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## Utilizing Uncertainty Multidisciplinary Design Optimization for Conceptual Design of Space Systems

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#### Abstract

With progress of space technology and increase of space mission demand, requirements for robustness and reliability of space systems are ever-increasing. For the whole space mission life cycle, the most important decisions are made in the conceptual design phase, so it is very crucial to take uncertainties into consideration in this initial phase to assure a feasible, reliable and robust conceptual design baseline which dominates the later design direction and life cycle cost. To enhance space system design quality in the conceptual design phase, the utilization of Uncertainty Multidisciplinary Design Optimization (UMDO) in the systems engineering process is systematically studied in this paper. The UMDO theory is introduced and its application in space system design is studied considering the complexity of the system. A small satellite system design case is further discussed to demonstrate the efficacy of UMDO in improving the space system design. Keywords: Uncertainty Multidisciplinary Design Optimization; Conceptual design; Space system engineering

### **1** Introduction

In systems engineering, the designers should consider all relevant aspects of the product life cycle from design, manufacturing, to operation maintenance and end of life in the realistic world. Among these factors, some are deterministic and can be obtained and modelled accurately. Some others are nondeterministic and difficult to predict, and usually cause unanticipated or even unprecedented problems to the product. To decrease the probability of product failure and maintain the desired product performance with the impact of uncertainties on the product, it is essential to design for reliability and robustness.

For space systems, there are many nondeterministic factors which should be taken into consideration, including the uncertainties resulting from the design method (simplified empirical models) and manufacture technology limitations, and the uncertainties arising from the spacecraft itself and the environment it is involved in during assembly, launch and on-orbit operation. These uncertainties may cause some of the spacecraft's performances to change or fluctuate, or even cause severe deviation and result in function fault and mission failure. To avoid vast economic loss. reliability and robustness of the space system are key issues during the design, especially the conceptual design. In the traditional space system design, the spacecraft is decomposed into several subsystems, the system function and performance requirements are allocated into subsystems. The subsystems designers carry out the design task according to the system requirement, and the system design scheme is formed based on the combination of these subsystem designs. Now there is considerable research addressing the design

problems with uncertainties in the design of spacecraft subsystems or single disciplines, such as structure and antenna. As these subsystem designs are separately conducted and the designers mainly consider the uncertainties within the subsystem scope, the cross impacts of uncertainties of different coupling subsystems are ignored, which may result in either redundant or inadequate robustness / reliability. Considering the complex coupling feature of space system design, Uncertainty Multidisciplinary Design Optimization (UMDO) is an efficient method to solve the uncertainty problem. UMDO is a new trend of MDO (Padmanabhan 2003, Zang 2002). It can capture the cross impact and coupling effect of all the disciplines, especially the propagation of uncertainties among coupling disciplines, to achieve a system design optimum by efficient optimization and disciplinary organization strategy. It can greatly improve the design by digging out the potential value of coupling disciplinary collaboration design, and meanwhile enhance the reliability and robustness. Being more close to the systems engineering realistic, UMDO has attracted wide attention and is now under rapid development.

The following parts of the paper will discuss the UMDO theory and its application to space system design.

## **2 UMDO Theory**

UMDO is referred to the methodology that solves the uncertainty design optimization problem of complex systems by fully considering the coupling relationship and uncertainty propagation between disciplines involved in the system. From this point, it could be considered as a tool to support the process. systems engineering For an multidisciplinary uncertainty design optimization problem, the general flowchart of solving procedure is depicted in figure 1.



# Figure 1. Flow Chart of Uncertainty Optimization.

In the diagram, the solving process is mainly divided into the following two parts.

(1) Uncertainty system modelling

Uncertainty system modelling is the first step to mathematically describe the design optimization problem, which is the premise of the further design optimization. It consists of system modelling and uncertainty modelling.

• System modelling

System modelling is the same as the traditional system modelling of product design optimization, which refers to the mathematical modelling procedure of product system and disciplines, and mathematical description of optimization problem, including the design variables, optimization objectives, constraints, robustness and reliability requirements, etc.

• Uncertainty modelling

Uncertainty modelling refers to the uncertainties classification and quantification involved in the product. There are many mathematical theories and methods to model uncertainties (DeLaurentis 2000, Uebelhart 2005, Wang 2006), such as the probability theory, fussy theory, evidence theory, and clouds theory (Neumaier 2007), etc. From product design and manufacturing to final operation and maintenance, there exist a vast number of uncertainties. To take every uncertainty into consideration, an unacceptable calculation burden is to arise based on the present computation capability, especially further considering the coupling influence and thousands of iterations in the optimization. To simplify the uncertainty problem and reduce calculation burden, it is generally necessary to utilize sensitivity analysis to screen out the factors which have no significant influence on system design. Only those greatly exerting impact on the system performance or constraints should be tackled during design optimization.

(2) UMDO procedure

UMDO procedure refers to the executive sequence of system (multidisciplinary) and disciplinary analysis, design of experiment (DOE), approximation modelling, design space searching algorithm, uncertainty analysis etc (Zhao 2007). It is the methodology about how to efficiently organize and realize UMDO in computing environment. As mentioned above, the key elements of the UMDO procedure include DOE and approximation modelling, optimization, and uncertainty analysis.

• DOE and approximation modelling

In UMDO, the system analysis and disciplinary analysis need be run thousands of times, which result in great calculation burden. So approximation methods should be utilized to construct metamodels of the high-fidelity models and substitute them in the optimization so as to balance the accuracy and cost (Padmanabhan 2002). To build approximation models, DOE techniques can be used to sample data in the design domain. The number of samples and the accuracy of approximation models are directly relevant. Generally speaking, more samples can achieve more information about the system so as to improve the approximation accuracy. But more samples

means more calculation needed to get the system response of these samples, which result in calculation burden in the construction of approximation model itself. So there is a trade-off between the sampling and approximation accuracy as well. There is lots of research studying these issues as how to obtain as much information as possible of the system in the design space with as few sample data as possible and how to improve approximation model accuracy with limited information (Jin 2000).

## • Optimization

Optimization refers to the design space exploration method, which is one of the most important and widely studied issues in UMDO. In traditional single discipline optimization problem, it is relatively mature to select the feasible algorithm according to specific features of the design optimization problem. But in UMDO, the optimization problem is usually large-scale, highly nonlinear, and non-convex. These characteristics result in multi local optimums, which can't be well solved by traditional search algorithm. So the intelligent algorithms which are random, non-gradient, robust, and insensitive to initial baseline features are widely studied, such as genetic algorithm (GA), simulated annealing (SA) algorithm, and Taboo algorithm etc (Wang 2006). As a matter of fact, both the traditional and the intelligent algorithm, have advantages, disadvantages and specific applicable fields. So the trend in this field is to study the hybrid optimization algorithm which is robust and efficient in global optimization.

• Uncertainty analysis

Uncertainty analysis is the key element of UMDO, which is the means to quantitatively analyze the uncertainty distribution characteristics of the system performances under the impacts of the uncertainties, so as to further analysis the reliability and robustness of the system. Especially for the complex system with multi-disciplines, the cross propagation of uncertainties causes great difficulty to the uncertainty analysis, which becomes the hot issue in the research of UMDO (Du 1999, Du 2000, Du 2002, Gu 2001, Oberkampf 2000, Marvris 1999).

According to the preceding analysis of the UMDO problem solving flow, the key technologies to realize UMDO and the UMDO theory architecture can be depicted as the figure 2.





## **3 UMDO Application in Satellite** Conceptual System Design

Because of the advantages of UMDO in solving complex system design optimization problem with uncertainties, it becomes one of the forefronts in the research of the systems especially in aerospace. In engineering. (DeLaurentis, 1998) a probabilistic approach is proposed and applied to an aircraft robust design. In (Aminpour 2002) a reliability-based MDO framework is proposed and applied in a Boeing transportation aircraft wing design. In (Uebelhart 2006) the non-deterministic design and analysis method is applied in a space telescope optical structures conceptual design. In (Hassan, 2008), a genetic algorithm with Monte Carlo sampling is proposed for probabilistic reliability-based design optimization of satellite systems. In (Fuchs 2008), an approach based on the clouds formalism is proposed to elicit and process the uncertainty information provided by expert designers and to incorporate this information into the automated search for a robust and optimal design of space system.

The previous works provide a good foundation for the application of UMDO in space system design. But further considering the specific features of space systems, the following aspects should be taken into consideration:

• The uncertainty modelling

In the conceptual design, there is limited information about the spacecraft. Many empirical models are used to predict the performance. The uncertainties stemming from the lack of knowledge and the simplification of the design models should be considered.

In addition, the spacecraft is the subsystem of the larger scale space-ground system, which includes launch vehicles, ground tracking and control stations, and other spacecrafts. So in the design procedure, not only the spacecraft product itself but also its interface with other components in the larger-scale system should be considered. For example, the performance and uncertainty characteristics of launch vehicles should be taken into consideration when design the spacecraft structure and make decision about the choice of launch vehicles.

• The decision for UMDO procedure

The space system design involves several disciplines, such as orbit, payload, structure, thermal control, power, onboard data handling (OBDH), telemetry tracking and control (TTC). These disciplines are closely coupled which brings great complexity to the system analysis to obtain a consistent design. In single level optimization procedure, all the disciplines are coupled together to run the analysis, which is very time-consuming. So it is better to use optimization multi-level procedure to decompose the complex problem into small subsystems within manageable scope, so as to problem solve the whole efficiently. Meanwhile, in industry, different discipline specialists usually do the design work separately and independently, where concurrent design is desirable. The multilevel optimization procedure can support concurrent design effectively, for example Concurrent Subsystem Robust Design Optimization procedure (Chen 2004), and Game Theory Composite SubSpace Uncertainty based Optimization procedure (Yao 2009).

### 4 Case Study

To demonstrate the application of UMDO in space system design, an earth observatory small satellite is chosen to exemplify the efficacy of UMDO.

• Satellite Design Modelling

The task requirement of the satellite is to observe a specific area with minimum resolution of 30m and minimum swath width of 50km. The discipline models, including orbit, payload, structure, and other satellite bus subsystems, are set up based on the approaches given in (Wertz, 1999). The mission orbit is a sun synchronous circular recursive orbit. In the orbit discipline, the altitude is chosen as the design variable to calculate other orbit parameters. The payload is a CCD camera with the working spectrum from 0.4 to 0.9 um. The focus length is the design variable, and the payload mass and power are predicted with scaling empirical equations. The configuration of the satellite is a box with height, width (the cross section is square), thickness of the structure wall as the design variables. The coupling relationships of the disciplines are shown in the design structure matrix in figure 3. In the diagram, "M" and "P" with subscript "\*" mean the mass and power value of the discipline "\*".



Figure 3. Design structure matrix of satellite system design.

In this diagram, only five design variables are considered, including: the orbit altitude h (km), the CCD camera focus length  $f_c$  (mm), the structure configuration dimensions width b (mm), height l (mm), and thickness t (mm).

• Uncertainty modelling

The uncertainties are classified into two groups. One is the group of design variables (to be defined and optimized) with uncertainties, and the other one is the group of parameters (constants during design and optimization) with uncertainties.

The uncertainties with structure dimension design variables and the optical lens are mainly induced by manufacturing uncertainties. The orbit altitude prediction uncertainty mainly results from perturbation influence. We assume these five design variable deviation distributions to be normal. The mean values are the design values of the variables. The uncertainty standard deviations are listed in table 1.

Table 1: Uncertainty Design Variables inSatellite Conceptual System Design

Discipline	Parameters	Distribution	
Structure	Width /mm	Normal	
		S.d. 0.5	
	Height /mm	Normal	
		S.d. 0.5	
	Thickness /mm	Normal	
		S.d. 0.01	
Orbit	Altitude /km	Normal	
		S.d. 0.5	
Payload	Lens focus /mm	Normal	
		S.d. 0.1	

The uncertainty parameters considered are the structure material quality uncertainties (e.g. Young's modulus, material density, material vield stress. etc.), the launch vehicle characteristic uncertainties (e.g. the launch vehicle axial natural frequency, axial overload coefficient, etc.), and the conceptual design model uncertainties as a result of the utilization of the simplified empirical equations (e.g. the scaling prediction models). Not all of the uncertainties should be taken into consideration; otherwise the calculation burden

will be unacceptable. So sensitivity analysis is utilized to find out the factors with significantly influence on the system design. The analysis shows thirteen design parameters to be considered with uncertainties, which are listed in table 2.

Table 2: Uncertainty Parameters in Satellite					
Conceptual System Design					

DisciplineParametersDistributionStructureLaunch vehicle axial natural frequency /HzNormal Mean 30.0 S.d. 0.3Launch vehicle lateral natural frequency /HzNormal Mean 15.0 S.d. 0.15Axial overload coefficientNormal Mean 6.0 S.d. 0.06Lateral overload coefficientNormal Mean 3.0 S.d. 0.06Lateral overload coefficientNormal Mean 3.0 S.d. 0.03Axial ultimate tensile strength / N/m2Log normal Mean 4.2e8 S.d. 4.2e5Axial stretch yield stress / N/m2Log normal Mean 3.2e8 S.d. 3.2e5Young's modulus / N/m2Normal Mean 7.1e10 S.d. 7.1e7Thermal ControlPower prediction scaling factorNormal Mean 0.05 S.d. 0.0005TTCPower prediction scaling factorNormal Mean 0.05 S.d. 0.0005		
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S.d. 0.0005		
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scaling factor [0.04, 0.05]		

• UMDO optimization problem model

The optimization objective is to minimize the satellite cost, which grows as satellite mass grows. As the cost estimation models are mainly empirical equations which are quite inaccurate, we directly define minimization of

satellite mass as the optimization objective. Considering the uncertainty influence, the objective is to minimize the mass expectation  $(\mu_{M,\mu})$ . Meanwhile, the observation resolution is variable according to the orbit parameter prediction uncertainty and optical instrument manufacturing uncertainty. To maintain a required observation capability, the standard deviation of the resolution ( $\sigma_d$ ) is also chosen to be minimized as the robustness objective of the design. So the optimization is a multi-objective problem. These two objectives are linearly summed to simplify the problem into a single-objective optimization. The coefficients can be adjusted according to the preference of these two separate objectives.

Several constraints are set to meet the design requirements, such as the structure volume V (to accommodate the installation of instruments), the structure reliability safety index Index<sub>str</sub> (the ratio between the design thickness and the structure critical thickness), observation resolution d, orbit coverage swath width  $S_w$ , and orbit eclipse factor  $k_e$  (to meet the charging requirement of solar panels). Taking uncertainties into consideration, the values of the states in these requirements are variable as well. To assure that all the constraints are satisfied under influence of the uncertainties, the reliability requirements are set to satisfy the constraints with given reliable index 0.9999. To sum up, the UMDO mathematical description is as following:  $\{find \mathbf{X} = \{h, f, h, l, t\}$ 

find	$\mathbf{X} = \{h, f_c, b, l, t\}$
Min	$f(\mathbf{X}, \mathbf{p}) = \frac{k_1}{w_1} \mu_{M_{inteal}} + \frac{k_2}{w_2} \sigma_d$
s.t.	$g_1: P_r\{V(\mathbf{X}, \mathbf{p}) \ge 0.5m^3\} \ge 0.9999$
J	$g_2: P_r \{ Index_{str}(\mathbf{X}, \mathbf{p}) > 1 \} \ge 0.9999$
]	$g_3: P_r\{d(\mathbf{X}, \mathbf{p}) \le 30m\} \ge 0.9999$
	$g_4: P_r\{S_w(\mathbf{X},\mathbf{p}) \ge 50km\} \ge 0.9999$
	$g_5: P_r\{k_e(\mathbf{X}, \mathbf{p}) \le 0.35\} \ge 0.99999$
	$500 \le h \le 1200, 200 \le f_c \le 1000$
l	$500 \le b \le 1500, 500 \le l \le 1500, 2 \le t \le 80$

329

In the equation,  $w_1$  and  $w_2$  are scalar factors to adjust the two single optimization objectives to be in the same order of magnitude.  $k_1$  and  $k_2$ are weight coefficients to adjust the preference of the multi-objectives. **p** is the state vector in the design and optimization process. The symbol " $P_r$  {\*} " represents the reliability of the event in the braces to exist. It can be seen that the robustness and reliability requirements are integrated into the optimization problem.

The UMDO optimization is organized with Game Theory based Composite SubSpace Uncertainty Optimization (GBCSSUO) procedure, as depicted in figure 4. Firstly, the satellite system design and optimization problem is decomposed into several subsystem optimization (SSO) problems. In this case, SSOs correspond to the disciplines with design including orbit, payload, and variables. structure. Design of experiment is used to select the initial feasible design as the basement of the optimization. In the subsystem uncertainty optimization, the three disciplines are organized in such a way that payload is firstly optimized and followed by the optimization of orbit and structure. In the subsystem uncertainty optimization, the uncertainty characteristics of the design is analysed with the Taylor series approximation method. In the system optimization, the system reliability and robustness are calculated with Monte Carlo method. As the system design analysis models are mainly simple empirical equations, approximation models are not used in the optimization.



Figure 4. GBCSSUO procedure of the satellite system UMDO.

The results are shown in figure 5.





In the figure 5, the iteration history of the satellite mass mean value, the resolution mean value and its standard deviation are plotted. At the early iterations, the mass mean value is decreased greatly compared to the initial design baseline. The resolution is on the verge of the constraint, which may violate the constraint with large probability as the standard deviation line plotted in the figure crosses the constraint line. As the optimization procedure evolves, the resolution mean value moves away from the constraint and maintains the reliability with  $3\sigma$  requirement. Meanwhile, it can be seen that the standard deviation of the resolution has been reduced as well. But the satellite mass mean value increases a little as the sacrifice. This validates the efficacy of UMDO in improving the conceptual design of space systems. The UMDO optimization result is also compared with that of MDO optimization without considering uncertainties, listed in table 3.

		UMDO		MDO	
Variables	h	502.943		500	
	$f_c$	236.185		233.354	
	b	951.096		937.642	
Va	l	561.872		573.350	
	t	2.323		2.762	
ints	$S_w$	61.579	$P_{r} = 1$	61.960	$P_{r} = 1$
	d	29.812	$P_{r} = 1$	29.997	$P_r = 0.54$
Constraints	$k_{e}$	0.263	$P_{r} = 1$	0.264	$P_{r} = 1$
Cor	V	$0.504  P_r = 1$		0.500	$P_r = 0.48$
	Index <sub>str</sub>	1.221	$P_{r} = 1$	1.4549	$P_{r} = 1$
Objective	$\mu_{_{M_{total}}}$	123.926		123.489	
	$\sigma_{_d}$	0.0322		0.0327	

Table 3: Optimization Results Comparisonbetween UMDO and MDO

It can be seen that the satellite mass mean value of MDO result is better than that of UMDO. But there are two constraints in the MDO result can't meet the reliability requirements. The standard deviation of resolution in the MDO result is also not as good as that of UMDO. This confirms that with UMDO reliability and robustness of design optimization can be achieved.

#### **5** Conclusions

In this paper, the problem of utilizing the UMDO methodology in the conceptual design of space systems is studied. A case study of using UMDO in the system design of a small earth observatory satellite is discussed and the result demonstrates the efficacy of UMDO. But the disciplinary analysis models in the case study are mainly empirical equations, and the uncertainty models are based on theoretical assumptions, which are much simpler than the real industry system design models, so future study should be carried out in cooperation with the industry to root the uncertainty system modelling in the real engineering world. Meanwhile in the realization of MDO procedure in the case study, we found that different initial baseline has great influence on

optimization result. To select a feasible start design is very important to guarantee the optimization search convergence. An efficient way to select the feasible start point is to design by use of the existed knowledge and past experience according to the design task requirements. So to utilize knowledge based engineering (KBE) in UMDO will be an important issue in the future research.

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9

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