is done on the basis of it. The main problem with this approach is that, determining the magnitudes of weight coefficients, besides the main issue is an optimization problem itself. That's why in MDO, using optimization algorithm which has got the ability to solve problems, preferred [1].

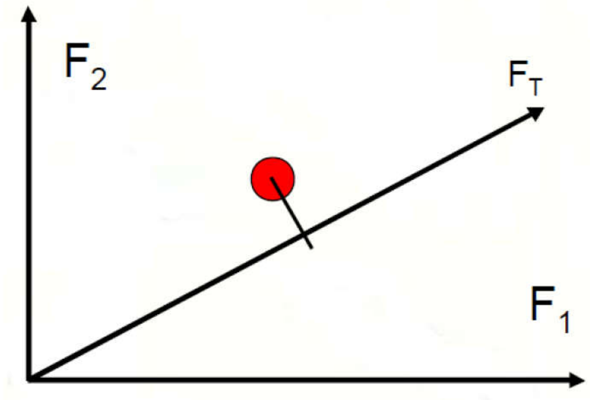


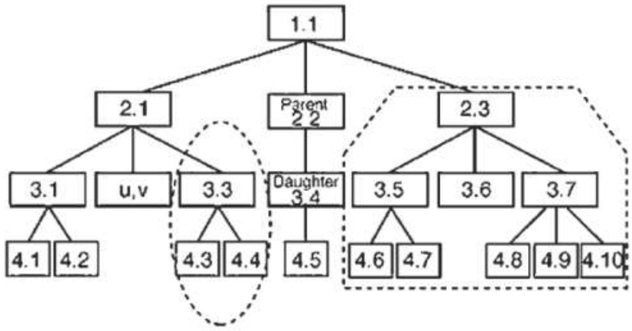
Figure 1: goal function weighting sum method [4].

In the conceptual design level, using of multidisciplinary optimization methods have different advantages. First, this method in general will achieve to conceptual design`s final parameters so rapidly by means of mathematical logic and computer tools respect to traditional design methods. In fact, the design cycles for parameters convergence and satisfying the constraints and limitations are being followed automatically. Second, in traditional design, final design will be only one possible layout of variables and parameters changing permitted limitation and no proof of the optimization will exist in design. But in the design, optimization algorithm leads variables in such a way that optimal point be achieved in design [2]. It should be noted that heuristic optimization (initiative) and meta-heuristic (trans-initiative) algorithms which have been most widely used in optimization problems, there is no guarantee to provide a general optimum response, But based on the evidences and records, the best contrast between quality and time to solve the problem on average will be merged[3].

• Conceptual definition of MDO

Multidisciplinary design optimization is a system approach for optimizing the design of a complex engineering system with associated elements (coupled) is one of the various engineering subjects. Multidisciplinary design optimization is employed in system design which has distinct subsystems affecting each other. As a matter of a fact, MDO is system design in which the effect of different subjects is intended and topics are optimized so that the whole system is desirable in performance. So the system, whose subjects have not got any interactions with each other, wouldn`t be called as multidisciplinary. In the MDO, each issue analysis should be examined first, by using subject constraints to see, if it's feasible or not. If it is feasible, in this case, it refers to as SDF (Single Discipline Feasibility). If all the issues become feasible, it is said that system is in the IDF (Individual Discipline Feasibility). In this case, the total issue may still not be feasible. Finally, if a MDO problem is feasible, refers to MDF (Multidisciplinary Feasibility). If in MDO problem, can divide a system into smaller subsystems in order that each subsystem identifies the constraints and goal functions, hierarchical analysis capability can be taken into account for MDO [4]. Figure 2 shows a system with hierarchical analysis capability.

Figure 2: System with hierarchical analysis capability [5]



In this case, system design can be divided into several subsystem design problem and distributed between the respective design teams. This design is referred to be distributed. Otherwise, if the subsystems exchange information among themselves and optimization process is run once executed for the whole system, system hasn`t got analysis hierarchical capability. This feature is especially for tightly coupled systems. Most aerospace systems due to severe couplings are subject of this type. Figure 3 shows a non-hierarchical.

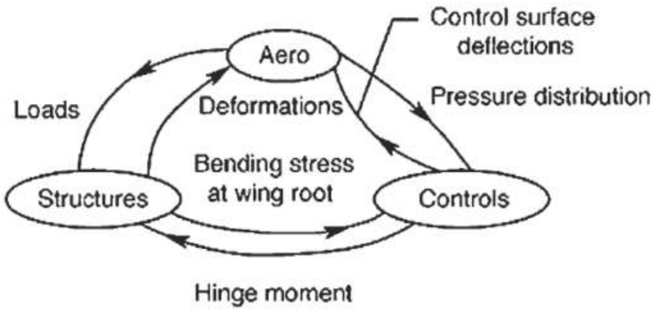


Figure 3: non-hierarchical system [5].

• Mathematical definition of MDO

Multi-disciplinary design optimization problems have got two or more analyst. Each disciplinary analyst may look like a simulator tool or be a set of simulation models which are coupled to each other by inputs performance and every disciplinary output. Coupling such systems includes design variables shared form and input and output status functions. This systems analysis for a given set of designs variables magnitude, to final convergence needs iterations between separate disciplines. Following relation defines a generic multi-disciplinary optimization design problem by means of two disciplines:

$$\textit{Find}\,\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_c)^{\mathrm{T}}$$

$$\text{to minimize}\quad \mathbf{f}(\mathbf{x},\mathbf{z}) = \begin{bmatrix} f_1(\mathbf{x}_1, \mathbf{x}_c, \mathbf{z}_1) \\ f_2(\mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_2) \\ f_c(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_1, \mathbf{z}_2) \end{bmatrix}$$

$$\text{subject to}\quad \mathrm{g}(\mathbf{x},\mathbf{z}) = \begin{bmatrix} g_1(\mathbf{x}_1, \mathbf{x}_c, \mathbf{z}_1) \\ g_2(\mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_2) \\ g_c(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_1, \mathbf{z}_2) \end{bmatrix} \leq 0$$

$$\mathrm{h}(\mathbf{x},\mathbf{z}) = \begin{bmatrix} h_1(\mathbf{x}_1, \mathbf{x}_c, \mathbf{z}_1) \\ h_2(\mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_2) \\ h_c(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_c, \mathbf{z}_1, \mathbf{z}_2) \end{bmatrix} = 0$$

$$\mathrm{z}_1 = \mathrm{w}_1\,(\mathrm{x}_1, \mathrm{x}_c, \mathrm{z}_2{}^{c})$$

$$\mathrm{z}_2 = \mathrm{w}_2\,(\mathrm{x}_2, \mathrm{x}_c, \mathrm{z}_1{}^{c})$$

In the above equations, x is design variables vector which x1 and x2 are specific local variables vectors, and Xc is shared variables vector .f (x) is goal function vector, including local goal functions vectors f1 and f2 and shared one which is fc. g (x) and h (x) vector functions, inequality constraints, and equality and vector functions w1 and w2, are 1 and 2 disciplines analysts, respectively .which parameters vector associated with the z1 and z2 disciplines are calculated by them [1]. To solve Multi-disciplinary design optimization preceding problem ,several different ways can be found via existing resources[6, 7] .The key element in Classifications is a method which meets acceptance of cited constraints in preceding equations.

• Multidisciplinary optimum design methods

Multi-disciplinary design optimization methods can be divided into two groups; single -level and multi-level methods .Single-level methods are distribution analysis methods which are used for structures with non-hierarchical analysis capability, while the multilevel methods are used for structures that are capable of hierarchical analysis. In other words, a technique called single-level which in them, only system-level optimization problem is employed for design variables determination. In multi-level problems, when system-level optimizer acquires shared variables, optimization disciplinary is used for various disciplines variable determination.

Single-level MDO methods include:

1. All methods in one step
2. Multi-disciplinary feasibility method
3. Individual-disciplinary feasibility method

1. All in one-step method

All in one-step method is known as simultaneous design and analysis method or separation based on optimizer that considers all multi-disciplinary design problem as an optimization in which each analytical block will run in parallel (Figure 4). The all in one-step method main idea is based on this consideration which says to determine a possible plan and when the current scheme is not near to the optimal value, the number of iterations shouldn`t go to waste. This results in system analysis equations transformation and considering system design variables and subsystems outputs (status variables) as optimization variables. In this way there is no explicit connection the analysis. Instead, the optimizer creates coupling by entering constraints on input and output variables. It has been proven that the all method in one-step method is the most effective one in solving most prototype problems in terms of computational ways among other multi-disciplinary design optimization methods. This method has the advantage which eliminates iterations design loops to reach optimum design, though still some single-level optimization limitations will remain. The main limitation of this approach is that an optimizer needs to control all design variables and constraints, so it will create more computational cost. Another disadvantage of this approach is that disciplinary feasibility will be created only on a relative or absolute maximum limitation. Therefore, if the optimizer failed to achieve the throughout optimum, the chance of completing the solution loop with a possible design response will be reduced [6, 7].

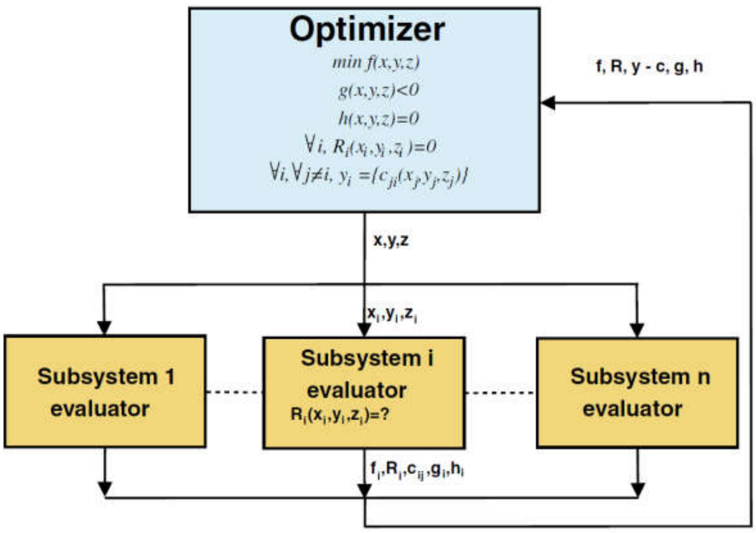


Figure 4: The all in one-step AAO method [6].

2. Multi-disciplinary feasibility method

Multi-disciplinary feasibility method can be supposed as multi-disciplinary analysis one loop which is followed by design updating. This method, which is the most common method of solving Multi-disciplinary optimization design problems is an example of non-linear programming for variable reduction. Where the z design variables and nine x state variables are employed as independent optimization variables .The main idea of this method, is entering a multi-disciplinary analyzer between the optimizer and disciplines (Figure 5).

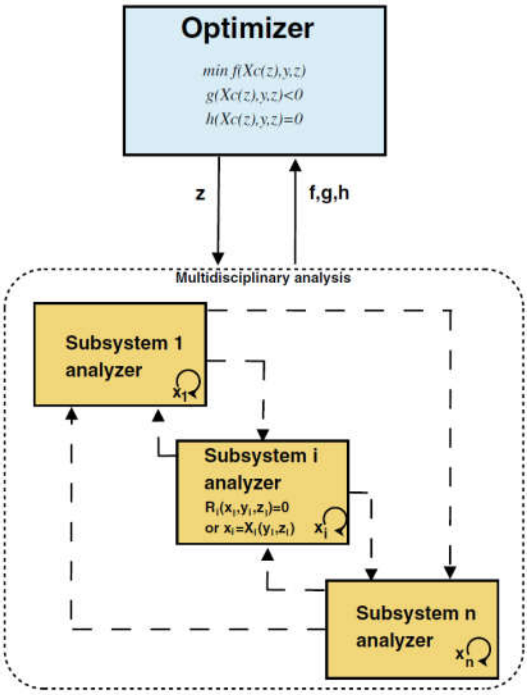


Figure 5: Multi-disciplinary feasibility method MDF [6].

In multi-disciplinary feasibility, z design variables vector will be used in coupled-system discipline analysis and a multi-disciplinary thorough analysis achieves u (z) besides z magnitude, by means of using a fixed point repetition. Then this value will be employed in assessing the value of the goal function f (z, x, y) and constraints g (z, x, y). Multi-disciplinary feasibility method have been used since nonlinear programming used first time in engineering design optimization. Therefore, this is very mellow way to solve multi-disciplinary design optimization problems. The first disadvantage of this method is its high computational cost. Furthermore, the optimization algorithms used in multi-disciplinary feasibility method in term of speed and resistance are so sensitive.

3. individual-disciplinary feasibility method

Individual -disciplinary feasibility method is a favorite alternative to the classic multi-disciplinary feasibility method and has got several characteristics which are situated among the multi-disciplinary feasibility and all in one-step methods. This method includes individual-discipline feasibility method which allows the optimizer to lead the individual-discipline to inter-disciplines coupling variables. The individual-disciplinary feasibility expression implies to preserve multi-disciplinary feasibility in each iteration (Not multi-disciplinary feasibility up to have a solution) which creates a way to prevent multi-disciplinary complete analysis. Individual-disciplinary feasibility method has resemblance characteristics in coupling and in problem separation in cooperative optimization. (Figure 6) It maintains its independence, according to analysis, but have lack of independent optimization in cooperative optimization. Another limitation of individual-disciplinary feasibility method is in how to deal with the constraints of the disciplines, that despite the need to consider the disciplinary-constraint, they are transferred to system-level [7].

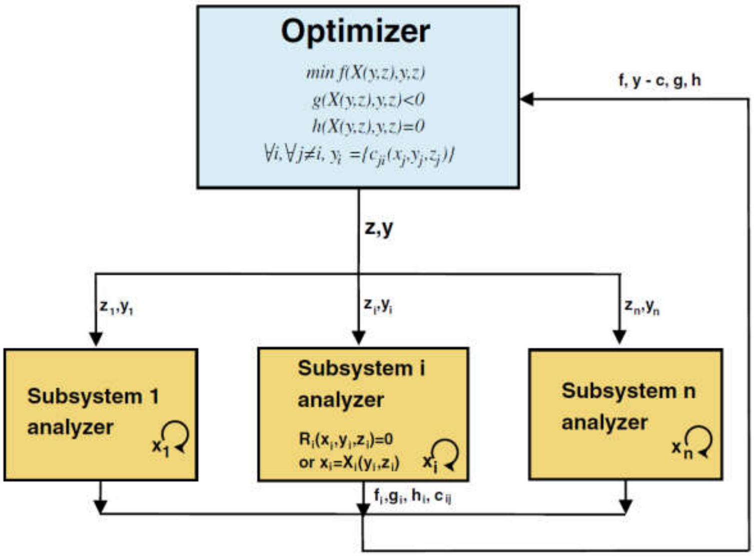


Figure 6: Multi-disciplinary feasibility method IDF [6].

• single-level optimization methods comparisons

The general characteristics of single-level optimization methods (all in one-step, multidisciplinary feasibility and individual-disciplinary feasibility) are shown in Table 1. In multi-disciplinary design, most optimization methods are based on a multi-disciplinary feasibility approach, however multi-disciplinary feasibility may be one of the easiest ways to run, but has limitations. Table 1 shows a comparison between a single-level optimization methods.

Characteristics	All in one-step	Multi-disciplinary feasibility	individual-disciplinary feasibility
Satisfying governing equations	Only in convergence	Optimization on each iteration	Optimization on each iteration
System convergence	Only in convergence	Optimization on each iteration	Only in convergence
Expected speed	Fast	Slow	Moderate
Resistance	unknown	Moderate	High

Table 1: single-level optimization methods comparisons

On the other hand, when the all in one-step can be the most effective method to obtain the optimal design, strategy implementation makes it difficult to solve and will have potential relevance requirements when using a single optimizer .

•Multi-purpose optimum design

As noted earlier, many MDO problems, inherently have more than one goal function because of having several disciplines. These goals can be against each other and a function optimization by search space causes function or functions get far from other corresponding optimization point. Most multi-disciplinary and multi-purpose optimization design problems have such a conditions. In some cases a function optimization in the search space makes other functions optimum. Which are called co-direction or colleague functions. There is also a third mode that is when goal functions have got independent design parameters and in this state are unrelated. In such cases the goal functions can be individually optimized in the search independent space [8]. Most of multi-purpose problems in the aerospace industry are at opposing states. The fact originates from constant confrontation between performance and cost. For example, increasing aerodynamic performance in flying vehicles often is accompanied by an increase in manufacturing costs. In these problems the first approach is regardless of some low-significant functions and examines the problem in a single-aim manner. Other minority approach is each function weighting in terms of its significance in the overall performance and converting all functions into a unit function. However, in this method selection of appropriate weight for each function is another optimization problem and even different functions comparison will be also a problem. The third alternative and more rational approach is use of non-dominant responses set and multi-purpose optimization methods. In this method contrary to single-aim optimization problems, which a response appears at the end of an optimization process, a set of responses which represent kind of compromise between some goal functions is considered as the final responses set. Each of this set responses could be an optimum response for goal function and picking up one response among a set of optimal responses will require a decision making process.

• Mathematical definition of multi-purpose optimization
In general, multi-purpose optimization problem can be stated as follows:

Find$x_i = [x_1, x_2, ..., x_n]^T$, $x \in \Omega$

To minimize $F(x) = [f_1(x), f_2(x),..., f_k(x)]$

Subject to $g_i(x) \le 0$, $i = \{1, m\}$

$h_j(x) = 0$, $j = \{1, p\}$

In the above equations, xi is the vector of design variables on the number of Pareto solutions, F (x) goal functions vector and vector functions g (x) and h (x), are inequality and equality constraints, respectively. Therefore, multi-aim optimization includes k goals, which are reflected in the k goal functions. m + p Constraints are on design variables and goal functions and n design variable. The goal functions can be linear, non-linear, and continuous or be separate. $F : \Omega \rightarrow \Lambda$ Vector, is a mapping of decision-making variables $x = (x_1, x_2, ..., x_n)$ to $y = a_1, a_2, ..., a_k$ vectors. Design variables Vector can be continuous or discrete. In fact, any point in the search space is map to a point in performance space. Figure 7 shows the multi-aim optimization problem mapping [9].

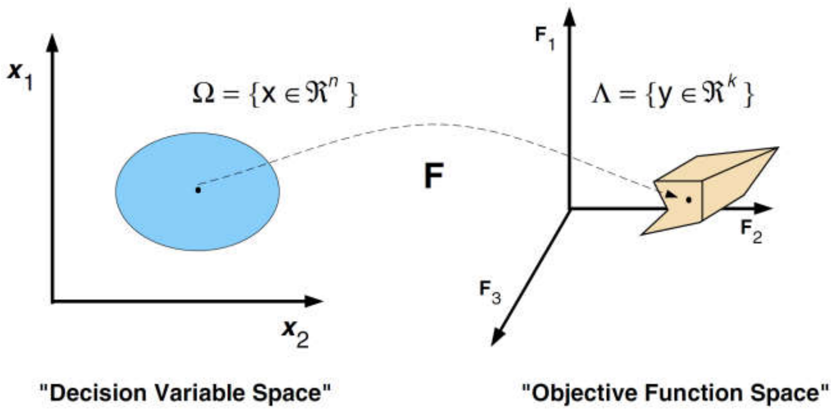


Figure 7:multi-disciplinary optimization problem mapping [9].

• The Pareto optimal Definition

$X \in \Omega$ Solution, called Pareto optimal or non-dominant point if and only if there is no $X' \in \Omega$ that $v = F(X') = (f_1(X'), ..., f_k(X'))$ vector overcomes to $u = F(X) = (f_1(X), ..., f_k(X))$ vector. In other form this definition cites that in assumption of minimizing problem solution, X^* is the Pareto optimal, if no other permitted X no longer there exists which decreases some goal functions without increasing at least one of the other goal functions simultaneously [9].

• Dominant Pareto Definition

$u = (u_1, ..., u_k)$ vector is dominant to other $v = (v_1, ..., v_k)$ vector (which are represented by $u \le v$) if and only if vector u is partially less than v vector , in other words :

$u_i \le v_i \quad \wedge \quad \exists \quad i \in \{1, \ldots, k\} : \quad u_i < v_i$, $\forall i \in \{1, \mathrm{K}, k\}$

In fact, the collection of non-dominant points, are referred to as Pareto front or optimum Pareto set. Pareto optimal solutions are responses in search space that their goal vector components couldn`t be improved simultaneously. These vectors are called the dominant vectors. Selection of one or more vectors of the vector set, shows acceptable optimum Pareto solutions and decision-making variables. These solutions may have no clear relation, except their membership in Pareto optimal set. These vectors have set of solutions which their associated vectors are dominant. Pareto optimal solutions, are classified based on calculated function values .The responses set of this solution are not dominant on each other and Pareto responses are so -called non-dominant responses set [7].

CONCLUSION

Multidisciplinary design optimization can be defined as a multi-disciplinary nature with a large number of conceptual sectors which includes technologies and specific principles. There is always the need of definition usage rather than detailed and costly analyzes, involving complex numerical codes or physical experiments. In The following, some of the factors affecting the performance of multi-disciplinary optimum design are pointed out. Mathematical modeling is so significant in the success of multi-disciplinary optimization design method. To predict the behavior of the system and its sensitivity to changes in design variables an appropriate model is needed. Models can be linked to Physical and non-physical wide categories. The analysis based on design deals with the issue of cost and accuracy in optimization. In some cases, mathematical models can be created which only predict behavior of the system and provide raw models for preliminary design. Thus, complexity of the mathematical model and the reality of the model can specify the level of optimization accuracy. A separate issue is important in multi-disciplinary optimization design, which includes a problem breakdown with large-scale in the number of sub-problems which are examinable. Depending on the considered issue, the interaction between the small-scale problems can be hierarchical or non-hierarchical. Design space detection is another important factor in the multi-disciplinary optimization design which is done by traditional mathematical programming algorithms or new search technics based on random sampling such as evolved algorithms. Developing Isolation methods and coordination is the most active areas of research. Several multi-disciplinary design optimization separation methods design of system-level coordinators have been proposed in the past two decades. Important characteristics that distinguish these method of solving are disciplinary independence authorized level in the analysis and optimization process, ease of run, computational strength and efficiency. Simultaneous Optimization of the sub-spaces and cooperative optimization are known as two main ways of multi-disciplinary optimization method which make disciplinary independence possible in coupling processes. However cooperative optimization in control of correlated variables (coupled) differs from simultaneous sub-space optimization method. In Cooperative Optimization method each subsystem will control its local design variables sets and responsibility for meeting local constraints are on them. Also a system-level optimizer is employed to adjust this action during minimizing the main purpose. This level of disciplinary-independence in cooperative optimization creates many underlying advantages in conveninet-desinge for designers and transforms it to an attractive method for solving multi-disciplinary design complex problems. However, this method has lots of disadvantages which limits its application in high accuracy simulation.

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