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Multi-objective multidisciplinary design of Space Launch System using Holistic Concurrent Design

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A B S T R A C T

In the present paper, a new multi-objective technique using Holistic Concurrent Design (HCD) is applied to optimize multidisciplinary design of Space Launch System (SLS). The HCD methodology could effectively be used to find the overall satisfaction of objective functions (selecting the design variables) in the early stages of design process. Furthermore, the HCD formally reduces the multi-objective constrained optimization problem to a single-objective unconstrained optimization. The coupling of objective functions due to design variables in an engineering design process will result in difficulties in design optimization problems. The most important selected disciplines to improve the mass and energy characteristics of SLS are propulsion and structure. Then, the design problem is established using the fuzzy rule set based on designer's expert knowledge with a holistic approach. The independent design variables in this model are nozzle exit pressure, combustion chamber pressure, oxidizer to fuel mass flow rate (O/F), stringer thickness, ring thickness, shell thickness. To handle the mentioned problems, a fuzzy – Multi-Objective Genetic Algorithm (MOGA) optimization methodology is developed based on the Pareto optimal set. The obtained results show a very good performance of the HCD technique to find the overall satisfaction and communication enhancement between designer with various backgrounds and clients. Consequently, this methodology will be evaluated and validated with one of the stages of the existing SLS.

1. Introduction

Multidisciplinary engineering systems are complex systems whose interconnected subsystems belong to different physical domains. Traditional design methodologies for such systems rely on subsystem partitioning, and hence they often result in more iteration and less desirable outcomes. Whereas traditional design methodologies suffer from the aforementioned drawback, a concurrent approach emphasizes the physical integration and communication amongst the subsystems.

As research on Multidisciplinary Design Optimization (MDO) has matured, the number of methods available to solve a given problem has increased. These methods can be divided into two classes: monolithic formulations and multilevel formulations. Monolithic formulations, which include the multidisciplinary design feasible (MDF), the simultaneous analysis and design (SAND) and all at once approaches, use a single system-level optimizer for the whole problem. However, the challenge is to consider a large number of design variables and attributes simultaneously [6,35,36].

Researchers have developed different MDO formulations [16,17,24] suitable for various applications [7,45,33,29,18,38].

Multilevel methods such as collaborative optimization (CO) [8], concurrent subspace optimization (CSSO) [49], and bi-level integrated systems synthesis (BLISS) [43] use subspace optimizations to promote discipline autonomy. The system level optimizer is then responsible for managing the interactions between the discipline optimizations and also this approach mimics an industrial setting. With the various MDO methods available, how does one decide which one to use for a given MDO problem? Typically, the selection of an MDO method is done in an ad hoc manner, since few benchmarking studies are available to make an informed decision [4]. Results from various studies have shown that the performance of a method can be dependent on its implementation, the characteristics of the problem being solved, and the optimizer employed [4,10,39]. Furthermore, for some problems, specific methods may either fail to return an optimum, or may not be suited to implementation [10]. Additionally, comparing the results between the studies can be difficult as the performance of an MDO method can depend on specific implementation details [51].

Moreover, after selecting an MDO method, it can be difficult to determine its proper or most efficient implementation. In the

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case of collaborative optimization, there are at least four major variants [5,42,9]. Though many of the implementations have been used to solve specific problems, there has been no study that has thoroughly tested each implementation in a statistically significant manner. Therefore, it is left to the practitioner to search through the literature, in an attempt to find an implementation that may work well for their particular problems [47].

As the review of the foregoing papers, these MDO disadvantages influenced the development of the Holistic Concurrent Design (HCD) methodology [12]. This paper introduces the HCD methodology that addresses the above-reminded issues. The methodology utilizes the tools of fuzzy logic to systematically define some subjective aspects, such as satisfaction, preference, and designer's attitude, which play a vital role in a design process in addition to objective aspects in the form of design attributes. Further, the HCD formally reduces the multi-objective constrained optimization problem to a single-objective unconstrained optimization problem. Consequently, not only does the HCD facilitate the communication between different disciplines, but it also results in a more practical solution for a Multi-objective Multidisciplinary Design Optimization (MMDO) problem. In order to adjust the subjective notions considered in the optimization model, the methodology examines the set of satisfactory design candidates against a performance super criterion that is defined based on a holistic multidisciplinary model of the system [13]. Another recent study, discussed a practical approach to the concurrent design of robot manipulators, which is based on HCD, as well as the utilization of a modular hardware-in-the-loop simulation [15].

The developed tools are intended to help to select the proper specifications of the design variables of SLS without going through elaborate details of other direct approaches. Then, this methodology utilizes the revealed research advantages and removes their disadvantages to apply HCD methodology in liquid propellant SLS. The HCD methodology can be used in MMDO problems.

The future work would be developing the framework of HCD reliability based design [2,3,37], risk identification, assessment and management [34].

Hence, the organization of the paper is as follows. In Section 2, the HCD methodology is described. In Section 3, Multi-Objective Genetic Algorithm (MOGA) is introduced. In Section 4, the SLS subsystems selection and their important parameters are presented in details. In Section 5, the presentation and evaluation of the Liquid Propellant Space Launch System HCD methodology are outlined. Finally, in Section 6, conclusions are drawn.

2. HCD methodology

2.1. Formulation of design process

A design problem consists of two sets: design variables $X = \{X_j\} = (j = 1, 2, \ldots, n)$ and design attributes $A = \{A_i\} = (i = 1, 2, \ldots, N)$. Design variables are to be configured to satisfy the design requirements assigned for design attributes, subject to the design availability $D = \{D_j\} = (j = 1, 2, \ldots, n)$. Each design attribute stands for a design function providing a functional mapping $F_i : X \to A_i$ that relates a state of design configuration X to the attribute A_i, i.e., $A_i = F_i(X)$ $(\forall i \in [1, N])$. These functional mappings can be of any form, such as closed-form equations, heuristic rules, or sets of experimental or simulated data. A design process can be defined as a multi-objective optimization subject to a number of constraints on the design variables and attributes due to the design availabilities and design requirements specified by the customer.

$$\min_{X\in D}\big[F_1(X), \ldots, F_{N_W}(X)\big]^T$$
$$\text{subject to} \quad \big\{F_i(G) \in G_i,\ G_i \subset R,\ i = N_W + 1, \ldots, N\big\} \qquad (1)$$

where N_W and $N_M \equiv N - N_W$ are the number of attributes that should be optimized and the number of constraints, respectively.

The process of HCD is performed in three phases: (i) primary phase in which proper intervals for the design variables are identified subject to design availability; (ii) secondary phase in which design variables are specified in their intervals in order to maximize an overall design satisfaction based on the design requirements and (iii) performance super criterion that is the criteria for evaluation of the best known solutions. Thus, the secondary phase will involve optimization of a single-objective function, yet it is critically dependent on the initial values of a large number of design variables. The primary phase makes the optimization more efficient by providing proper intervals for the design variables from where initial values are selected. The overall satisfaction is an aggregation of satisfactions for all design attributes. The satisfaction level depends on the designer's attitude that is modeled by fuzzy aggregation parameters. However, different designers may not have the consensus of opinion on satisfaction. Therefore, the system performance must be checked against a holistic super criterion to capture the objective aspect of design considerations in terms of physical performance. Designer's attitude is adjusted through iterations over both primary and secondary phases to achieve the enhanced system performance. Consequently, the HCD process is satisfaction-driven, using iterations to proceed to a higher degree of satisfaction until the ultimate achievement of the system performance. Therefore, this methodology incorporates features of both human subjectivity (i.e., designer's intention) and physical objectivity (i.e., performance characteristic) in multidisciplinary engineering design.

Satisfaction: A mapping μ such that $\mu : Y \to [0, 1]$ for each member of Y is called satisfaction, where Y is a set of available design variables or design attributes based on design requirements. The grade one corresponds to the ideal case or most satisfactory situation. On the other hand, the grade zero means the worst case or least the satisfactory design variable or attribute.

In HCD the design attributes are divided into two subsets:

Must design attributes (*M*): A design attribute is called must if it refers to customer's demand, i.e., the achievement of its associated design requirement is mandatory with no room for compromise.

Wish design attributes (*W*): A design attribute is called wish if it refers to customer's desire, i.e., its associated design requirement permits room for compromise and it should be achieved as much as possible [12].

Therefore,

$$M \cap W = \phi, \qquad M \cup W = A \qquad (2)$$

The satisfaction specified for wish attributes W_i $(i = 1, 2, \ldots, N_W)$ is $w_i(X) = \mu_{W_i}(X)$, and the satisfaction specified for must attribute M_i $(i = 1, 2, \ldots, N_M)$ is $m_i(X) = \mu_{M_i}(X)$. For each design attribute A_i (corresponding to either M_i or W_i), there is a predefined mapping to satisfaction a_i (m_i or w_i), i.e., $\{(A_i, a_i)$: $\forall i \in [1, N]$ $A_i \in A\}$. Consequently, fuzzy set theory can be employed for defining the satisfactions through fuzzy membership functions and also for aggregating the satisfactions using fuzzy-logic operators.

Overall satisfaction: For a specific set of design variables X, overall satisfaction is the aggregation of all wish and must satisfactions, as a global measure of design achievement.

2.2. Calculation of overall satisfaction

Must and wish design attributes have inherently-different characteristics. Hence, appropriate aggregation strategies must be applied for aggregating the satisfactions of each subset. Aggregation of must and wish satisfactions have shown in [19,50].