MULTIDISCIPLINARY AEROSPACE DESIGN OPTIMIZATION: SURVEY OF RECENT DEVELOPMENTS

Jaroslaw Sobieszczanski-Sobieski[*]
NASA Langley Research Center
Hampton, Virginia 23681
(j.sobieski@larc.nasa.gov)

Raphael T. Haftka[†]
University of Florida
Gainesville, Florida 32611
(haftka@ufl.edu)

Abstract

The increasing complexity of engineering systems has sparked increasing interest in multdisciplinary optimization (MDO). This paper presents a survey of recent publications in the field of aerospace where interest in MDO has been particularly intense. The two main challenges of MDO are computational expense and organizational complexity. Accordingly the survey is focused on various ways different researchers use to deal with these challenges. The survey is organized by a –breakdown of MDO into its conceptual components. Accordingly, the survey includes sections on Mathematical Modeling, Design-oriented Analysis, Approximation Concepts, Optimization Procedures, System Sensitivity, and Human Interface. With the authors' main expertise being in the structures area, the bulk of the references focus on the interaction of the structures discipline with other disciplines. In particular, two sections at the end focus on two such interactions that have recently been pursued with a particular vigor: Simultaneous Optimization of Structures and Aerodynamics, and Simultaneous Optimization of Structures Combined With Active Control.

1. Introduction

The term "methodology" is defined by Webster's dictionary as "a body of methods, procedures, working concepts, and postulates, etc." Consistent with this definition, multidisciplinary optimization (MDO) can be described as a methodology for the design of systems where the interaction between several disciplines must be considered, and where the designer is free to significantly affect the system performance in more than one discipline. Using this definition, structural optimization of an aircraft wing to prevent flutter will not be considered multidisciplinary optimization. For this case, the interaction of aerodynamics and structures is present only at the analysis level, and the designer does not attempt to change the aerodynamic shape of the wing.

The interdisciplinary coupling inherent in MDO tends to present additional challenges beyond those encountered in a single-discipline optimization. It increases computational burden, and it also increases complexity and creates organizational challenges for implementing the necessary coupling in software systems.

The increased computational burden may simply reflect the increased size of the MDO problem, with the number of analysis variables and of design variables adding up with each additional discipline. A case of tens of thousands of analysis variables and several thousands of design variables, reported in Berkes (90) for just the structural part of an airframe design, illustrates the dimensionality of the MDO task one has to prepare for. Since solution times for most analysis and optimization algorithms increase at a superlinear rate, the computational cost of MDO is usualIy much higher than the sum of the costs of the single-discipline optimizations for the disciplines represented in the MDO. Additionally, even if each discipline employs linear analysis methods, the combined system may require costly nonlinear analysis. For example, linear aerodynamics may be used to predict pressure

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[*]Multidisciplinary Research Coordinator, Fellow, AIAA

[†]Professor, Associate Fellow, AIAA

distributions on a wing, and linear structural analysis may be then used to predict displacements. However, the dependence of the pressures on the displacements may not be linear. Finally, for each disciplinary optimization we may be able to use a single-objective function, but for the MDO problem we may need to have multiple objectives with an attendant increase in optimization cost.

In MDO of complex systems we also face formidable organizational challenges. The analysis codes for each discipline have to be made to interact with one another for the purpose of system analysis and system optimization. The kind and breadth of interaction is affected by the MDO formulation. Decisions on the choice of design variables and on whether to use single-level optimization or multilevel optimization have profound effects on the coordination and data transfer between analysis codes and the optimization code and on the degree of human interactions required. The interaction between the modules in the software system on one side and the multitude of users organized in disciplinary groups on the other side may be complicated by departmental divisions in the organization that performs the MDO.

One may discern three categories of approaches to MDO problems, depending on the way the organizational challenge has been addressed. Two of these categories represent approaches that concentrated on problem formulations that circumvent the organizational challenge, while the third deals with attempts to address this challenge directly.

1. The first category includes problems with two or three interacting disciplines where a single analyst can acquire all the required expertise. At the analysis level, this may lead to the creation of a new discipline that focuses on the interaction of the involved disciplines, such as aeroelasticity or thermoelasticity. This may lead to MDO where design variables in several disciplines have to be obtained simultaneously to ensure efficient design. The past two decades have created the discipline of structural control, with analysts who are well versed in both structures and control system analysis and design. There has also been much work on simultaneous optimization of structures and control systems (e.g., Haftka, 90). Most of the papers in this category represent a single group of researchers or practitioners working with a single computer program, so that organizational challenges were minimized. Because of this, it is easier for researchers working on problems in this category to deal with some of the issues of complexity of MDO problems, such as

the need for multiobjective optimization (e.g., Gupta and Joshi, 90, Rao and Venkayya, 92, Grandhi et al., 92, and Dovi and Wrenn, 90).

2. The second category includes works where the MDO of an entire system is carried out at the conceptual level by employing simple analysis tools. For aircraft design, the ACSYNT (Vanderplaats, 76, Jayaram et al., 92) and FLOPS (McCullers, 84) programs represent this level of MDO application. Because of the simplicity of the analysis tools, it is possible to integrate the various disciplinary analyses in a single, usually modular, computer program and avoid large computational burdens. Gallman et al. (94), Gates and Lewis (92), Lavelle and Plencner (92), Morris and Kroo (90), Dodd et al. (90), Harry (92), Reddy et al. (92), and Bartholomew and Wellen (90) provide instances of this approach. As the design process moves on, the level of analysis complexity employed at the conceptual design level increases uniformly throughout or selectively (Adelman et al., 92, presents an example of the latter). Therefore, some of these codes are beginning to face some of the organizational challenges encountered when MDO is practiced at a more advanced stage of design process.

3. The third category of MDO research includes works that focus on the organizational and computational challenges and develop techniques that help address these challenges. These include decomposition methods and global sensitivity techniques that permit overall system optimization to proceed with minimum changes to disciplinary codes. These also include the development of tools that facilitate efficient organization of modules or that help with organization of data transfer. Finally, approximation techniques are extensively used to address the computational burden challenge, but they often also help with the organizational challenge.

The present review emphasizes papers that belong to the third category. The survey is organized by the MDO breakdown into its conceptual components suggested in Sobieszczanski-Sobieski (95). Accordingly, the survey includes sections on Mathematical Modeling and Design-oriented Analysis, Approximation Concepts, Optimization Procedures, System Sensitivity, Decompositio, and Human Interface (and an Appendix on the Design Space Search algorithms). With the authors main expertise being in the structures area, the bulk of the references focus on the interaction of the structures discipline with another discipline such as structures and electromagnetic performance (Padula et al., 89). In particular, two

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sections at the end focus on two such interactions that have recently been pursued with a particular vigor: Simultaneous Optimization of Structures and Aerodynamics and Structures Combined With Active Control. This emphasis on structures reflects also the roots of aerospace MDO in structural optimization and the central role of structures technology in design of aerospace vehicles.

2. MDO Components

This section comprises references grouped by the MDO conceptual components defined as proposed in Sobieszczanski-Sobieski (95).

2.1 Mathematical Modeling of a System

For obvious pragmatic reasons, software implementation of mathematical models of engineering systems usually takes the form of assemblages of codes (modules), each module representing a physical phenomenon, a physical part, or some other aspect of the system. Data transfers among the modules correspond to the internal couplings of the system. These data transfers may require data processing that may become a costly overhead. For example, if the system is a flexible wing, the aerodynamic pressure reduced to concentrated forces at the aerodynamic model grid points on the wing surface has to be converted to the corresponding concentrated loads acting on the structure finite-element model nodal points. Conversely, the finite-element nodal structural displacements have to be entered into aerodynamic model grid as shape corrections.

The volume of data transferred in such couplings affects efficiency directly in terms of I/O cost. Additionally, many solution procedures (e.g., Global Sensitivity Equation, Sobieszczanski-Sobieski, 90) require the derivatives of this data with respect to design variables, so that a large volume of data also increases computational cost. To decrease these costs, the volume of data may be reduced by various condensation (reduced basis) techniques. For instance, in the above wing example one may represent the pressure distribution and the displacement fields by a small number of base functions defined over the wing planform and transfer only the coefficients of these functions instead of the large volumes of the discrete load and displacement data. An example of such condensation for supersonic transport design was reported in Barthelemy et al. (92) and Unger et al. (92).

In some applications, one may identify a cluster of modules in a system model that exchange very large volumes of data that are not amenable to condensation. In such cases, the computational cost may be substantially reduced by unifying the two modules, e.g., August et al. (92) or merging them at the equation level. A heat-ransfer-structural-nalysis code is an example of such merger as described in Thornton (92). In this code, the analyses of the temperature field throughout a structure and of the associated stress-strain field share a common finite-element model. This line of development was extended to include fluid mechanics in Sutjahjo and Chamis (94).

Because of the increased importance of computational cost, MDO emphasizes the tradeoff of accuracy and cost associated with alternative models with different levels of complexity for the same phenomena. In single-discipline optimization it is common to have an "analysis model" which is more accurate and more costly than an "optimization model". In MDO, this tradeoff between accuracy and cost is exercised in various ways. First, optimization models can use the same theory, but with a lower level of detail. For example, the finite-ment models used for combined aeroelastic analysis of the high-speed civil transport (e.g., Scotti, 95) are much more detailed than the models typically used for combined aerodynamic-structural optimization (e.g., Dudley et al., 94) .

Second, models used for MDO are often less complex and less accurate than models used for a single disciplinary optimization. For example, structural models used for airframe optimization of the HSCT (e.g., Scotti, 95) are substantially more refined than those used for MDO. Aircraft MDO programs, such as FLOPS (McCullers, 84) and ACSYNT (Vanderplaats, 76), Jayaram et al., 92) use simple aerodynamic analysis models and weight equations to estimate structural weight. Similarly Livne et al. (92) use an equivalent plate model instead of a finite-element models for structures-control optimization of flexible wings.

Third, occasionally, models of different complexity are used simultaneously in the same discipline. One of them may be a complex model for calculating the discipline response, and a simpler model for characterizing interaction with other disciplines. For example, in many aircraft companies, the structural loads are calculated by a simpler aerodynamic model than the one used for calculating aerodynamic drag

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(e.g., Baker and Giesing, 95). Finally, models of various levels of complexity may be used for the same response calculation in an approximation procedure or fast reanalysis described in the next two sections.

Recent aerospace industry emphasis on economics will, undoubtedly, spawn generation of a new category of mathematical models to simulate man-made phenomena of manufacturing and aerospace vehicle operation with requisite support and maintenance. These models will share at least some of their input variables with those used in the product design to account for the vehicle physics. This will enable one to build a system mathematical model encompassing all the principal phases of the product life cycle: formulation of desirements, product design, manufacturing, and operation. Based on such an extended model of a system, it will be possible to optimize the entire life cycle for a variety of economic objectives, e.g., minimum cost or a maximum return on investment, as forecasted in Tulinius (92) . There are several references that bring the life cycle issues into the MDO domain; examples are Korngold and Gabriele (94), Fenyes (92), Bearden et al. (94), Brockman et al. (92), Current et al. (90), Shupe and Srinivasan (92), Briggs (92), Claus (92), Godse et al. (92), Dolvin (92), Eppinger et al. (94), Lokanathan et al. (95), Marx et al. (94), Niu and Brockman (95), Kirk (92), and Yeh and Fulton (92). Schrage (93) discussed the role of MDO in the Integrated Product and Process Development (IPPD), also known as Concurrent Engineering (CE), and surveyed references on the subject.

Mathematical modeling of an aerospace vehicle critically depends on an efficient and flexible description of geometry. This subject is addressed in Smith and Kerr (92).

2.2 Design-Oriented Analysis

The engineering design process moves forward by asking and answering "what if" questions. To get answers to these questions expeditiously, designers need analysis tools that have a number of special attributes. These attributes are: selection of the various levels of analysis ranging from inexpensive and approximate to accurate and more costly, "smart" reanalysis which repeats only parts of the original analysis affected by the design changes, computation of sensitivity derivatives of output with respect to input, and a data management and visualization infrastructure necessary to handle large volumes of data typically generated in a design process. The term "Design-oriented Analysis" introduced in Storaasli and

Sobieszczanski (73) refers to analysis procedures possessing the above attributes.

The data management and visualization infrastructure, e.g., (Herendeen et al., 92) is a vast field beyond the scope of this survey. Sensitivity analysis is discussed in section 2.4, and the issue of the selection of analysis level was discussed in the previous section, and will be returned to in the next section on approximations.

An example of a design-oriented analysis code is the program LS-CLASS developed by Livne and Schmit (90), Livne et al. (92, 93) for the structures-control-aerodynamic optimization of flexible wings with active controls. The program permits the calculation of aeroservoelastic response at different levels of accuracy ranging from a full model to a reduced one based on vibration modes. Additionally, various approximations are available depending on the response quantity to be calculated.

A typical implementation of the idea of smart reanalysis has been reported in Kroo and Takai (88a, b) and Gage and Kroo (92). The code (called PASS) is a collection of modules coupled by the output-to-input dependencies. These dependencies are determined and stored on a data base together with the archival input/output data from recent executions of the code. When a user changes an input variable and asks for new values of the output variables, the code logic uses the data dependency information to determine which modules and archival data are affected by the change and executes only the modules that are affected, using the archival data as much as possible. One may add that such smart reanalysis is now an industry standard in the spreadsheets whose use is popular on personal computers. It contributes materially to the fast response of these spreadsheets.

2.3 Approximation Concepts

Direct coupling of a the design space search code (DSS) to a multidisciplinary analysis may be impractical for several reasons. First, for any moderate to large number of design variables, the number of evaluations of objective function and constraints required by DSS is high. Often we cannot afford to execute such a large number of exact MDO analyses in order to provide the evaluation of the objective function and constraints. Second, often the different disciplinary analyses are executed on different machines, possibly at different sites, and communication with a central DSS program may become unwieldy. Third, some

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disciplines may produce noisy or jagged response as a function of the design variables (e.g., Giunta et al., 94). If we do not use a smooth approximation to the response in this discipline we will have to degrade the DSS to less efficient nongradient methods.

For all of the above reasons, most optimizations of complex engineering systems couple a DSS to easy-to-calculate approximations of the objective function and/or constraints. The optimum of the approximate problem is found and then the approximation is updated by the full analysis executed at that optimum and the process repeated. This process of sequential approximate optimization is popular also in single-discipline optimization, but its use is more critical in MDO as the principal cost control measure

Most often the approximations used in engineering system optimization are local approximations based on the derivatives. Linear and quadratic approximations are frequently used, and occasionally intermediate variables or intermediate response quantities (e.g., Kodiyalam and Vanderplaats, 89) are used to improve the accuracy of the approximation. For example, instead of a Taylor series in the variables, structural response has been approximated by a Taylor series in the reciprocals of all the variables or some of them (Starnes and Haftka, 79). Similarly, instead of approximating eigenvalues directly, we can approximate the numerator and denominator of the Rayleigh quotient that defines them (e.g., Murthy and Haftka, 88, Canfield, 90, Livne and coworkers, e.g., Livne et al., 93, and 95). Li and Livne (95) have explored extensively various approximations for structural, control and aerodynamic response quantities. A procedure for updating the sensitivity derivatives in a sequence of approximations using the past data was formulated for a general case in Scotti (93).

Global approximations have also been extensively used in MDO. Simpler analysis procedures can be viewed as global approximations when they are used temporarily during the optimization process, with more accurate procedures employed periodically during the process. For example, Unger et al. (92) developed a procedure where both the simpler and more sophisticated models are used simultaneously during the optimization procedure. The sophisticated model provides a scale factor for correcting the simpler model. The scale factor is updated periodically during the design process. Because this approach employs models of variable complexity it was dubbed `variable complexity modeling (VCM). For example, Unger et al. (92) applied the procedure to aerodynamic drag

calculation for a subsonic transport, while Hutchison et al. (94) applied the procedure to predict the drag of a high-speed civil transport (HSCT) during the optimization process. Similarly, Huang et al. (94) employed structural optimization together with a simple weight equation for predicting wing structural weight in combined aerodynamic and structural optimization of the HSCT. Traditional derivative-based approximation can be combined with such global VCM approximations by using a derivative-based linear approximation for the scale factor (Chang et al., 93) .

Another global approximation approach that is particularly suitable for MDO is the response-surface technique. This technique replaces the objective and/or constraints functions with simple functions, often polynomials, which are fitted to data at a set of carefully selected design points. Neural networks are sometimes used to function in the same role. The values of the objective function and constraints at the selected set of points are used to "train" the network. Like the polynomial fit, the neural network provides an estimate of objective function and constraints for the optimizer that is very inexpensive after the initial investment in the net training has been made.

Response surface techniques are not commonly used in single-discipline optimization because they do not scale well to large number of variables. For MDO, response surface techniques also provide a convenient representation of data from one discipline to other disciplines and to the system. Since design points are preselected rather than chosen by an optimization algorithm, it may be possible to plan and coordinate the solution process by different modules with less tight integration than required with derivative-based methods. In fact, this feature has motivated the use of response surfaces even for single-discipline optimization when the analysis program is not easy to connect to an optimizer (e.g., Mason at al., 94).

Indeed, response surface techniques have recently gained popularity as a simple way to connect codes from various disciplines, or more generally, to facilitate communication between specialists on the design team. In this sense, these techniques are becoming one of the means to meet the organizational challenge of MDO. For example, Tai et al. (95) have used response surface technique to couple a large number of disciplinary analysis programs for the design of a convertible rotor/wing concept. Giunta et al. (95) have used response surfaces to combine aerodynamic and structural optimization. They have also taken advantage of the inherent parallelism of response

surface generation to employ extensively parallel computation.

Additionally, the discrete models employed in various disciplines can occasionally generate discontinuities in response due to the effect of shape changes on grids (e.g., Giunta et al., 94). Multilevel design schemes can produce similar phenomena due to changes in sets of critical constraints at lower-level optimizations. MDO procedures, which use many modules and often resort to multilevel techniques are particularly vulnerable to the occurrence of such discontinuities. Traditional derivative-based approximation techniques can become useless in such circumstances, while response surface techniques smooth the design space and proceed without difficulty. For smooth response quantities where derivatives can be calculated cheaply, we can employ response surfaces based on these derivatives.

Finally, the global nature of response surface approximation means that they can be repeatedly used for design studies with multiple objective functions and different optimization parameters for gradual building of the problem database (e.g., Wujek et al., 95). Furthermore, they permit visualizations of the entire design space. These features have been used extensively by Mistree and his coworkers (e.g., Mistree et al., 94).

2.4 <u>System Sensitivity Analysis</u>

In principle, sensitivity analysis of a system might be conducted using the same techniques that became well-established in the disciplinary sensitivity analyses (see surveys, Haftka and Adelman, 89, Adelman and Haftka, 93, Barthelemy et al., 95, for automatic differentiation, and Bischof and Knauff, 94, and Altus et al., 96 for application examples). However, in most practical cases the sheer dimensionality of the system analysis makes a simple extension of the disciplinary sensitivity analysis techniques impractical in applications to sensitivity analysis of systems.

Also, the utility of the system sensitivity data is broader than that in a single analysis. In design of a system that typically engages a team of disciplinary specialists these data have a potential of constituting a common vocabulary to overcome interdisciplinary communication barriers in conveying information about the influence of the disciplines on one another and on the system. Utility of the sensitivity data for tracing interdisciplinary influences was illustrated by an application to an aircraft performance analysis in Sobieszczanski-Sobieski (86).

An algorithm that capitalizes on disciplinary sensitivity analysis techniques to organize the solution of the system sensitivity problem and its extension to higher order derivatives was introduced in Sobieszczanski-Sobieski (90a) and (90b). There are two variants of the algorithm: one is based on the derivatives of the residuals of the governing equations in each discipline represented by a module in a system mathematical model, the other uses derivatives of output with respect to input from each module.

So far operational experience has accumulated only for the second variant. That variant begins with computations of the derivatives of output with respect to input for each module in the system mathematical model, using any sensitivity analysis technique appropriate to the module (discipline). The module-level sensitivity analyses are independent of each other, hence, they may be executed concurrently so that the system sensitivity task gets decomposed into smaller tasks. The resulting derivatives are entered as coefficients into a set of simultaneous, linear, algebraic equation, called the Global Sensitivity Equations (GSE), whose solution vector comprises the system total derivatives of behavior with respect to a design variable. Solvability of GSE and singularity conditions have been examined in Sobieszczanski-Sobieski (90a). It was reported in Olds (94) that, in some applications, errors of the system derivatives from the GSE solution may exceed significantly the errors in the derivatives of output with respect to input computed for the modules.

The system sensitivity derivatives, also referred to as design derivatives, are useful to guide judgmental design decisions, e.g., Olds (94), or they may be input into an optimizer (e.g., Padula et al. (91). Application of these derivatives extended to the second order in an application to an aerodynamic-control integrated optimization was reported in Ide et al. (88).

A completely different approach to sensitivity analysis has been introduced in Szewczyk and Hajela (94) and Lee and Hajela (95) It is based on a neural net trained to simulate a particular analysis (the analysis may be disciplinary or of a multidisciplinary system). Neural net training, in general, requires adjustments of the weighting coefficients in the net internal algorithm until a correlation of output to input is obtained that is a satisfactory approximation of the output to input dependency in the simulated analysis over a range of

interest. The above references show that the weighting coefficients may be interpreted as a measure of the sensitivity of the output with respect to input. In other words, they may be regarded as the derivatives of output with respect to input averaged over the range of interest

In Sobieszczanski-Sobieski et al. (82) and Barthelemy and Sobieszczanski-Sobieski (83) the concept of the sensitivity analysis was extended to the analysis of an optimum, which comprises the constrained minimum of the objective function and the optimal values of the design variables, for sensitivity to the optimization constant parameters. The derivatives resulting from such analysis are useful in various decomposition schemes (next section), and in assessment of the optimization results as shown in Braun et al. (93).

2.5 Optimization Procedures with Approximations and Decompositions

Optimization procedures assemble the numerical operations corresponding to the MDO elements (Sobieszczanski-Sobieski, 95) into executable sequences. Typically, they include analyses, sensitivity analyses, approximations, design space search algorithms, decompositions, etc. Among these elements the approximations (Section 2.3) and decompositions most often determine the procedure organization, therefore, this section focuses on these two elements as distinguishing features of the optimization procedures.

The implementation of MDO procedures is often limited by computational cost and by the difficulty to integrate software packages coming from different organizations. The computational burden challenge is typically addressed by employing approximations whereby the optimizer is applied to a sequence of approximate problems.

The use of approximations often allows us to deal better with organizational boundaries. The approximation used for each discipline can be generated by specialists in this discipline, who can tailor the approximation to special features of that discipline and to the particulars of the application. When response surface techniques are used, the creation of the various disciplinary approximations can be performed ahead of time, minimizing the interaction of the optimization procedure with the various disciplinary software.

In addition to approximations, it is desirable to have flexibility in selection of different search techniques for different disciplines and different phases of optimization. By the same token, one should be able to choose among various types of sensitivity analysis because in some disciplines derivatives are readily available, while in others they may not be available or may not even exist. Examples of references that illustrate evolution of the use of approximations in optimization procedures are Schmit and Farshi (74), Fleury and Schmit (80), Vanderplaats (85), Sobieszczanski-Sobieski (82), and Stanley et al. (92), whose focus was on response surface approximation based on the Taguchi arrays. A procedure to accommodate a variable complexity modeling in application to a transport aircraft wing was described in Unger et al. (92). An application of approximations in rotorcraft optimization was reported in Adelman et al. (91).

Decomposition schemes and the associated optimization procedures have evolved into a key element of MDO (Gage, 95, Logan, 90). One important motivation for development of optimization procedures with decomposition is the obvious need to partition the large task of the engineering system synthesis into smaller tasks. The aggregate of the computational effort of these smaller tasks is not necessarily smaller than that of the original undivided task. However, the decomposition advantages are in these smaller tasks tending to be aligned with existing engineering specialties, in their forming a broad workfront in which opportunities for concurrent operations (calendar time compression) are intrinsic, and in making MDO very compatible with the trend of computer technology toward multiprocessing hardware and software.

Much of the theory for decomposition has originated in the field of the Operations Research, e.g, Lasdon (70) and more recently Cramer and Dennis (94). In parallel, several approaches have emerged from applied research and engineering practice of optimization applied to large problems both within disciplines and in system optimization. This survey focuses primarily on the latter.

Many decomposition schemes (Bloebaum et al., 93) are possible, but they all have in common the following major operations that together constitute a system synthesis: system analysis including disciplinary analyses, disciplinary and system sensitivity analyses, optimizations at the disciplinary level, and optimization at the system level (the coordination problem). Even

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though the coordination problem is now regarded as the key element in decomposition, it was absent in some of the early optimization procedures, e.g., Sobieszczanski and Loendorf (72), and Giles and McCullers (75). However, true MDO presupposes taking advantage of interdisciplinary interactions, hence a need for coordination in optimization procedures that implement decomposition.

Three basic optimization procedures have crystallized for applications in nonhierarchic aerospace systems. The simplest procedure is piece-wise approximate with the GSE used to obtain the derivatives needed to construct the system behavior approximations in the neighborhood of the design point. In this procedure only the sensitivity analysis part of the entire optimization task is subject to decomposition and the optimization is a single-level one encompassing all the design variables and constraints of the entire system. Hence, there is no need for a coordination problem to be solved. This GSE-based procedure has been used in a number of applications, e.g., Sobieszczanski-Sobieski et al. (88), Barthelemy et al. (92) Coen et al. (92), Consoli and Sobieszczanski-Sobieski (92), Hajela et al. (90), Abdi et al. (88), Dovi et al. (92), Padula et al. (91), and Schneider et al. (92). The cost of the procedure critically depends on the number of the coupling variables for which the partial derivatives are computed.

Disciplinary specialists involved in a design process generally prefer to control optimization in their domains of expertise as opposed to acting only as analysts. This preference has motivated development of procedures that extend the task partitioning to optimization itself and enable one to organize the numerical process to mirror the existing human organization. A procedure called the Concurrent Subspace Optimization (CSSO) introduced in Sobieszczanski-Sobieski (89) allocates the design variables to subspaces corresponding to engineering disciplines or subsystems. Each subspace performs a separate optimization, operating on its own unique subset of design variables. In this optimization, the objective function is the subspace contribution to the system objective, subject to the local subspace constraints and to constraints from all other subspaces. The local constraints are evaluated by a locally available analysis, the other constraints are approximated using the total derivatives from GSE. Responsibility for satisfying any particular constraint is distributed over the subspaces using "responsibility" coefficients which are constant parameters in each

subspace optimization. Postoptimal sensitivity analysis generates derivatives of each subspace optimum to the subspace optimization parameters. Following a round of subspace optimizations, these derivatives guide a system-level optimization problem in adjusting the "responsibility" coefficients This preserves the couplings between the subspaces. The system analysis and the system– and subsystem level optimizations alternate until convergence.

In Bloebaum (91) and (92), the above system-level optimization was reformulated by using an expert system comprising heuristic rules to adjust the responsibility coefficients, to allocate the design variables, and to adjust the move limits. In Korngold et al. (92), the algorithm was extended to problems with discrete variables. A variant of the algorithm introduced in Wujek et al. (95) allows the variable sharing between the subspaces, and it bases the system-level optimization on a response surface functions for the objective and each of the constraints. These functions are fitted to all the design points that have been generated in all the previous subspace optimizations (including the intermediate ones). The "responsibility" coefficients are not used, and the system-level optimization is being solved in the space of all the design variables. A trained Neural Net algorithm was used instead of the response surface fitting in the system-level optimization in Sellar et al. (96). A number of application examples for the CSSO variants have been reported in Wujek et al. (96) and Lokanathan et al. (96). The procedure has also been implemented in a commercial software described in Eason et al. (94 a,b) and Nystrom et al. (94).

The degree to which CSSO is expected to reduce the system-optimization cost strongly depends on problem sparsity. To see that, consider that in the extreme case, when every design variable affects every constraint directly, each subspace optimization problem may grow to include all the system constraints in the Sobieszczanski-Sobieski (88) version and all the system variables and all the system constraints in the Wujek et al. (95) version.

Another procedure proposed in Kroo et al. (94) and Kroo (95) is known as the Collaborative Optimization (CO). Its application examples for space vehicles are in Braun and Kroo (95) and Braun et al. (95 a,b) and for aircraft configuration, in Sobieski and Kroo (96). This procedure decomposes the problem even further by eliminating the need for a separate system and system sensitivity analyses. It achieves this by blending the design variables and those state variables that couple

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the subspaces (subsystems or disciplines) in one vector of the system-level design variables. These variables are set by the system level optimization and posed to the subspace optimizations as targets to be matched. Each subspace optimization operates on its own design variables, some of which correspond to the targets treated as the subspace optimization parameters, and uses a specialized analysis to satisfy its own constraints. The objective function to be minimized is a cumulative measure of the discrepancies between the design variables and their targets. Optimization in subspaces may proceed concurrently; each of them is followed by a postoptimum sensitivity analysis to compute the optimum sensitivity derivatives (Sobieszczanski-Sobieski et al., 82 and Barthelemy and Sobieszczanski-Sobieski, (83) with respect to the parameters (targets). The ensuing system-level optimization satisfies all the constraints and adjusts the targets so as to minimize the system objective and to enforce the matching. This optimization is guided by the above optimum sensitivity derivatives.

As in the other procedures, the subspace optimizations, their postoptimum sensitivity analyses, and the system-level optimization alternate until convergence. Similar to CSSO, the system optimization sparsity is critical for the CO to be able to reduce the system optimization cost because, reasoning by the extremes again, in case of everything influencing everything else directly, each subspace problem would have to include all the design variables (but still only the local constraints). The CO procedure is in the category of simultaneous analysis and design (SAND) because the system analysis solution and the system design optimum are arrived at simultaneously at the end of an iterative process. A different implementation of the SAND concept is described in Hutchison et al. (94).

Each of the above procedures applies also to hierarchic systems. A hierarchic system is defined as one in which a subsystem exchanges data directly with the system only but not with any other subsystem. Such data exchange occurs in analysis of structures by substructuring. A concept to exploit this in structural optimization was formulated in Schmit and Ramanathan (78) and generalized in Sobieszczanski-Sobieski (82) and (93). (It was shown in the latter how the hierarchic decomposition derives from the Bellman's optimality criterion of the Dynamic Programming.) The concept was also contributed to by Kirsch, (e.g., Kirsch, 81) It was demonstrated in several applications, including multidisciplinary ones, e.g., Wrenn and Dovi (88) and Beltracchi (91). One iteration of the procedure comprises the system analysis from the assembled system level down to the individual system components level and optimization that proceeds in the opposite direction. The analysis data passed from above become constant parameters in the lower level optimization. The optimization results that are being passed from the bottom up include sensitivity of the optimum to these parameters. The coordination problem solution depends on these sensitivity data. As shown in Thareja and Haftka (90), one may encounter numerical difficulties in that solution when discontinuities occur in the optimum sensitivity derivatives. Recently, a variant of this procedure was developed (Balling and Sobieszczanski-Sobieski, 95) which differs in the way the local and system constraints are treated.

It was shown in Balling and Sobieszczanski-Sobieski (94) that the above procedures may be identified as variants of the six fundamental approaches to the problem of a system optimization. This reference offers also a compact notation for describing a complex procedure without using a flowchart, and it assesses the computational cost of the fundamental approaches as a function of the problem dimensionality.

The current practice relies on the engineer's insight to recognize whether the system is hierarchic, non-hierarchic, or hybrid and to choose an appropriate decomposition scheme, Logan (90). For a large unprecedented system this decision may be difficult. Motivated by this, a formal description of the inter-module data flow in the system model has been developed. This led to techniques, e.g., Rogers (89) and Steward (91), for visualization of that flow in the so-called n-square matrix format and for identification of the arrangements of the modules in computational sequences that maximize user-defined measures of efficiency. Examples of such maximization using heuristics and/or formal means, such as genetic algorithms, were reported in Rogers et al. (96), Altus et al. (95), Johnson and Brockman (95), Jones (92), Bloebaum (96), and McCulley and Bloebaum (94). Identification of such sequences results also in a clear determination of the system as hierarchic, non-hierarchic, or a hybrid of the two. A code described in Rogers (89) is a tool useful in the above; Grose (94) and Brewer et al. (94) are application examples. An alternative to the above approach to decomposition is mentioned in the Appendix on Design Space Search. It is a transformation of the design space coordinate system that identifies orthogonal subspaces described in Rowan (90).

Independently of its use for optimization, decomposition has also been used as a means, based

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predominantly on the directed graph approach, to develop a broad workfront in a human organization or in a production plant and in design to allocate functions among components in complex systems. Representative to this category of decomposition are Eppinger et al. (94), Pimmler and Eppinger (94), and Kusiak et al. (94) An extension of this approach to the use of hypergraphs and a model-based partitioning was introduced in Papalambros and Michelena (95) and Michelena and Papalambros (95). It was shown in Cramer and Huffmall (93) that computational burden in MDO applications may be alleviated without decomposition by a judicious exploitation of sparsity of the matrices involved.

2.6 Human Interface

MDO is, emphatically, not a push-button design. Hence, the human interface is crucially important to enable engineers to control the design process and to inject their judgment and creativity into it. Therefore, various levels of that interface capability is prominent in the software systems that incorporate MDO technology and are operated by industrial companies. Because these software systems are nearly exclusively proprietary no published information is available for reference and to discern whether there are any unifying principles to the interface technology as currently implemented.

However, from personal knowledge of some of these systems we may point to features common to many of them. These are flexibility in selecting dependent and independent variables in generation of graphic displays, use of color, contour and surface plotting, and orthographic projections to capture large volumes of information at a glance, and the animation. The latter is used not only to show dynamic behaviors like vibration but also to illustrate the changes in design introduced by optimization process over a sequence of iterations. Development has already started in the next level of display technology based on the virtual reality concepts. In addition to the engineering data display, there are displays that show the data flow through the project tasks, the project status vs. plans, etc. One common denominator is the desire to support the engineer's train of thought continuity because it is well known that such continuity fosters insight that stimulates creativity. The other common denominator is the support the systems give to the communication among the members of the design team.

One optimization code, usable for MDO purposes and available to general public, is described in Parkinson et al. (92). This code informs the user on the optimization progress by displaying the values of design variables, constraints, and objective function continually from iteration to iteration.

The above features support the computer-to-user communication. In the opposite direction, users control the process by a menu of choices and, at a higher level, by meta-programming in languages that manipulate modules and their execution on concurrently operating computers connected in a network, e.g., code FIDO in Weston et al. (94). One should mention at this point, again, the nonprocedural programming introduced in Kroo and Takai (88). This type of programming may be regarded as a fundamental concept on which to base development of the means for human control of software systems that support design. This is so because it liberates the user from the constraints of a prepared menu of preconceived choices, and it efficiently sets the computational sequence needed to generate data asked for by the user with a minimum of computational effort.

A code representative of the state of the art was developed by General Electric, Engineous, (94), and Lee et al. (93), for support of design of aircraft jet engines. The distinguishing feature of the code called Engineous is interlacing of the numerical and AI techniques combined with an intrinsically interactive operation that actively engages the user in the process. Similar emphasis on the user interaction is found in Bohnhoff et al. (92). Examples of other codes that provide MDO features to support design process are in Kisielewicz (89), Volk (92), Woyak, Malone, et al. (95), and Brama and Rosengren (90).

3. Simultaneous Aerodynamic and Structural Optimization

One of the most common applications of multidisciplinary optimization techniques is in the field of simultaneous aerodynamic and structural optimization, in particular for the design of aircraft wings or complete aircraft configurations. The reason for this prominence is that the tradeoff between aerodynamic and structural efficiency has always been the major consideration in aircraft design: slender shapes have lower drag but are heavier than the stubby, more draggy shapes. The bi-plane wings that dominated early aircraft configurations were the concession of the aerodynamicists to the need for structural rigidity. Only after advances in structural design and structural materials permitted building monoplanes with enough wing rigidity, were we able to

take advantage of the superior aerodynamic efficiency of monoplanes.

The interaction between aerodynamics and structures in the form of aeroelastic effects, such as load redistribution, divergence, flutter, and loss of control surface effectiveness, has given rise to the discipline of aeroelasticity. Structural optimization was often coupled with aeroelastic constraints. Occasionally, structural optimization was even used to improve aerodynamic efficiency (e.g., Haftka, 77) and Friedmann, 92). However, here we focus our attention only on studies where both the aerodynamic and structural design were optimized simultaneously. The reader interested in work on aeroelastic optimization is referred to Shirk et al. (86), Haftka (86), and Friedmann (91).

The trade-off between low drag and low structural weight for aircraft wings is affected by two mechanisms of interaction between aerodynamic and structural response. First, structural weight affects the required lift and hence the drag. Second, structural deformations change the aerodynamic shape. The second effect is compensated for by building the structure, so that the structural deformation will bring it to the desired shape. This so called jig-shape approach nullifies most of the second interaction when the deformations of the aircraft structure are approximately constant through most of the flight time. This is the case for many transports. For fighter aircraft, structural deformations during various maneuvers can adversely affect aerodynamic performance, and the jig shape can correct only for the most critical maneuver or cruise conditions. Similarly, for very long range or high-speed transports, where the weight and cruise conditions can vary a lot, the jig-shape correction will only partially compensate for the adverse effects of structural deformations.

If the effects of structural deformation on aerodynamic performance are assumed to be corrected by the jig shape, the interaction between the aerodynamicist and structural designer becomes one-sided. The aerodynamic design affects all aspects of the structural design, while the structural design affects the aerodynamic design primarily through a single number—the structural weight. This asymmetry in the mutual influence of aerodynamic and structural designs means that the problem can be treated as a two-level optimization problem, with the aerodynamic design at the upper level and the structural design at the lower level. However, this means that for each aerodynamic analysis one has to do a structural optimization, which makes sense because the cost of structural analysis is usually much lower than the cost of the aerodynamic analysis. For example, Chattopadhyay and Pagaldipti (95) employ such an approach for a high-speed aircraft with a Navier Stokes model for the aerodynamic and a box beam model of the structure. Similarly, Baker and Giesing (95) demonstrated this approach with an Euler aerodynamic solver and a large finite-element model optimized by the ADOP program.

Taking advantage of the asymmetric interaction between structures and aerodynamics presents an enormous saving in computational resources because we do not need to calculate the large number of derivatives of aerodynamic flow with respect to structural design variables. Further savings are realized by taking advantage of this asymmetry to generate structural optimization results for a large number of aerodynamic configurations and fit them with an analytical surface usually called the "weight equation" (see Torenbeek, 92, for references on the subject). The structural weight of existing aircraft can also be used for the same purpose. McCullers developed a transport weight equation based on both historical data and structural optimization for the FLOPS program (McCullers, 84). This equation was used for including structural weight considerations in aerodynamic optimization of a high-speed civil transport configurations by Hutchison et al. (94).

At the conceptual design level, structural weight has traditionally been estimated by algebraic weight equations and similar algebraic expressions for aerodynamic performance measures such as drag. The simplicity of these expressions allowed designers to examine many configurations with a minimum of computational effort. More recently, such tools have been combined with modern optimization tools. For example, Malone and Mason (91) optimized transport wings in terms of global design variables, such as wing area, aspect ratio, cruise Mach number and cruise altitude, using simple algebraic equations for structural and other weights and aerodynamic performance. The same authors (92) then used such models also to examine the effect of the choice of objective function (maximize range, minimize fuel weight, etc.)

At the preliminary design level, numerical models of both structures and aerodynamics are employed. Early studies of combined aerodynamic and structural optimization relied on simple, usually one-dimensional aerodynamic and structural models and a small number of design variables (e.g., McGeer, 84, and references therein), so that computational cost was not an issue.

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Rather, the goal was to demonstrate the advantages of the optimized design. For example, Grossman et al. (88) used lifting line aerodynamics and beam structural models to demonstrate that simultaneous aerodynamic and structural optimization can produce superior designs to a sequential approach. Similar models were used by Wakayama and Kroo (90) and (94) who showed that optimal designs are strongly affected by compressibility drag, aeroelasticity, and multiple structural design conditions. Gallman et al. (93) used beam structural models together with vortex lattice aerodynamic to explore the advantages of joined-wings aircraft.

Modern single-disciplinary designs in both aerodynamics and structures go beyond such simple models. Aerodynamic optimization for transports is often performed with three-dimensional nonlinear models (e.g., Euler equations, Korivi et al., 94) While structural optimization is performed with large finite-element models. For example, Tzong et al. (94) performed a structural optimization with static aeroelastic effects of a high-speed civil transport using a finite-element model with 13,700 degrees of freedom and 122 design variables. The validity of results obtained with simple models is increasingly questioned, and there is pressure to perform multidisciplinary optimization with more complex models. However, because of the asymmetric interaction between aerodynamics and structures, discussed above, the emphasis in multidisciplinary optimization is on improved aerodynamic models (e.g., Giesing et al., 95). Thus, modern conceptual design tools such as FLOPS (McCullers, 84) or ACSYNT (Vanderplaats, 76), and Mason and Arledge, 93) incorporate aerodynamic panel methods at the same time that they use algebraic weight equations to represent structural influences on the design.

Computational efficiency becomes an issue when the complexity of the aerodynamic and structural models and the number of design variables increase. Borland et al. (94) performed a combined aerodynamic-structural optimization of a high-speed civil transport using a large finite-element model and thin Navier Stokes aerodynamics. However, they were able to afford only 3 aerodynamic variables along with 20 structural design variables. Chattopadhyay and Pagaldipti (95) used parabolized Navier Stokes aerodynamic model and beam structural model, but with only four aerodynamic variables. Similarly, Baker and Giesing (95) used Euler code for aerodynamics and a detailed finite-element analysis, but with only two

aerodynamic design variables representing the aerodynamic twist distribution.

One of the major components of the computational cost is the calculation of cross-sensitivity derivatives such as the derivatives of aerodynamic performance with respect to structural sizes and derivatives of structural response with respect to changes in aerodynamic shape. Grossman et al. (90) reduced the interaction front between the aerodynamic and structural analysis in the Global Sensitivity Equation approach (Sobieszczanski-Sobieski 90) to substantially lower the computational cost of calculating such derivatives. Automated derivative calculations, obtained by differentiating the computer code used for the analysis, may also help, as demonstrated by Unger and Hall (94).

Additional savings in computational resources were achieved by the use of variable complexity modeling techniques (see Section 2.3). For example, Dudley et al. (94) used structural optimization to periodically correct the prediction of algebraic weight equations. Using this approach they have optimized a high-speed civil transport using 26 configuration design variables and 40 structural design variables. However, because they did not calculate and use derivatives of the weight obtained by structural optimization with respect to configuration design variables, the performance of the procedure was not entirely satisfactory. It is possible that there is no need to couple structural optimization tightly with aerodynamic optimization. Instead, as done by McCullers (84) in FLOPS, structural optimizations may be performed ahead of time to obtain improved weight equations for the class of vehicles under consideration (see also Haftka et al. 95).

Of course, limiting structural influences to weight equations may not always work, in particular, when aerodynamic performance is important for multiple design conditions whose structural deformations are very different. Then a completely integrated structural and aerodynamic optimization may be necessary for obtaining high-performance designs. In such cases we may want to tailor the structure so that structural deformation will help aerodynamic performance under the multiple flight conditions. However, an alternate approach is to use control surfaces to compensate for structural deformations for multiple flight conditions. In that case, the aerodynamicist can still assume that aerodynamic performance will not be compromised by structural deformations. The structural designer will

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have to design the jig shape, the structure, and the control surface deflections simultaneously to minimize structural weight while safeguarding aerodynamic performance. Miller (94) employed this type of an approach in a study of an active flexible wing. Another example where such approach may be necessary is a supersonic transport design for efficient flight in both the supersonic and subsonic speed regimes (AIAA 91), the latter required by sonic boom restrictions.

In the past few years there has been also a lot of progress for combined aerodynamic and structural optimization of rotor blades, and in the requisite analytical advances, the latter illustrated by He and Peters (92), Lim and Chopra (91), and Kolonay et al. (94). Work in this direction started with structural optimization subject to aerodynamic constraints (e.g., Yuan and Friedmann, 95). However, there is also much work which includes both aerodynamic and structural design variables. Callahan and Straub (91) used a code called CAMRAD/JA to design rotor blades for improved aerodynamic performance and reduced structural vibration with up to 17 design variables. Walsh et al. (92) has integrated the aerodynamic and dynamic design of rotor blades, and Walsh et al. (95) have added structural optimization to the former capability, using a multilevel approach. As in the case of fixed wing optimization, the multilevel approach was aided by the relative simplicity of the structural model. However, unlike fixed wings, rotor blades naturally lend themselves to inexpensive, beam structural models. Chattopadhyay and McCarthy, (93a, b) have explored the use of multiobjective optimization for similar integration of aerodynamics, dynamics and structures for the design of rotor blades. Other examples of applications in rotor blade design were given in Celi (91) and Chattopadhyay et al. (91).

Additional examples of optimization that accounts for interaction of aerodynamics and structures in flexible wing design may be found in Rais-Rohani et al. (92), Yurkovich (95), Scotti (95), and Rohl et al. (95). Interaction of aerodynamics and structures occurs also in the emission, transmission, and absorption of noise generated by propulsion and by the airframe moving through the air. This interaction has spawned the discipline of structural acoustics, e.g., Lamancusa (93) and Pates (95), whose approach is based on the boundary finite elements.

4. Simultaneous Structures and Control Optimization

Another common application of multidisciplinary optimization is in simultaneous design of a structure

and a control system. A typical aeronautical application is active flutter suppression, and typical space structure application is the suppression of transient vibration triggered by transition from Earth shadow to sunlight.

Past practice has been sequential so that the structural layout and cross-sectional dimensions were decided first, and a control system was added subsequently to eliminate or alleviate any undesirable behavior still remaining. Occasionally, when it was known in advance how effective the control system would be in reducing a particular behavior constraint, violation the structural design was carried out first to satisfy the above constraint partially, and the design of the control system followed to achieve the full satisfaction of the constraint. Iterations ensued if the control system design was unable to satisfy its share of the constraint. An example of this approach was reported in Sobieszczanski-Sobieski et al. (79) in which structural sizing was used to provide flutter-free airframe of a supersonic transport up to the diving velocity (VD), and an active flutter suppression provided the required 20 % velocity margin beyond VD.

The sequential practice is deficient because it does not accommodate general objective function or functions, nor does it enable one to explicitly trade structural stiffness, inertia, and weight for the active control system effort and weight. These deficiencies are remedied by simultaneous optimization of the structure and the system for control of its behavior. Haftka (90) surveys various simultaneous formulations ranging from ad hoc ones to those in the multiobjective (pareto-optimal) category. In general, one expects the simultaneous approach to generate designs whose structural weight and control effort are less than those achievable under the sequential approach. Even though there is no doubt as to the superiority of the integrated approach, still the integrated structures-control optimizations on record typically use a composite objective function that is a weighted sum of the structural mass and the control effort, with the weighting factors set by subjective judgment. This is so despite availability of tools that are ready for a less subjective approach under which the airframe mass could be traded off for the mass of the control system, the latter including the mass of the requisite power generation equipment.

When all the objectives cannot be converted to a single one, such as mass, a pareto optimization is called for. A full pareto-optimal optimization would seek to

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generate a locus of all the pareto-optimal solutions. Unfortunately, this locus can have discontinuities and branches, as demonstrated by Rakowska et al. (91) and (93). Tracing the entire locus may be very expensive, even though homotopy techniques, Rakowska et al. (93), may alleviate this burden. However, even less ambitious simultaneous optimization approaches are computationally expensive. That has motivated a number of papers that addressed that problem. Reducing the mathematical model dimensionality was proposed in Karpel (92) as a means to save computational cost in synthesis of aeroservoelastic systems. To alleviate cost of the particularly expensive unsteady aerodynamics, Hoadley and Karpel (91) used approximate surrogate for a full unsteady aerodynamic analysis in the optimization loop combined with infrequent repetitions of the full analysis. In the same vein, Livne (90) reported on the accuracy of reduced-order mathematical models for calculation of eigenvalue sensitivities in control-augmented structures. Chattopadhyay and Seeley (95) have developed an efficient simulated annealing approach for the solution of the multiobjective optimization problem for rotorcraft applications.

The dimensionality of the design space of an actively controlled structure dramatically increases for composite structures when fiber orientations are included among the design variables, and even more so when overall shape variables, e.g., the wing sweep angle, are added. Livne (89) gave a comprehensive introduction to optimization of that category applied to aircraft wings and continued it in Livne (92). The computational cost issue was addressed in context of the above applications in Livne and Friedmann (92) and in Livne (93). Livne and Wei-Lin (95) assert that the sensitivity analysis and approximation concepts in aerodynamics and airframe structures, the latter modeled by equivalent stiffness plate, have progressed to a point where a realistic wing/control shape optimization with active controls and aeroservoelastic constraints begins to appear to be within reach.

In space applications, recent thrusts have entailed synthesis of structure-control systems designed to maintain pointing accuracy, shape control of reflective dishes (both transmitting and receiving), and elimination of vibrations that might be induced by external influences, e.g., a thermal excitation by sun, or the spacecraft maneuvers. Many of these applications involve locations of sensors and actuators that are determined by discrete variables, therefore, search techniques capable of handling discrete variables have been added to the toolbox. An example is the use of

modified simulated annealing for a combinatorial optimization melded with a continuous variable optimization of honeycomb infrastructures for spaceborne instrumentation in Kuo and Bruno (91). A multiobjective optimization was used in Milman and Salama (91) to generate a family of designs optimized for competing objectives of disturbance attenuation and minimum weight in spaceborne interferometers. Design for the global optimum has been achieved by the use of a homotopy approach by Salama et al. (91) in development of families of the actively controlled space platform designs for conceptual trade studies. Briggs (92) reported on adding optics to control-structures optimization, and in Flowers et al. (92) that type of optimization was extended to a multibody system. Further application examples may be found in Harn et al. (93), Hirsch et al. (92), Padula et al. (93), Park and Asada (92), Sepulveda and Lin (92), Suzuki and Matsuda (91), Suzuki (93), Weisshaar et al. (86), and Yamakawa (92).

A system sensitivity analysis based on the Global Sensitivity Equations (GSE) (see section 2.5 on System Sensitivity Analysis) was introduced in the control-structure optimization by Sobieszczanski-Sobieski et al. (88). Padula et al. (91) reported on an optimization of a lattice structure representative of a generic large space structure in which they used a GSE-based system sensitivity analysis. They integrated a finite-element model of the structure, multivariable control, and nonlinear programming to minimize the total weight of the structure and the control system under constraints of the transient vibration decay rate. Fifteen design variables governed the structural cross-sections and the control system gains. James (93) extended optimization dimensionality in the above application to 150 design variables, 12 for the control system gains and the remainder for the structural member cross sections.

Actuator placement on a large space structure is a typical example of an MDO discrete problem. Padula and Sandridge (92) presented a solution using an integer programming code and a finite-element structural model. Alternatives to the above approach were given by Kincaid and Barger (93) who used a tabu search and by Furuya and Haftka (93) who applied a genetic algorithm. An evaluative discussion and comparison of several methods applicable to optimization of structures with controls was given in Padula and Kincaid (95). The comparison included the simulated annealing, tabu search, integer programming, and branch and bound algorithms in the context of applications ranging into 1500+ design variables in

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space structures, as well as in airframes. An acoustic structural control was the case in the latter.

An unusual case of optimization of a large space structure to make its dynamic behavior deliberately difficult to control was reported in Walsh (87) and (88). The object was a long lattice beam mounted to protrude out of the Space Shuttle orbiter and having its natural vibration frequencies spaced very closely in order to challenge the system identification algorithm and the control law synthesis in the design of the control system. Potential of a relatively recent technology of neural nets to control structural dynamics of elastic wings was demonstrated in Ku and Hajela (95).

5. Concluding Remarks

The survey revealed that in aerospace, MDO methodology has transcended its structural optimization roots and is growing in scope and depth toward encompassing complete sets of disciplines required by applications at hand. It has broadened its utility beyond being an analysis and optimization engine to include functions of interdisciplinary communication. It has also formed a symbiosis with the heterogeneous computing environments for concurrent processing provided by advanced computer technology.

The two major obstacles to realizing the full potential of MDO technology appear to be the twin challenges posed by very high computational demands and complexities arising from organization of the MDO task. To deal with these twin challenges the major emphasis in MDO research has been on approximation and decomposition strategies. Both hierarchical and non-hierarchical decomposition techniques have been proposed to deal with the organizational challenge. Response surface approximations are emerging as a useful tool for addressing both the computational and organizational challenges.

In general, there are still very few instances in which the aerospace vehicle systems are optimized for their total performance, including cost as one of the important metrics of such performance. However, a vigorous beginning in that direction has been evident in the number of references devoted to mathematical modeling of manufacturing and operations, and to the use of these models in optimization. In addition, despite the very well-known fact that engineering design is intrinsically multiobjective, there is a dearth of papers addressing the very formulation of that multiobjective problem, the structure-control optimization being a case in point.

For the human interface, the MDO developers and users seem to have arrived at a consensus that the computer-based MDO methodology is an increasingly useful aid to the creative power of human mind which is the primary driving force in design. The once-popular notions of automated design have been notably absent in the surveyed literature, nor were there any expectations expressed that AI techniques will change that in the foreseeable future.

The survey leaves no doubt that the MDO theory, tools, and practices originate in the communities of mathematicians, software developers, and designers whom these products ultimately serve. Therefore, its is remarkable that there is little evidence of close collaboration among these three groups that have been to a large extent working apart missing on valuable cross-fertilization of ideas and understanding of needs and opportunities. Only recently there were indications of increasing interest in the three communities in working more closely together (e.g., AIAA 91). In a similar vein, there has been almost no interaction of the aerospace multidisciplinary optimization research with other engineering research communities; it would be beneficial to increase the awareness of similar research in fields such as chemical engineering and electrical engineering.

If one were to end on a speculative note, it is likely that future similar surveys will find a number of papers devoted to virtual design and manufacturing built on the foundation laid out by the works included herein.

Acknowledgment

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Appendix: Design Space Search

Theoretical and applied mathematics of the design space search is a very large area of endeavor beyond the scope of this survey. (A recent review is in Frank et al. 92.) Nevertheless, a few remarks pertaining directly to the use of search algorithms in optimization of large systems are included below.

In large-scale optimization it is now customary to connect search algorithm to an approximate analysis (See section on Optimization Procedures.) rather than to the full-fledged analysis of the problem. This gave rise to a notion that the efficiency of that algorithm does not have much impact on the total computational cost of optimization as long as the algorithm solves the approximate problem because the bulk of the computational effort and cost is in the full analysis. However, this notion is not entirely true for at least two reasons. When the number of design variables goes up into the range of thousands, the computational cost of search itself goes up superlinearly and begins to matter even relatively to the full analysis cost. Even more importantly, the algorithm memory requirements driven primarily by the size of the Jacobian of the constraints go up as a product of the number of constraints and the number of design variables, and may quickly exceed the fast memory capacity forcing the operation into a time-consuming mass storage communications.

If there are many more constraints than design variables and the constrained minimum is defined by only a few active constraints, then a search technique that clings to the constraint boundary is efficient. The usable-feasible directions algorithm is an example. However, if the constrained minimum lies at a full, or nearly-full, vertex of the feasible space, then such a search technique may be forced into small steps moving from one constraint boundary intersection to the next. In that situation an interior point methods may be expected to move through the design space over a longer distance. This advantage of the interior point methods has been recognized in linear programing, e.g., Polyak (92). A broader discussion of the interior point methods is given in Nesterov (94) and Nash (94).

Even though the gradient-guided search is more efficient that the one based on the zero-th order information only; still the computational cost of gradients is of concern. Hence, a continued research has been pursued into the zero-th order methods. It has resulted in improvements in the pattern search algorithms, such as those reported in Torczon (93) and Dennis (91). A related development was described in Rowan (90) in which the search is assisted by transformation of the design space coordinates. That transformation results in a set of subspaces that are mutually orthogonal, hence each may be searched independently. This results in a process amenable to concurrent processing. It may also be regarded as a form of decomposition based entirely on mathematical properties of the design space, in contrast to decomposition based on physical insight used in previously described optimization by decomposition. Search efficiency may also be improved by tailoring its mathematics to the special features of the problem as shown in Arora (92).

Genetic Algorithms (GA) offer another alternative to gradient-guided search, e.g., Hajela et al. (92). An GA algorithm treats a set of design points in the design space as a population of individuals that produces another set of points as a generation of parents produces the next generation of children. A GA algorithm comprises a mechanism for pairing up the design points into the pairs of parents for transfer of the parent characteristics to children and for mutations that occasionally endow children with features absent in either parent. The mechanism favors probabilistical creation of children that are better than parents in terms of the objective function and satisfaction of constraints. The mutation mechanism in GA is particularly important to prevent the process from ending up in a local minimum. It was also demonstrated in Gage et al. (95), on an example of an aircraft wing design that this mechanism may be used to create new designs with features that were absent not only in the pair parents but anywhere in the entire parent generation. This amounts to extending design space by adding new variables and is entirely beyond the capability of gradient-directed search. References Gage and Kroo (92 and 95), Gage et al. (95), Gage (95), and King et al. (91) provide other examples of applications and discussion of issues that arise in the use of GA.

The capability of escape from local minima is one characteristic that Simulated Annealing (SA) class of search algorithms, e.g., Khalak et al. (94) and Kuo et al. (91) has in common with GA. In SA the search is random, and acceptance of a new design worse than the previous one is occasionally and probabilistically allowed to provide for such escape.

Both the GA and SA techniques generate a large number of calls to analysis, hence, their usability is limited by the cost of analysis. In this regard they are inferior to methods that generate and exploit search

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directions in the design space, for instance Snyman et al. (87).Despite that, judging by the number of the reported applications, they are gaining popularity in MDO applications probably because they are very simple to couple with the analysis modules, and they do not incur the cost of computing the derivatives. However, the extent to which these algorithms can be combined with approximations as the gradient-guided ones can, is a question open to further investigation.

An alternative to numerical search of design space for constrained minima is an optimality criteria approach. It comprises two elements: the optimality criteria appropriate to the case at hand and an algorithm for transformation of the design variables to achieve satisfaction of the criteria. This approach was successful mostly in structural engineering where the criteria of fully stressed design and uniform strain energy density indeed ensure that design is at, or near, a constrained optimum. In multidisciplinary systems whose various parts and aspects are governed by different physics, it is difficult to identify a common, physics-based optimality criterion. However, if the system is dominated by structures, e.g., optimization of airframes with aerodynamic loads, the optimality criteria method may be successfully extended from structures to encompass the entire system, as shown in a review provided in Venkayya (89).

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