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THE OTHER SIDE OF MULTIDISCIPLINARY DESIGN OPTIMIZATION: ACCOMODATING A MULTIOBJECTIVE, UNCERTAIN AND NON-DETERMINISTIC WORLD

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The evolution of multidisciplinary design optimization (MDO) over the past several years has been one of rapid expansion and development. In this paper, the evolution of MDO as a field is investigated as well as the evolution of its individual linguistic components: multidisciplinary, design, and optimization. The theory and application of each component have indeed evolved on their own, but the true net gain for MDO is how these piecewise evolutions coalesce to form the basis for MDO, present and future. Originating in structural applications, MDO technology has also branched out into diverse fields and application arenas. The evolution and diversification of MDO as a discipline is explored but details are left to the references cited.

Key Words: Multidiscipline, Design, Optimization, Decomposition, Approximation

1. CHANGE OF PERSPECTIVE

In the past several years, there has been a shift in the interest and application of the MDO community from mainly aerospace applications, which stemmed from MDO's origins in the field of structures, to fields including mechanical, civil, and electrical engineering, operations research, and materials science. In each of these fields, there are indeed multidisciplinary research issues in the design, development, production, and support of complex systems. Recently, the multidisciplinary research and development in each field

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are merging into fundamental approaches to complex system design problems. Also, with the advent of systems thinking and doing "more with less," issues usually reserved for the later stages of a design process are brought forward into the initial stages, MDO technology and research is moving from the detailed analysis design stages to the conceptual stages where multidisciplinary system tradeoffs can be rapidly explored effectively and efficiently. This shift parallels a similar shift from traditional calculus based optimization algorithms, where precise mathematical models and couplings are known, to more imprecise techniques where laws of uncertainty guide mathematical models and their interactions. The former certainly has its place in the later stages of design, but in the early stages, the information about a multidisciplinary, complex system may not be fully known and many times is unstructured. This gives rise to the requirement of imprecise techniques for decomposing, analyzing and synthesizing a system model. Thus, the study of complex systems moves into a new age of research and technology, one characterized by both precise and imprecise models, and exact mathematics and fuzzy heuristics.

One of our aims in this paper is to update Sobieszczanski-Sobieski's papers on the status of MDO [81, 82]. In this paper, we survey the work in MDO from largely only the United States. This is mainly because of time and space constraints. Our hope is to present the current status of the field from the United States research community's perspective as a status report to build upon globally. In Figure 1, we give an overview of this paper. In Section 2, we begin by identifying the trends in MDO by evaluating the distinct areas of research in MDO, namely its three linguistic components, *multidisciplinary, design, and optimization*. In Section 3, the research and application issues under the umbrellas of each research area are surveyed and summarized. As shown in Figure 1, these issues overlap beneath the research areas, as they are motivated by questions from more than one area. This is part of the difficulties researchers in MDO face, as the integration of various fields and disciplines poses complex problems. In Section 4, we close with hypotheses on the future areas of focus in MDO. The work presented here includes government, industry and academia contributions to this emerging area of research and practical application.

2. MDO: AN INTERNAL DECOMPOSITION

System decomposition is a valuable and many times necessary approach in solving complex systems. The method used to decompose a system, however, is another issue, addressed in Section 3. Capitalizing on the advantages of decomposition, the field of MDO is investigated in this paper by applying a linguistic decomposition approach to the term "MDO". This stems from the simple approach used to determine the meaning of "complicated" compound words such as schoolbus, where combining the meanings of the root words "school" and "bus" result in the connotation of the compound word.

Decomposing "MDO", the root words "multidisciplinary", "design", and "optimization" are discovered. Each area calls on certain capabilities from the others to perform its required duties. These calls and demands among the areas are illustrated in Figure 2. Each of these terms and the demands each makes on MDO as a whole is investigated in this section.

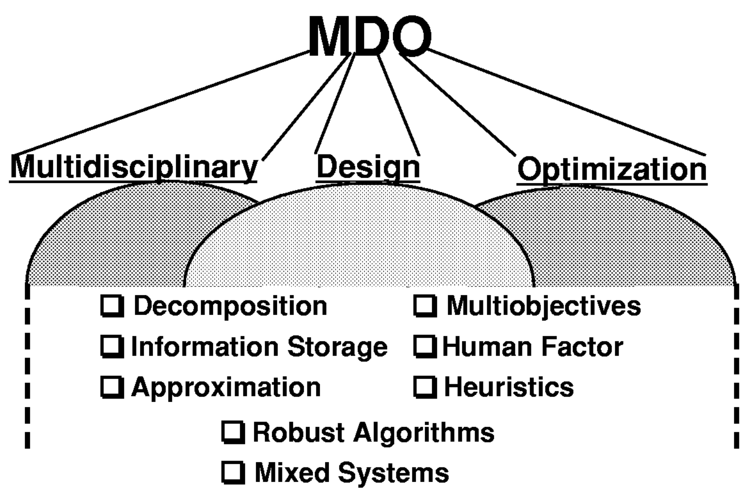

Figure 1. Overview of Paper

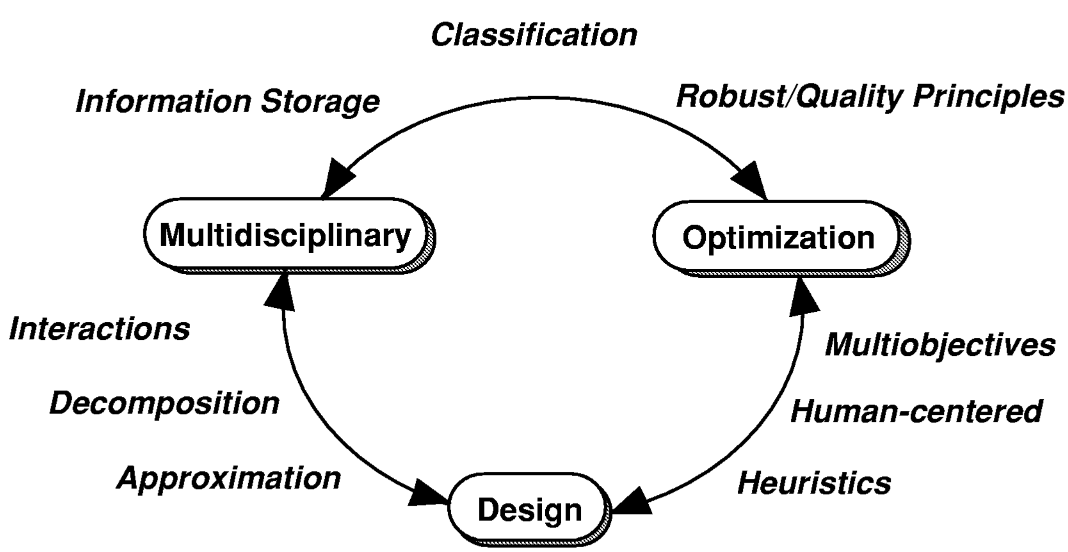

Figure 2. Couplings of M, D, and O

2.1 Multidisciplinary

The term "multidisciplinary" plays an important role in the complexity of system problems. Individual disciplines have developed mature methods to analyze disciplinary problems. However, when two or more disciplines and their analyses are combined, such as Computational Fluid Dynamics (CFD) in aerodynamics and Finite Element Methodology (FEM) in structures, the problem becomes many times too computationally expensive. Therefore, some sort of decomposition method is necessary for most multidisciplinary problems to establish less complex, disciplinary-level problems. Many decomposed problems are still too complex to effectively analyze because of the size of the analysis routines. Consequently, a form of approximation may be necessary to replace the exact analysis. But, how approximate a model can be and still maintain acceptable accuracy is another research issue in complex systems design. The key notion here is that each discipline plays an important role in the function of the entire system.

In a given discipline, there may exist system variables which are continuous, integer, discrete, or Boolean. Examples of these are wing span, number of engines, gear diameter, or control variables, respectively. Integer, discrete, and Boolean variables will be referred to as discrete variables in the remainder of this paper. There are well established methods for solving either purely continuous problems, or purely discrete problems. Continuous methods are largely calculus based, while discrete methods range from integer programming methods to heuristic search methods. Yet, it is the development of robust methods to support the decision making of designers in problems with mixed continuous/discrete variables that the presence of multiple disciplines demands.

2.2 Design

The term "design" mandates the investigation of other issues, including multiobjective system formulations. Practical systems are not single objective in nature. In vessel design, minimizing resistance is similar to minimizing weight in aerospace design, but there are many other design objectives a designer may want to consider. A naval designer may want to minimize the vessel powering and keep seakeeping at acceptable levels for various seastates. Complex systems are always multiobjective, but these objectives may be of different priorities, according to system requirements and designers preferences.

Process and human designer issues are also brought in with the term "design". Design consists of a series of decisions made by a designer or design team along a timeline.

Designers repeatedly use their *ability* together with the computer's *capability* to make decisions regarding various system and subsystem tradeoffs. Hence, the notion of a designer interface and human-centered design is inherent in any design process. The sense of time, past and present, in a process requires some way of storing and retrieving information to expedite future decisions. Hence, some type of database that links the information from all disciplines for efficient retrieval throughout a design process is necessary.

2.3 Optimization

Regardless of decomposition, there is a need for the determination of system variables based on system constraints, variable bounds, and with respect to system objectives. Independent of the modeling approach taken or domain of application, optimization techniques are required to solve decision models and support the decision making abilities of a designer. Optimization techniques have even be used to synthesize, to coordinate a number of subsystems into a system level "optimum". In addition, single point global solutions are often difficult to achieve and unrealistic when information about complex systems is imprecise or incomplete. Therefore, some researchers are moving towards identifying "satisficing" or sets of solutions which are "good enough" and can be developed into better solutions throughout a design process [78]. Problems in MDO demand optimization techniques for multiobjectives, mixed continuous/integer systems, designer interfaces, robust global solutions, and post-solution analysis, among others. Researchers have addressed one or more of these various issues, but there does not presently exist a single algorithm to encompass all the needs of MDO in a decision-based environment. This may be a problem too great to handle at present, but certainly is a research issue. There has been extensive work in single objective optimization, but since the term "multidisciplinary" implies multiple objectives, issues in multiple objective modeling, solution, and decision support are the focus of this paper.

In this section, the innate issues in MDO are examined by simple decomposition and analysis among the components. The harmonious coordination of these issues is the basic task in MDO. In the next section, the developments and fundamentals of each issue will be investigated, including the various applications that MDO has addressed.

3. ISSUES IN MULTIDISCIPLINARY DESIGN OPTIMIZATION

Researchers, when addressing the areas from the previous section, must keep the inherent global issues of MDO in mind. Some researchers in MDO have addressed some of these issues by themselves, while others have looked at a combination of a few. However, any development in MDO must keep all of these issues at the core of the research, as it will add to the integrity, broaden the acceptance, and establish the value of MDO.

3.1 Decomposition: Friend or Foe?

The decomposition or partitioning of large systems has long been viewed as being beneficial to the efficient solution of the system. Although breaking a system up into smaller, less complex subsystems may allow for the effective solution at the subsystem level, decomposition makes the system design problem more complicated by requiring the coordination of subsystem solutions into a harmonious system solution. A mirror can be broken apart, the pieces reassembled, and in no way function as a mirror again. This problem in analyzing and synthesizing various subsystems poses a difficult problem in MDO. So why not simply analyze systems at one level, the system level? This creates analysis problems, as complex system models may become too large to handle. When do systems become too large for single-level analysis and require decomposition and multilevel analysis? The answer may lie in the amount and quality of information in a system model at any point in a design process. Both single-level and multilevel approaches are being developed as fundamental approaches to a MDO problem. General decomposition approaches have been developed for generic problems which include information overlap among various tasks, events, or disciplines by Rogers [71] and Kusiak [40, 41]. A general decomposition procedure based on the hypergraph representation of known mathematical analysis models is presented in [55]. More specific decomposition and coordination approaches for MDO problems are explored below.

Decomposition schemes initially were hierarchical in nature. However, researchers found that many systems lend themselves to nonhierarchical decompositions instead of hierarchical ones. The development of nonhierarchical decomposition schemes is relatively new compared to hierarchical ones. Implementations of decomposing larger, more complex problems into smaller, temporarily decoupled disciplinary problems have been studied in [12, 38, 61, 72]. Various decomposition and coordination strategies have been developed and implemented based on the Global Sensitivity Equation (GSE) [80] approach to couple the nonhierarchical subsystems [15, 27], [67-69], and [8]. In Balling [8], an approach to the nonhierarchic decomposition problem is developed whose coordination procedure focuses on the minimization of the norm of the coupling constraint and design constraint violation (called a discrepancy function). In Kroo [39], compatibility constraints are used at the system and subsystem levels to account for the coupling between levels. At the system level, a single objective is used (aircraft range in the case study) and the system constraints ensure that the coupling among the subsystems is maintained.

The decomposition approaches in this section have been focused in primarily two areas:

- hierarchical modeling where bilevel models are present
- nonhierarchical modeling where some form of cooperation is modeled mathematically

Realistically, these models are not always applicable. First, because of informational or geographical barriers, a model that incorporates noncooperative notions may simulate actual processes better. Second, it is common for certain disciplines to lead or dominate a design process and for others to follow their lead of decision-making [35]. This type of process would demand a model that incorporates sequential relationships among decision makers. The leader/follower formulation is a special case of a bilevel model. In the next section, strategic interactions are addressed.

3.2 Strategic Decomposition and Interaction

The design of multidisciplinary systems requires a series of decisions which are made by multiple decision makers, design teams, or organizations. Implementation of Concurrent Engineering principles have made certain strides to facilitating this integrated decision making process at a personal interaction level. However, at the analysis and synthesis levels, a seamless computer infrastructure among the disciplinary software is rare. That is, cooperation at the analysis and synthesis levels does not occur even though the majority of the research in this area has assumed cooperation. When cooperation is not present, game theory principles of noncooperation and multilevel processes can be beneficial to the modeling of the system and process. For instance, assume that a complex system such as an aircraft has been decomposed into disciplinary subsystems such as propulsion and structures. It is readily asserted that a model such as

$$\begin{aligned} &\textit{minimize}\ f(x,p) = \{f_1(x,p),\ldots,f_r(x,p)\} \qquad (1) \\ &x \in X(p) \subset \Re^n \end{aligned}$$

is the typical starting point for much of the current research and practice in systems modeling and applied optimization. And yet in specific design instances, this assertion should be boldly challenged. For example, since the propulsion designer only controls x and the structures designer controls p, how is p chosen in the propulsion design? Can the propulsion designer assume that the structural designer will always select the vector that is most advantageous to the propulsion design? If not, how should the propulsion designer respond to this conflict? Ideally, complete cooperation occurs and each designer is aware of all the others and the decisions made by each. In well-controlled design problems with perfect communication, previous approaches to this problem are extremely beneficial. However, realistically, perfect communication and cooperation does not always occur. In some cases, a noncooperative formulation models a system and the actual interactions among design teams more accurately [60]. In many cases, a Stackelberg leader/follower formulation more accurately models the actual interactions among design teams which act *sequentially*. The Stackelberg leader/follower formulation is a special case of a bilevel model and have been extensively studied in [2-4, 49, 50, 75-77].

Different variations of a two-player strategic game have just been described where one player controls x and the other player controls p and where p represents all decisions which are outside the scope of the designer controlling x [1, 24, 93]. The use of game theory to model multidisciplinary design processes where cooperation may or may not exist among decision makers in engineering design is of relatively recent origin; its usefulness in many other decision-making sectors such as economics, politics, and strategic warfare is well-established. Game theory was explicitly proposed as a design tool originally in [92]. The notion of game theory in engineering design and optimization has since been limited [5, 23, 35, 45], but there are rich research and implementation opportunities in applying game theoretic principles to MDO problems.

By using system level analysis many issues involved in decomposition strategies can be avoided and Pareto solutions can be found, but system analyses may be too complex to handle computationally. One issue brought on by decomposition strategies is approximation on many levels, from the approximation at the system level to approximation to nonlocal information at the subsystem level. In the next section, the use of approximation in MDO is presented.

3.3 Approximations in MDO

In a perfect world, approximation would not be needed, as the actual analysis routines across a multidisciplinary system could be used without concern for the computational cost or time constraints. However, until computers become infinitely fast, approximation is necessary at some level in a MDO process. This approximation may take many forms.

Derivative approximations may become obsolete with the emergence of Automatic Differentiation in FORTRAN (ADIFOR) [13]. In ADIFOR the exact derivatives of a FORTRAN code are calculated analytically by using the numerical entities at a given design point, and employing the chain rule to find total local and global derivatives. ADIFOR, however, cannot be used to compute derivatives of output with respect to a system of codes. Having the exact derivatives of a single code with acceptable efficiency is a major step in numerical analysis and approximation, and may pave the way for further developments.

Another area of research in approximation is design space approximation, locally, nonlocally and globally. From a global or systems perspective, less detailed analytical models have effectively been used to approximate the behavior of an aircraft system [18, 19, 51]. Livne and coworkers [47], accomplished comprehensive wing optimization including structural, aerodynamic, and active control requirements using realistic approximations along with nonlinear programming techniques. In [18, 25, 90], response surface methodology is shown to be both effective and efficient in design space approximation. Response surfaces have been used to effectively represent more detailed analysis routines that are typically very expensive to use in an optimization setting where repeated analysis calls are necessary. They have also been used to facilitate robust design, where good, flat regions are preferred to unstable, optimal points [18, 25, 90]. This again points to the use of "satisficing" solutions, which are insensitive to changes, as opposed to optimal solutions, which can be very sensitive and difficult to find. While researchers have found success using response surfaces to approximate continuous spaces, there are difficulties when discrete spaces are approximated. Another common approximation method is Neural Nets (NN) which "learn" about the behavior of the system from training data. NN's have been shown to produce effective approximations of the design space [11]. For problems that may not change much over long periods of time, neural networks are beneficial, but for systems that are continuously undergoing improvements and changes, neural networks are limited. Yet, with any approach, poor fidelity may lead to poor approximation. A surface fit equation of too low an order, or not enough training data may easily lead to erroneous and unacceptable results. On the other hand, with higher order fits and more training data comes more computation time. The customary manner to seek this balance of accuracy and efficiency is through trial-and-error, but this approach is obviously not a satisfactory solution.

The use of low fidelity models is useful in the early stages of design, but it may sacrifice accuracy in more detailed design stages. High fidelity approximation models have effectively been used in more detailed design, but are more computationally expensive. So the question becomes, when does a designer "switch" or evolve from less detailed models to more realistic or very detailed models? Or when can approximate models be used in place of full analytical models? The answer to these questions may lie in rigorous domain independent experimental and theoretical investigations combining information theory, applied mathematics, system identification, and innate experience of designers.

The issues in approximating local design spaces also hold true for approximating nonlocal design spaces in hierarchical or nonhierarchical design optimization. Designers of one subsystem must account for the effects upon other subsystems. Therefore, the ability for a given subsystem to "see" how it is affecting and being affected by other subsystems is vital. However, seeing the effects on actual behavior of other subsystems is not realistic. Typically, subsystems can see effects only on approximate nonlocal behaviors. Various strategies have been implemented to approximate nonlocal states [8, 45, 67]. Inherent in these approaches is accommodating the approximate coupling between subsystems via objective functions, constraints, or additional design variables.

Many times the level of approximation that is needed or effective is based on heuristic insight or rules. Heuristics play a large role in the design of complex systems from a human decision-making standpoint to a computer-based AI standpoint. There is a need for some sort of heuristics to account for the inevitable uncertainty in any given design process. Heuristics many times take the form of solution algorithm "facelifts" where certain ad-hoc rules, based on the designer's experience or naturally occurring phenomena help solution algorithms become more effective or efficient. In the next section the spectrum of heuristics in MDO is presented.

3.4 Heuristics: Rule--Based Approaches

Heuristics, or rules based on intuition, experience, or natural phenomena have been used in various stages of a design process to "smooth" over rough spots where insufficient or unstructured information is present. In Bloebaum [14], heuristic rules are employed to allocate variables to subsystems, determine the most appropriate move limits, and assign coordination coefficients during system synthesis. In [37, 65, 66], decision support heuristics are formulated based on sets of evaluation criteria and rules. These evaluation criteria are based on uncertain information in the concepts. The best concept is selected based on multiple measures of merit. These rules are based on designers' experience with the design of complex systems and are used when the mathematical information to make these decisions is not fully defined, or in other words, uncertain. These type of heuristics are shown originating from the human in Figure 3.

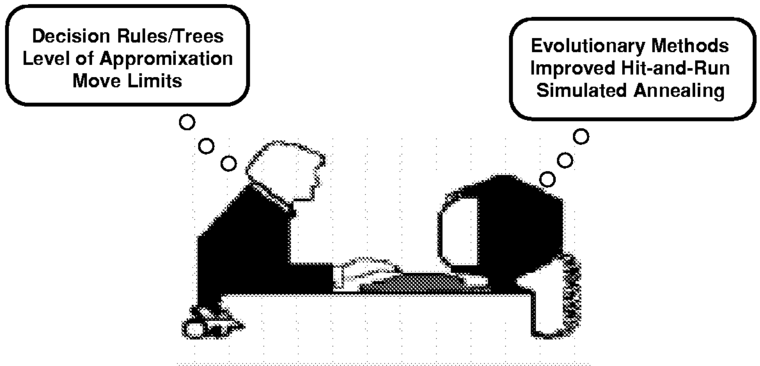

Figure 3. Heuristics Across the Design Spectrum: From Human to Computer

Heuristics are also being incorporated in MDO from a computational perspective primarily to aid in the solution of discrete and mixed models. Multidisciplinary design problems inherently consist of both discrete and continuous variables, and solving them requires implementation of computer-based heuristics, as shown in Figure 3. The solution of mixed problems is identified in [64] as being "one of the most daunting problems in design optimization." Unlike its continuous counterpart, optimality criteria such as the Karush-Kuhn-Tucker conditions for discrete problems do not exist. Glover [29] postulates that integer programming methods and artificial intelligence based methods, both stemming from a common origin, are now reuniting and creating a new class of algorithms capable of solving a large class of problems, including mixed problems. These artificial intelligence methods are based on various heuristic based searches or pattern moves. A brief review of the most recent advancements with these algorithms follows.

In Renaud [70], the simulated annealing (SA) algorithm is used to solve mixed discrete/continuous problems. This algorithm involved sequential discretizing of the continuous domain and then solving the resulting problem using the SA algorithm. In Zhang [94] a similar approach is taken in developing a SA which modifies the step sizes and neighborhood move strategy based on 1) discrete or continuous variables and 2) optimization process stage. In Ford [27], the discrete and continuous variables are partitioned and the tabu search [30] is used as the discrete solver in the discrete subspace optimizations. In Lewis [44], the tabu search is used as the foundation for a mixed discrete/continuous search algorithm based on empirical models of animals foraging for food in the wild. Genetic algorithms have shown promise in scheduling and optimization problems in MDO. In Lin [46], genetic algorithms are used to solve mixed discrete/continuous problems with good success compared to other approaches. In Hajela [33], genetic algorithms are shown to be an alternative to solving nonconvex optimization problems and in Hajela [32], genetic algorithms are used in the multidisciplinary design of rotor blades. In McCulley [53] genetic algorithms (GA) are used to order the tasks in a multidisciplinary design process.

Other attempts to solve mixed discrete/continuous problems have had limited success. Cutting plane algorithms in general require a large number of cuts to produce an integer solution. Branch and bound techniques in nonconvex problems may fathom nodes which are not feasible and also require a large number of function evaluations. In Loh and Papalambros [48], a sequential linearization technique is used to solve well-behaved mixed problems. In Fu [28], a strict penalty function is used to enforce integer values. The continuous problem is solved first, then the penalty function is used to further constrain the integer variables.

These algorithms have been relatively successful for certain problems, but further investigation and development is needed. A major concern with most algorithms is the computational expense associated with the solution processes, from discretizing continuous variables to generating and evaluating new solution points to identifying stopping criteria. However, these types of algorithms, whether calculus based or heuristic in nature are presented as being parallel developments that MDO researchers can utilize. Algorithms to solve mixed discrete/continuous problems are necessary in MDO whether it be at the subsystem level or at the system level. Systems invariably consist of discrete and continuous variables and the development of robust algorithms to handle the pitfalls involved in continuous, discrete, and non-convex optimization are necessary to the practical evolution of MDO. A fundamental notion in design, many times overlooked, is the presence of multiple objectives in a design problem. Developing the mathematical capabilities to handle multiple objectives to study tradeoff scenarios in complex systems design is necessary to facilitate satisfying the various customer requirements in an effective manner. In the next section, methods to model and handle multiobjectives in design are presented.

3.5 Multiobjective Algorithms

Multiobjective algorithms and approaches have largely been developed outside the aerospace field, but are now becoming more accepted based on their successful application in fields such as marine design and structures. Many multiple objective or attribute approaches have been developed for application in MDO. A general approach, proposed in Sen [74] calls for the analysis of design concepts based on multiple criteria (attributes *or* objectives) without clarifying distinct disciplinary boundaries. Attributes are used to make a selection from a set of choices, and objectives are used in the synthesis of a concept. In Sen's approach, both objective and subjective factors can be used in a design process. Sen uses an analytical hierarchy process [73] to combine the different criteria from different levels.

In order to analyze a system based on multiobjectives, a solution scheme must be based on a ranking of these objectives. If precise weightings are known (the preference of one objective over another is precisely known), a single objective formulation can be constructed based on relative weights. However, if a designer only knows the preferences (and not by how much one is preferred over another) a priority ranking scheme must be used. In Messac [54], "physical programming" is used to capture a designer's preferences in a mathematically consistent manner in order to avoid needless iterations to determine the objective weightings. In Hajela [31], a branch and bound algorithm is used to incorporate integer and discrete design variables in multiobjective problems. In Matsumoto [52], a fuzzy logic scheme where objectives are ranked as being either "soft" or "hard" is used. Then, once the system is solved using the "hard" objectives, the "soft" objectives are used. If no improvement can be gained from the design based on the "hard" objectives, then a designer may sacrifice some of the "hard" objective in order to improve the "soft" objective. The authors also present objective categories for which the labels "soft" and "hard" apply. For instance, those objectives concerned with the protection of the environment should be "hard" while those concerned with comfort should be "soft". This approach is very similar to the fuzzy priority scheme implemented in [95].

Another approach to handling multiple objectives is through the use of the compromise Decision Support Problem (DSP) [56], a generic multiobjective decision model. Mathematically, the compromise DSP refers to a class of constrained, multiobjective optimization problems which are used in a wide variety of engineering applications (Mistree, et al., 1993). Solutions to compromise DSPs yield the values of design variables which satisfy a set of constraints and achieve as closely as possible a set of conflicting goals. The compromise DSP facilitates the paradigm shift necessary to evaluate the multiobjective tradeoffs and identify robust solutions when designing large scale complex systems. In Lewis [42], the compromise DSP is used to explore and analyze multiobjective aircraft design based on the *lexicographic minimum* concept. This concept is defined as follows [36].

> **LEXICOGRAPHIC MINIMUM** Given an ordered array $\mathbf{f} = (f_1, f_2, \ldots, f_n)$ of nonnegative elements f_k's, the solution given by $f^{(1)}$ is preferred to $f^{(2)}$ iff
>
> $$f_k^{(1)} < f_k^{(2)}$$
>
> and $f_i^{(1)} = f_i^{(2)}$ for $i = 1, \ldots, k-1$; that is all higher-order elements are equal. If no other solution is preferred to **f**, then **f** is the lexicographic minimum.

The lexicographic minimum concept is also similar to the approach developed by Stadler [83] who stresses the history and importance of multiobjective approaches in all types of design. This concept has been implemented in the mixed discrete/continuous solution algorithm presented in [44, 56].

With many conflicting goals and nonlinear functions and complex analytical routines, finding exact solutions to a multiple objective problem is close to impossible. Therefore, one of two strategies can be used to solve complex optimization problems: 1) solve the approximate problem exactly, or 2) solve the exact problem approximately. In [56, 57], the first strategy is implemented through an augmented linearization approximation (Adaptive Linear Programming). The dominant second order terms in a Taylor series approximation are used to enhance the linear approximation. Moreover, a convex transformation is used to handle the nonconvexity of the objective functions. This second-order transformed approximation seems to be a pre-cursor for modern day quadratic response surface approximations of complex functions in systems optimization. Approximation techniques, such as those reviewed in Section 3.3 can be used in both solution strategies depending upon the assumptions made.

One issue touched on by these approaches to multiobjective design is the uncertainty and changing of the information in a design process. In Sen [74], a group of concepts may be analyzed based on multiple attributes, and the final concept will be analyzed based on multiple objectives. In Matsumoto [52], it is recognized that precise rankings are often unavailable, and identifying broad groups of objectives may be the only alternative for a designer when there is much uncertainty about the design. Further, preemptive ordering of objectives may precede Archimedean ordering in the earlier stages of design before precise weighting are known [56]. In any case, the interaction of a designer with the computer-based tools, as a means to update system models and/or tools as knowledge is gained, is essential in MDO. In the next section, this issue of human-computer interaction is addressed.

Tapetta and Renaud [87] address the issue of Multiobjective Collaborative Optimization. Collaborative Optimization strategies provide design optimization capabilities to discipline designers within a multidisciplinary design environment. To date these strategies have been applied to system design problems which have a single objective function. Tapetta and Renaud in their excellent paper provide an in depth comparison of different MOCO strategies that they have developed.

3.6 The Human Factor

In Barkan [9], a very important but many times overlooked point is made about design methodologies. Citing studies from U.S. firms, it stresses that following one set of design steps or rules could many times lead to suboptimal designs and highly inefficient design processes. The point Barkan tries to make is for designers in any field to keep their minds open to many theories, methods, and rules concerning what should be done in design. Single structured methodologies such as Functional Analysis, Quality Function Deployment, Robust Design, and Design for Assembly should not be applied blindly across the design process. Using aspects from various methodologies and philosophies throughout a design process is how MDO has been evolving recently.

In Hale [34], a design infrastructure is being developed which integrates a decision-based architecture called DREAMS with a computing infrastructure called IMAGE. This work addresses both process and product issues in a design process and establishes the human interface to both the computer-implemented design product and process models. The Framework for Interdisciplinary Design Optimization (FIDO) [88] program has recognized this need and is developing a "housing" for MDO, but the contents of the various "rooms" are up to the specific residents. In Figure 4, the type of framework being implemented in DREAMS and FIDO is illustrated. The residents in the house of a complex problem are the various disciplines in a MDO problem. Each discipline has its own solution software, formulation philosophy, and analysis approach. A framework would allow for the combination of various disciplinary methodologies and technologies under a single roof, all based on the foundation of research in MDO. Yet, how do the various methodologies of each discipline "see" into the other rooms in the house? This question is being researched and implemented using different approaches to decision support. Technological advances in virtual reality, the internet, and the World Wide Web are facilitating the progression of real-time visualization among designers and design teams. However, there are still rich research questions concerning information representation, decision support methods, and strategic disciplinary integration.

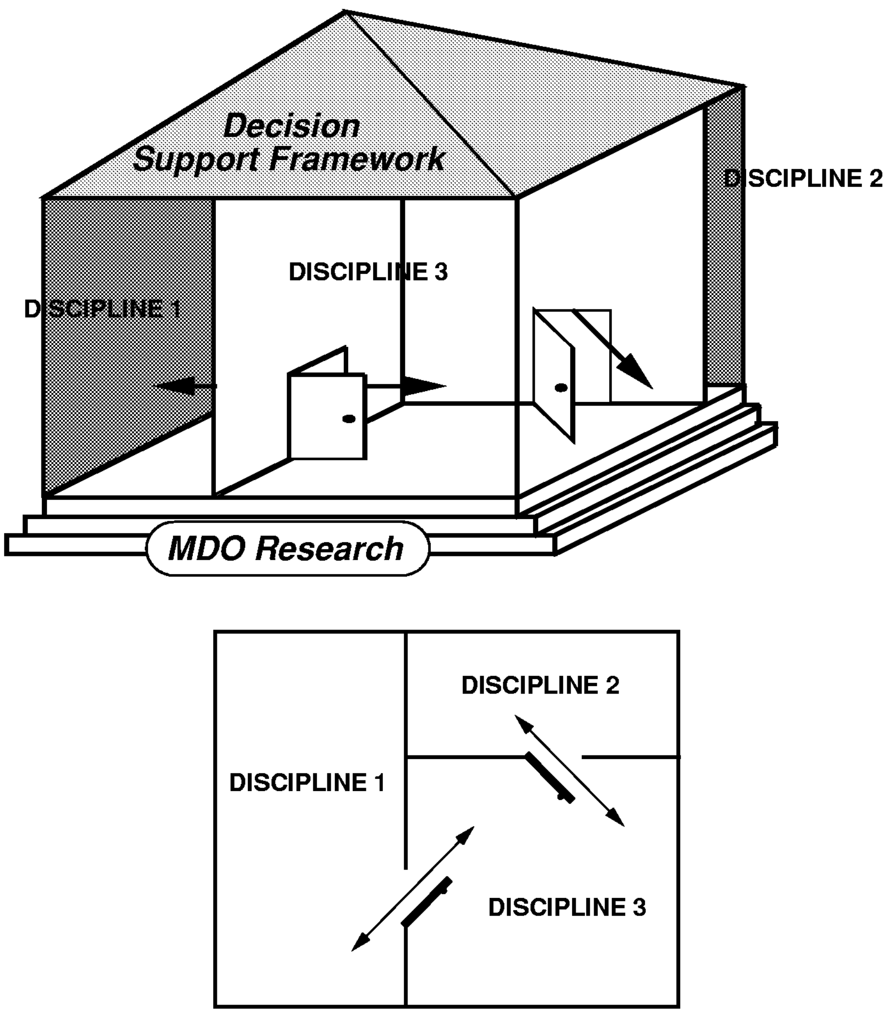

Figure 4. Framework of MDO Implementation

The focus of a designer as an interactive decision maker throughout a design process leads to the need of being able to refine and update system models according to progress in a design process. Certainly, in detailed design, with precise mathematical models, a design process can be more-or-less automated. However, since MDO starts at concept generation, imprecision and uncertainty exists in a design product and process and must be accounted for. Experimental design techniques have been developed and used to simulate systems and their innate uncertainty, while robust design techniques have been developed to minimize the effects of unwanted uncertainty on the behavior of a system. In the next section, these techniques and their applicability to effective and efficient system design and simulation are discussed.

3.7 Experimental Design Methods: Balancing Efficiency and Quality

System simulation is performed at all levels of design from "back of the envelope" calculations in the early stages of design to prototyping in the later stages of design. Making the simulation as efficient as possible while maintaining an acceptable level of effectiveness is an important and difficult issue in system and subsystem simulation. In the following, efficient experimental design methods as well as robust design techniques are presented, as a way to efficiently sample and simulate a system's behavior.

3.7.1 Experimental design methods

In the design of experiments, a finite number of designs in the design space are simulated using prescribed settings of the design variables and system evaluation routines. How small or large a number the term "finite" implies is the dilemma of full factorial experiments versus fractional factorial experiments. Taguchi utilizes a special class of fractional factorial matrices, called Orthogonal Arrays (OA) to span the design space efficiently while maximizing the effectiveness of the information. OAs also can simulate control factors (design variables) and noise factors (uncontrollable factors, such as environmental effect) in one OA. In Stanley [85] Taguchi's OAs have been applied to the design of Single Stage To Orbit (SSTO) vehicles. In Lewis [42], OAs are used to simulate and explore the multidisciplinary behavior of a Boeing 727-200 effectively. Box [17] has introduced the Central Composite Design (CCD) experiments as modifications to the OA. These types of experimental methods combined with response surface methodologies produce a powerful simulation tool that can be linked to optimization techniques in complex systems design. This is demonstrated and further explained in [18, 20, 62, 89].

It is pointed out in [79] that many times there are misconceptions concerning the use of deterministic computer simulations in experimental design. When using a deterministic computer simulation program to generate data points, the fundamental assumption of the presence of random error in the experiment is not applicable. Therefore, experimental design techniques in design must be used with great caution in order to avoid erroneous results because of invalid assumptions. One approach taken in [45] is to treat nonlocal design variables which are unknown as random noise variables. Then, the assumption of the presence of random error is valid. Also, since some variables in a multidisciplinary design may be unknown, they can be considered random variables to some designers. This approach is similar to those pointed out in [79] that are applicable in constructing approximations of deterministic computer simulation routines.

3.7.2 Robust systems design

In robust design, the effects of noise factors are reduced without eliminating the causes of the noise. Robust design is an effective approach of designing quality into the design process and product. Taguchi, an early proponent of robust design, builds his philosophy on the notion of not finding optimums, but regions of low variability [86]. This notion can be traced back to Simon [78], who introduced the notion of "satisficing" as opposed to optimizing. Simon states:

> *"The decision that is optimal in the simplified model will seldom be optimal in the real world. The decision maker has a choice between an optimal decision from an imaginary simplified world, or decision that are 'good enough', that satisfice, for a world approximating the complex real one more closely."* [78]

Another way of putting this is the "betterization" of a design instead of the optimization of a design [83]. Stadler states that the true optimization of a design is close to impossible. A more practical approach is making the design better, or the betterization of a design.

The techniques of Taguchi and the notion of "satisficing" have been applied in various MDO applications. Taguchi's measure of the quality of the design is the signal-to-noise ratio, a ratio of the mean value to its standard deviation. In [58, 63, 85] the Taguchi approach to robust design has been incorporated into the design of complex systems such as a Life Satellite Vehicle and Single Stage to Orbit (SSTO) space vehicle. There are drawbacks to Taguchi's approach to robust design. These drawbacks are well documented in [16] and include the single objective (signal-to-noise ratio) nature of the approach. Applying Taguchi techniques to the early stages of design requires certain modifications, such as establishing multiple quality loss functions. In addition, standard approaches strive to move the mean response to a specified target. However, in reality, the target could be moved to the mean, or both could be moved. Issues such as these are addressed in [21]. In general, sesearchers are finding excellent results integrating robust design methods into

MDO (e.g., [18]). However, they must not be applied blindly, but must be intelligently synthesized with other methods and strategies discussed in this paper. Measuring and maximizing the quality of a product or process along with efficient experimentation is a very important aspect of the design of any system, including multidisciplinary systems.

3.8 Applications of MDO

Although the roots of MDO are being attributed to the field of structures in aircraft design, multidisciplinary design optimization has been performed for years in many other disciplines. It is only recently that these areas are being recognized as multidisciplinary design optimization application and research areas. It is the unifying field of MDO which has brought together developments from a variety of applications.

Much of the focus of MDO applications is in the area of flight systems, both orbital and non-orbital. NASA, Boeing, Lockheed, and McDonnel-Douglas are each independently and jointly researching MDO technologies in aircraft design, including the High Speed Civil Transport (HSCT). In space system design, work concentrated at NASA-Langley focuses on applying MDO technologies to the design of advanced, manned transportation system concepts including the new family of space vehicles [61, 84]. Also, MDO technology has been applied to trajectory optimization problems in ground to mission vehicles [12]. In civil engineering, applications of MDO include the design of steel and concrete systems [6, 26]. In mechanical engineering, applications include the design of damage tolerant structural and mechanical systems, mechanisms [59], and thermal energy systems [10, 91]. Overlapping in each field is the study of materials which form the foundation of complex systems. Many times the selection of materials is coupled with the determination of physical design variables, further increasing the complexity of the system analysis.

4. CLOSURE

With many individual research directions, a linguistic framework for research and application is needed. In most pure science fields such as chemistry and biology, there is a standard framework and lexicon which are used now and forever. In order for MDO to continue to evolve and establish itself as a distinct field, a framework is needed, including a common lexicon for researchers and industries. This framework must be applicable to an entire MDO process from concept generation to detail design. The most promising attempts at these have come in two forms. In [7, 22, 43], lexicons and classifications of approaches to MDO problem formulation and solution are presented. These types of classification gives the field a form of common communication to base future developments and research upon. If a common lexicon were established, the various work in academia, industry, and government could be easily classified and compared. In the FIDO program, a computer framework for MDO is being generated. This type of framework has been shown to be an excellent interface for multidisciplinary design issues among distanced design teams throughout a design process. Uncertain is where the present research in MDO could fit into computer frameworks of this type. Computer frameworks may become simply the housing for MDO research, where developments are integrated into the "guts" of the framework at the system or discipline level. This would allow for future developments, and would permit a design team to design and analyze a system without having to know about the inner workings of the algorithms, schemes, and routines. Also, unclear is how the evolution of the design process from concept design to detailed component design would be accommodated in a computer framework.

Along these lines, hypotheses for the future areas of research and application are identified:

- establishment and acceptance of a common lexicon or framework for both research and application in MDO.
- investigation and validation of approaches to solve the multiobjective mixed integer/continuous problem at the subsystem or system level.
- methods of quantifying the tradeoff between accuracy and efficiency and predicting trends depending on information and design stage.
- development and application of game theoretic principles to model complex design product and processes.
- investigation of the notion of satisficing as opposed to optimizing in the early stages of a design process.

Investigation of these hypotheses in the context of the issues addressed in this report will help further the evolution of MDO as a field and a science.

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