UNCERTAINTY MULTIDISCIPLINARY DESIGN OPTIMIZATION OF SPACE SYSTEMS IN THE PRESENCE OF NEW ATTRIBUTES

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The problem of new attributes and the induced uncertainties has been extensively discussed in this paper. The methodology of uncertainty multidisciplinary design optimization has also been extended to spacecraft conceptual design in the presence of new attributes. The application of this methodology on fractionated spacecraft indicates that the proposed method is able to provide useful information under uncertainties induced by new attributes.

I. INTRODUCTION

The design of spacecraft is a challenging task due to the complexity and multidisciplinary nature of space systems. This implies that the spacecraft engineers should consider all relevant aspects of the space product life cycle from design, manufacturing, operation until the end-of-life disposal. However, the environment in which space systems are developed and operated is extremely dynamic. Some factors of life cycle cannot be accurately modelled due to the lack of knowledge, especially in the early stage of product development. Some factors are even inherently unpredictable. To maintain the desired product performance and avoid losses in later stages, it is essential to develop the space systems under uncertainties.

For the uncertainty design of innovative space systems, special attentions are to be put on two aspects. The first issue is the cross impact of uncertainties of various coupling subsystems or disciplines. If this cross impact is ignored, under- or over-redundancy may occur and, inadequately, robustness/reliability problem is likely to be caused. The other issue is the uncertainties induced by new attributes. Over the past few years, the emphasis on space systems has changed from performance to new attributes such as economics, flexibility and responsiveness. Many innovative space system architectures have been proposed according to these new attributes. For example, the concept of Operationally Responsive Space (ORS) focuses on the cost and responsiveness of future space systems while System F6 program aims to improve the flexibility through spacecraft fractionation. The introduction of new attributes results in new uncertainties, not only on technical aspect, but also in economics, market and policy domains, which makes the uncertainty design of innovative space systems much more complicated.

A considerable research has been done to address the uncertainty problem in the design of spacecraft subsystems. For example, Dando developed a robust direct adaptive control strategy for spacecraft attitude tracking maneuvers, in the presence of dynamic model uncertainty in the spacecraft inertia matrix[1]; Croisard et al. used Evidence Theory to investigate the trajectory optimization problem with a set of uncertain parameters[2]; Kristiansen et al. studies the control problem of a leader-follower spacecraft formation under parameter uncertainty (spacecraft mass) and uncertainty in the leader variables (true anomaly rate and rate of change)3; Calvi performed the uncertainty-based structural loads analysis for Ariane 5 and the ESA INTEGRAL satellite[4]; Lal et al. studied the propellant gauging system with the uncertainties in sensor measurements[5]; Fuchs et al. investigated the optimization problem of the AOCS subsystem for the NASA's Mars Exploration Rover (MER) mission, taking into account the uncertainties of variables and models[6].

At the system level, research work focuses on two aspects. The first one is quantifying uncertainty in space system architectures in the presence of new attributes. In this field, a serial of work has been done using the Generalized Information Network Analogy (GINA) or the Multi-Attribute Tradespace Exploration (MATE) methodologies[7,8,9,10,11]. The other field is the optimization of spacecraft with technical uncertainties. For example, Smith et al. proposed a reliability-based multidisciplinary optimization methodology to optimize the geometry of a reusable launch vehicle for minimum weight while satisfying uncertain aerodynamic constraints[12]; Yao et al. utilized Uncertainty Multidisciplinary Design Optimization (UMDO) method on the conceptual system design of an Earth observation small satellite[13].

This paper attempts to answer two questions:

1. How can the uncertainties that are induced by new attributes be better understood?
2. How can the space systems be optimized, more specially by utilizing Uncertainty Multidisciplinary Design Optimization (UMDO) technology, in the presence of uncertainties that are related to new attributes?

The paper consists of three primary parts. The first part introduces uncertainties and attributes of space systems, with a focus on uncertainties induced by new attributes. The second part provides an approach to integrate uncertainties induced by new attributes into existing UMDO infrastructure. Issues related to uncertainty system modelling are discussed in detail in the context of new attributes/architectures. In the final part, a case study is presented. Due to the revolutionary architecture and the involvement of new attributes, the fractionated spacecraft is chosen to demonstrate the efficiency of UMDO in spacecraft conceptual design.

II. ATTRIBUTE AND UNCERTAINTY OF SPACE SYSTEMS

Before the discussion of UMDO of space systems in the presence of new attributes, it is helpful to understand the meaning and relationship of attribute and uncertainty.

II.I Attribute

"Attribute" is usually defined as an abstraction of a characteristic of an entity or substance14. The decision-makes always desire a design that meets all of his needs. In this case, "attribute" refers to as a metric that measures how well the objectives defined by decision-makers are met[15]. Or in other words, the attributes are the criteria that decision-makers will use to determine the relative goodness of the design.

Traditional space missions are performance or mission driven, which implies that the attributes are usually selected from technical performances. Table 1 provides a list of traditional attributes of an Earth Observation (EO) system.

Attribute	Units	Acceptance Range
Global coverage	%	75-100
Swath width	km	20-100
Resolution	m	0.1-1
Revisit time	days	0.2-2
Availability	%	95-100

Table 1: Traditional attributes of an EO system.

Recently, the emphasis on space systems has changed from performance to other aspects, such as economics, robustness, responsiveness and flexibility. These new attributes are defined as follows:

- Economics: the lifecycle costs of the total space system to meet the mission demand;
- Robustness: the intrinsic ability of a space system to maintain functionality in response to unforeseen circumstances (internal or external perturbations)[16];
- Responsiveness: the timeliness with which the space system responds to the mission needs; and,
- Flexibility: the ability of a space system to adapt to new demands[16].

1st Level Attribute	2nd Level Attributes	Definition
Economics	Development cost	The cost of design, manufacturing and Assembly, Integration and Test (AIT) of a space system, including both space and ground segments
	Launch cost	The cost of launch the total system into orbit
	Operating cost	The cost of operating the system until the end of life
Robustness	Reliability	The ability of a system to function under normal conditions
	Survivability	The ability of a system to function under abnormal or unanticipated conditions
	Resilience to fragility	The (in)frequency with which a system succumbs to unmodeled failures
	Fault tolerance	The gradual loss of system functionality due to one or more failures
Responsiveness	Timeliness	The time from the identification of user needs to mission capability
Flexibility	Scalability	The ability to add capability to a system throughout its lifetime
	Upgradeability	The ability to upgrade part of a system due to technology progress
	Maintainability	The ability to replace part of a system that have failed or are near the end of life
	Adaptability	The ability to reconfigure existing system functionality to meet new needs

Table 2: Typical new attributes of space systems.

These attributes, here called as *first level attributes*, are sometimes too vague. Therefore, in practice it is necessary to refine them with *second* or even *third level attributes*. Table 2 provides corresponding *second level attributes* and their definitions. Further explanations of these attributes are mission-dependant and should be discussed case by case. In addition, performance-related attributes, such as those in Table 1, can be treated as second level attributes under the first level attribute "performance".

II.II Uncertainty

In this paper, the term "uncertainty" is defined as the inability to deterministically predict the characteristics of a space system. Uncertainty is sometimes positive, which is different with the term "risk" as the latter one always reflects a negative meaning of the probability of loss11.

Uncertainties come from various sources, such as incomplete information, disagreement between information sources, linguistic imprecision, variability and randomness5. They can be categorized according to different criteria. For example, based on mission phasing, uncertainties are classified as development uncertainty and operational uncertainty[11]; according to knowledge fields, uncertainties are grouped into political uncertainty, technical uncertainty, cost uncertainty, etc. In order to make a good design, it is essential to account for all uncertainties of the lifecycle at the beginning of system development.

During the traditional procedure of decision-making, only technical uncertainties in the model are considered since traditional attributes are performance-based only. These model uncertainties are caused by not capturing the physics correctly, or by the uncertain values of model parameters. An example of the former is the Finite Element Method (FEM), which can fail to accurately predict behavior in the high frequency. For the latter, examples of uncertain model parameters include material properties or controller gains. The problem of model uncertainties can be more or less solved by various approaches, such as increasing mesh density in FEM or utilizing the Design of Experiments (DoE) to filter uncertain parameters[17].

Under the existence of new attributes, the uncertainty problem is much more serious and complicated. This is reflected from following two aspects.

On one side, new attributes only make sense in the presence of uncertainties. Robustness and flexibility are both worthless in a world that is static, certain and a priori deterministic[16]. Responsiveness is important only when the environment is uncertain, because one needs to respond to sudden unexpected threats or opportunities. Therefore, uncertainty is an essential element of space system design, especially in the conceptual and preliminary stages.

On the other side, new attributes introduce new types of uncertainties, mainly non-technical ones, into consideration. These uncertainties already exit there, but have not been accounted for by decision-makers before. The categorization of possible uncertainties is provided in Table 3[11].

It can be found from Table 3 that each uncertainty is associated with one or more attributes. For example, the *schedule uncertainty* will strongly influence the responsiveness; and the *obsolescence uncertainty* and the *market uncertainty* are both vey important for flexibility. Moreover, the uncertainties are also linked

Uncertainty	Definition	Example(s) of uncertain situation
Cost uncertainty	Uncertainty of developing, launching and operating within a given budget	Budget overrun
Political uncertainty	Uncertainty of funding instability	Funding cut due to financial crisis; Funding increase due to increasing interests
Schedule uncertainty	Uncertainty of developing, launching and operating within a given schedule profile	Delay due to payload damage during tests
Technology uncertainty	Uncertainty of technology to provide performance benefits	Failure to mature a technology during the development phase
Requirement uncertainty	Uncertainty of requirements stability	Stakeholders change existing requirements or identify new requirements during the development phase
Launch uncertainty	Uncertainty of launch	Launcher fails to put the satellite to desired orbit
Lifetime uncertainty	Uncertainty of performing to requirements in a given lifetime	Mission is terminated before expected lifetime due to power failure
Obsolescence uncertainty	Uncertainty of performing to evolving expectation in a given lifetime	Emergence of novel antenna or sensor
Market uncertainty	Uncertainty of meeting demands of an unknown market	New multimedia communication requires increased bandwidth
Integration uncertainty	Uncertainty of operating with other necessary systems	Failure to communicate with data relay satellites

Table 3: Typical uncertainties of space systems.

with each other due to the multidisciplinary nature of space systems. A good example here is the schedule uncertainty and the cost uncertainty, as a delay of the development stage usually indicates an increasing of development cost.

III. UMDO OF SPACECRAFT WITH NEW ATTRIBUTES

UMDO is referred to as 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 systems engineering process. In this section, an introduction of the general UMOD method is provided, followed by a detailed description of the adaptation of UMDO on spacecraft conceptual design with the consideration of new attributes.

III.I General UMDO

For an UMDO problem, the general flowchart of solving procedure is depicted in Fig. 1[13].

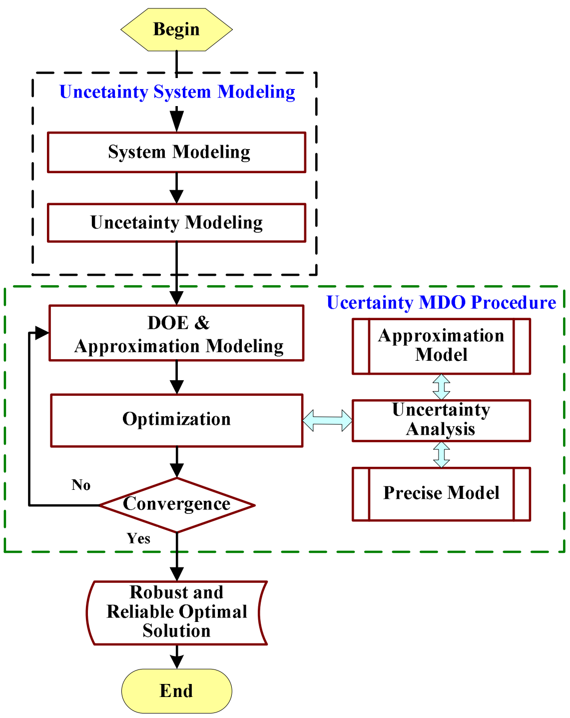

Fig. 1: General flow chart of UMDO.

According to Fig. 1, the UMDO solving process consists of two primary parts, i.e. *Uncertainty System Modelling* and *Uncertain MDO Procedure*.

III.I.I Uncertainty system modelling

Uncertainty System Modelling is to mathematically describe the UMDO problem, which is the premise of further design optimization.

The first step of *Uncertainty System Modelling* is to build up the system model, which is the same as the traditional system model of normal MDO problem. The system model usually is comprised of a set of independent variables, a set of dependent variables, and a set of equations (explicit or implicit) that reflect the mathematical relationship between the dependent and the independent variables.

Then the next step is *Uncertainty Modelling*, i.e. uncertainties classification and quantification. There are many mathematical theories and methods to model uncertainties[17,18], such as the probability theory, fussy theory, evidence theory, and clouds theory[19], etc. Usually the uncertainty is modelled from two aspects: the uncertainty of independent variables and the uncertainty of system model parameters.

Finally, the output of the uncertainty system modelling will be an optimization problem formulated as:

$$\begin{cases} Find & \mathbf{X} \\ Min. & f(\mathbf{X},\mathbf{p}) = \dfrac{k_1}{w_{\mu_f}}\mu_f(\mathbf{X},\mathbf{p}) + \sum_{l=1}^{r}\dfrac{k_{l+1}}{w_{\sigma_l}}\sigma_l(\mathbf{X},\mathbf{p}) \\ s.t. & P_r\{\mathbf{g}(\mathbf{X},\mathbf{p}) \le 0\} \ge R_g \\ & P_r\{|\mathbf{h}(\mathbf{X},\mathbf{p})| \le \varepsilon\} \ge R_h \\ & \mathbf{X}^L + \Delta\mathbf{X} \le \mu_{\mathbf{x}} \le \mathbf{X}^U - \Delta\mathbf{X} \end{cases} \qquad [1]$$

Where **X** are design (independent) variables, $\Delta\mathbf{X}$ are tolerance of **X**, **p** are system model parameters, f is objective function, μ_* and σ_* are the mean and the standard deviation of system output "*" subject to uncertain **X** and **p**, k_* and w_* are factors in multi-objective optimization, **g** and **h** are inequality and equality constraints, and $P_r\{*\}$ is the probability of * is true.

III.I.II UMDO procedure

UMDO procedure refers to the executive sequence of system analysis, system decomposition, design of experiment (DOE), approximation modelling, design space searching algorithm, uncertainty analysis etc13. It is the methodology about how to efficiently organize and realize UMDO in computing environment. As mentioned above, the key elements of UMDO procedure include DOE and approximation modelling, optimization, and uncertainty analysis.

In UMDO, approximation methods are utilized to construct metamodels of the high-fidelity models and substitute them in the optimization so as to balance the accuracy and cost20. To build approximation models, DOE techniques can be used to sample data in the design domain. The accuracy of approximation models is dependent on the number of samples. However, overmany samples could result in calculation burden in the construction of approximation model itself. So there is a trade-off between the sampling and approximation accuracy.

Optimization is referred as the design space search method. In UMDO, the optimization problem is usually large-scale, highly nonlinear, and no convex. These characteristics result in multiple local optimums, which cannot be well solved by traditional search algorithm. So the intelligent algorithms which have random, non-gradient, robust, and insensitive to initial baseline features are widely studied, such as genetic algorithm (GA), simulated annealing (SA), and Taboo algorithm etc. A trend in this field is to study the hybrid optimization algorithm that is robust and efficient in global optimization.

Uncertainty Analysis is another key element of UMDO, which quantitatively analysis the uncertainty distribution characteristics of the system performances under the impacts of the uncertainties. For the complex system with multiple disciplines, the cross propagation of uncertainties causes great difficulties to the uncertainty analysis[21]. Methods that could be used for uncertainty analysis include Monte-Carlo simulation, First Order-Second Moment (FOSM) analysis, Second Order-Second Moment (SOSM) analysis, and so on.

According to the preceding analysis of the UMDO problem solving flow, the parts involved in uncertainty are uncertainty modelling and uncertainty analysis, which can use uncertainty theory to manage and analysis the propagation of uncertainties.

III.II UMDO of Spacecraft with the Consideration of New Attributes

The general procedure introduced in Section III.I applies to UMDO of all engineering products. However, the constructions of most elements in Fig. 1 are problem-specific. For the UMDO of spacecraft, especially with new attributes, the focus is on uncertainty system modelling, including system modelling, uncertainty modelling and optimization problem modelling.

III.II.I System modelling with new attributes

The system modelling of spacecraft is traditionally only based on the attribute “performance”. For example, the system model of the EO system that was introduced in Table 1 consists of models of orbit, payload, structure and other subsystems, as shown in Fig. 2. These subsystem models are set up according to well-known approaches, such as those introduced in the famous book “Space Mission Analysis and Design” (SMAD)22. However, the system model in Fig. 2 cannot reflect the new attributes that are discussed in Section II.I, i.e. economics, robustness, responsiveness and flexibility.

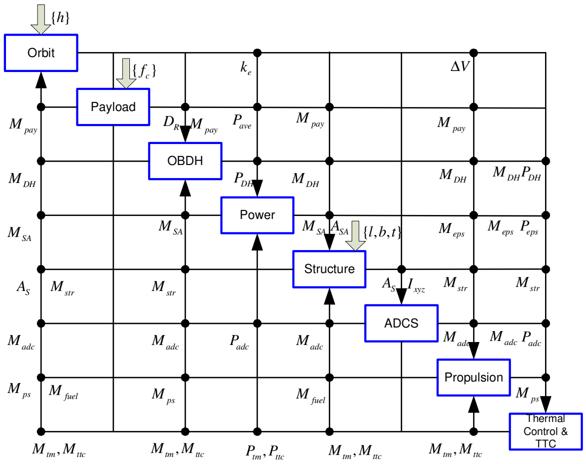

Fig. 2: General flow chart of UMDO.

In order to build up a system model incorporating new attributes, it is necessary to identify attributes and design variables.

Since the attributes are decision criteria, it is important that decision-makers are able to generate, perceive and articulate these attributes. Usually the generation of attributes is done through a top-down hierarchy process, wherein the decision-makers list high level goals and work downward in detail from them. The goal of this step is to find a shortlist (for practical not too many) of attributes that can be used to evaluate a proposed design and an acceptable range for each of the attributes.

The design variables are able to represent particular designs. On one hand, enough design variables are required to drive the first-order relationships between attributes and system designs[11]. On the other hand, a large number of design variables will cause serious computational burden because the number of designs grows geometrically as the number of design variables increases11. A possible way to select appropriate design variables is to utilize a derivative Quality Function Deployment (QFD) table. In this QFD table, a set of attributes are on one axis, and a full set of potential design variables are on the other. Relationships between attributes and design variables are captured with scores from 1 to 9, and attributes are weighted between 1 and 5. A small number of design variables are selected from the top list, and the others are treated as constants.

System modelling is done by linking disciplinary models, which (directly or indirectly) utilize (part or all) design variables as independent input and (part or all) attributes values as dependent output. Which disciplines should be involved in system modelling depends on the selection of attributes and design variables and, therefore, are very problem-specific. However, there are some general guidelines on how to build up non-traditional disciplinary models.

For example, in economics usually the development cost, launch cost and operation cost are the focuses. The development cost can be determined by Cost Estimation Relationships (CERs). Typical examples of CERs include the Air Force Space and Missile Center's Unmanned Space Vehicle Cost Model (USVCM) and the Aerospace Corporation's Small Satellite Costing Model (SSCM), both providing an estimation of the recurring and non-recurring costs associated with a satellite's development based upon some basic systems parameters such as size, mass and power. The launch cost is determined by the selection of launch vehicle and the ratio of the mass of the satellites to be launched. The operation cost can be modelled as fixed annual value considering the inflation.

Another example is the responsiveness. Since responsiveness is reflected by timelines, it is necessary to include a schedule model in the system model. Several 2nd level attributes can be used to assess responsiveness. For instance, it could be the timeline of receiving the first set of data, or the timeline of fully functional system. Many schedule models have been investigated and are now available. One of the models is based on a list of activities that are required to proceed from user needs to a pre-defined stage, e.g. a fully operational system. These activities each consist of many shorter tasks that are assigned a nominal timeline. The time to accomplish all the tasks within an activity is added together as the timeline of this activity[11].

It is also possible to build up models to reflect other new attributes. For example, the upgradeability model can be established according to Technology Readiness Levels (TRLs).

<u>III.II.II Uncertainty modelling with new attributes</u>

After incorporating new attributes into the system model, it is now the time to model uncertainties related to these new attributes.

Although there are many approaches to model uncertainties, the easiest way is to assign uncertainties to system model parameters. These parameters could be (independent) design variables, or any other variables that are not controlled by the designers. For instance, the market model of a communication satellite is determined by the total market size of customers, percent market capture for this project, and the discount rate used in the cash flow analysis. To model its market uncertainty, one could assume the mean value of the market size with a lognormal distribution that is consistent with previous market analysis[7].

It is also possible to incorporate uncertain events into the system model. For example, the schedule model consists of timelines of various activities and tasks; then any delay within an activity can be modelled as point event opportunity occurring stochastically. Another example is the more traditional attribute "*reliability*". The system reliability model is based on component failures that can occur throughout the lifetime; therefore the uncertain event of component failure can be modelled as a distribution, e.g. the Weibull distribution, along the time axis.

By setting up the uncertainty model, the assessment of system model with new attributes can be implemented through Monte-Carlo simulations. The output of this assessment will be the mean and the stochastic distribution of attribute values (i.e. dependent variables), which could be used in the *Uncertainty MDO Procedure* for optimization.

<u>III.II.III Optimization problem setup</u>

There are two issues related to setting up the optimization problem. The first one is the incorporation of new attributes into optimization problem.

Usually the attributes are selected by decision-makers and reflect their preferences and focuses. Therefore it is natural that these preferences are also captured by optimization objectives. In most cases more than one attribute will be selected, which results in a multi-objective optimization problem. Solving such an optimization problem maybe is not a big issue, and the traditional but efficient approach is to transform multi-objective optimization into single-objective through, e.g. weighting. However, the values of different objectives are likely to be at totally different order of magnitude, which will cause serious problem if the traditional approach is used. In this research, a method called Multi-Attribute Tradespace Exploration (MATE) is utilized. The MATE method was proposed by MIT as a methodology to evaluate space architectures[11]. The baseline of the MATE is: define a utility curve (magnitude from 0 to 1) for each attribute according to its maximally useful and minimally acceptable values; then a Multi-Attribute Utility (MAU) score $U(X)$ is assigned to the architecture by solving

$$KU(X)+1=\prod_{i=1}^{N}(Kk_iU(X_i)+1) \qquad [2]$$

for $U(X)$. Here $U(X_i)$ is the utility of attribute i, k_i is the weighting factor for attribute i, and K is the overall weighting factor. Since all objectives (attributes) are normalized to 0-1, the weighting factors in Eqn.2 only reflect the importance of each attribute, and are not related to the order of magnitude.

Another issue is the incorporation of uncertainties. As introduced in Section III.II.II, the output of the uncertainty model will be the mean and the stochastic distribution of each attribute. Therefore it is straightforward to normalize these values, resulting in the mean of the MAU score and its distribution.

IV. CASE STUDY

In this section, a case study will be presented to demonstrate the availability of UMDO for spacecraft conceptual design. Due to the revolutionary architecture and the involvement of new attributes, the fractionated spacecraft is possibly the best candidate for the case study.

IV.I Fractionated Spacecraft

Fractionated spacecraft represent a novel architecture for distributed space systems. The generalized concept of a fractionated spacecraft is to break a large monolithic spacecraft into smaller, heterogeneous, wirelessly interconnected modules23. Each module has a unique function such as Guidance, Navigation and Control (GNC), and command and data handling, and all modules fly freely in approximately the same orbit. Although doubts on its economics exist, the fractionated spacecraft is attracting more and more attention from academia, industry and governments due to its advantages of rapid response, enhanced mission and in-orbit robustness, potential for mass production, flexibility with later added features and lowered mission recovery costs[24]. In some sense the fractionated spacecraft may be regarded as a game-changing event in the history of space systems, just like the internet revolutionized data communications.

IV.II Problem Setup

The fractionated spacecraft under investigation here is for Earth observation applications. The system model, uncertainty model and the optimization problem setup of fractionated spacecraft are as follows.

IV.II.I System model of fractionated spacecraft

Due to various limitations, only two attributes, i.e. system availability and mission duration, are selected. Accordingly, several design variables are identified, which can be found in Table 4. It should be noticed that the attributes and design variables here are not decided strictly by the QFD form and are only for demonstration purpose.

The system model of the fractionated spacecraft consists of disciplinary models of orbit, payload, spacecraft subsystems, schedule, lifetime, and cost.

IV.II.II Uncertainty model of fractionated spacecraft

The uncertainty model of fractionated spacecraft is constructed using both the approaches introduced in Section III.II.II. The uncertainty distributions of design variables are presented in Table 4. In the table, the coefficient of variation represents the ratio of the standard deviation to the mean. The mean value for the design variables is the current value set by the optimization algorithm. For simplification, a wild assumption is made, which assumes that all the design variables have same coefficient of variation. In addition, uncertain events are also considered, which include funding cut, development delay, launch failure and in-orbit failure.

Design variable	Distribution	Unit	Coefficient of variation
Semi major axis	Normal	km	0.01
Inclination	Normal	degree	0.01
Cluster diameter	Normal	km	0.01
Power Lifetime	Normal	year	0.01
ADCS Lifetime	Normal	year	0.01
TTC Lifetime	Normal	year	0.01
CDHS Lifetime	Normal	year	0.01
Propulsion Lifetime	Normal	year	0.01

Table 4. Uncertainty of design variables.

IV.II.III Optimization setup of fractionated spacecraft

In order to more clearly identify the influence of cost, the attribute "lifecycle cost" is not incorporated into the MAU in this paper. Therefore, the optimization has two objectives, i.e. maximization of MAU and minimization of cost. According to Eqn.1, this multi-objective optimization problem is re-formulated as a single objective optimization problem as:

$$\begin{aligned} &\textit{find} \quad \mathbf{X} \\ &Min \quad f(\mathbf{X}) = \frac{k_1}{w_1}\mu_{Cost} + \frac{k_2}{w_2}\sigma_{Cost} - \frac{k_3}{w_3}\mu_{MAU} + \frac{k_4}{w_4}\sigma_{MAU} \\ &s.t. \quad \mathbf{X}_L \le \mathbf{X} \le \mathbf{X}_U \end{aligned} \quad [3]$$

where μ_{Cost} and σ_{Cost} are the mean and the standard deviation of lifecycle cost respectively, μ_{MAU} and σ_{MAU} are the mean and the standard deviation of MAU respectively, and k_i and w_i are weight and scaling factor for the i th objective. In this paper the weight and scaling factors as set as

$$\begin{aligned} &k_1 = 0.7, \quad k_2 = 0.3, \quad k_3 = 0.7, \quad k_4 = 0.3 \\ &w_1 = 3000, \quad w_2 = 20, \quad w_3 = 0.8, \quad w_4 = 0.01 \end{aligned} \quad [4]$$

IV.III Results

The uncertainty performance of each design point is calculated with Monte Carlo simulation method, and the simulation number is 100. After the whole optimization process, the uncertainty analysis of the final design is carried out with 1000 Monte Carlo simulations. The design space search method is the multi-island genetic optimization algorithm. The optimization results are presented in Table 5.

Objective	Initial mean	Initial std. dev.	Optimal mean	Optimal std. dev.
MAU	0.8245	0.1398	0.7732	0.0062
Cost/ M$	3798	96.8969	2578.12	14.8005
Synthetic Objective	7.2551	-	1.6851	-

Table 5. Optimization results of the objective.

From Table 5 it can be found that the total cost has been reduced by sacrifice of MAU. In total, the synthetic objective has been greatly improved with the weight and scaling factors that were set in Eqn. 4.

The information behind Table 5 is more explicitly explained by the iteration history that is depicted in Fig.3~6. In Fig.3, Fig.4 and Fig.6, the bars indicate the standard deviation of corresponding parameter, i.e. its uncertainty, at the design point.

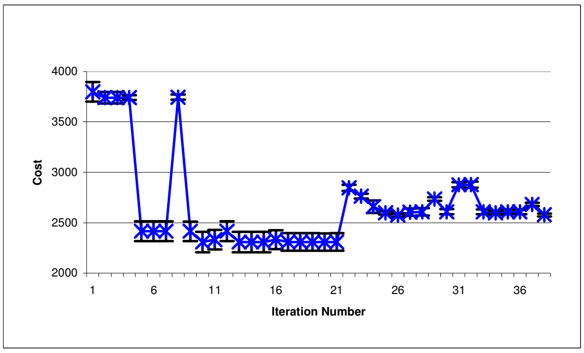

Fig. 3: Optimization history (Cost vs. Iteration number).

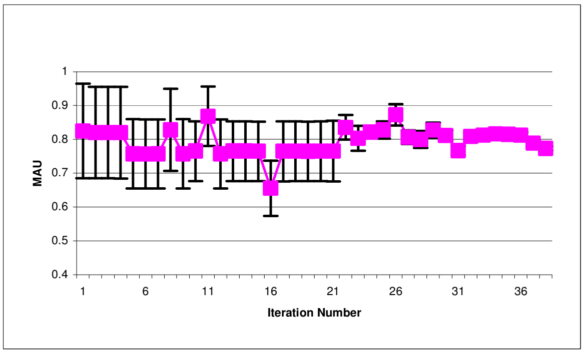

Fig. 4: Optimization history (MAU vs. Iteration number).

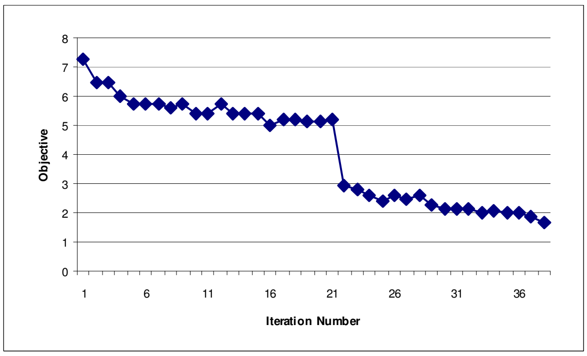

Fig. 5: Optimization history (Objective vs. Iteration number).

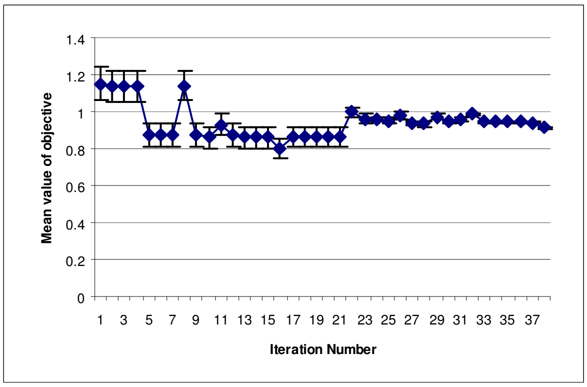

Fig. 6: Optimization history (Mean value and std. deviation of objective vs. Iteration number).

Compare Fig.3 with Fig.4, it can be found that the mean of lifecycle cost has similar trend with the mean of MAU in the first 20 iterations (design points). A higher mean of MAU is observed in the 11th iteration where the lifecycle cost is relatively low. It seems that the design point in the 11th iteration should be the optimal solution as the lifecycle cost of this design is lower than that of the final design, and meanwhile the MAU is higher. However, this is not true as uncertainties exist. In the first 20 iterations, the standard deviations of the lifecycle cost and the MAU are both very large. These deviations result in serious uncertainties of the synthetic objective, which could also be observed from Fig.6. According to Fig.5, the synthetic objective has been greatly reduced by the optimization after 20 iterations. This is due to the fact that the synthetic objective is not going to minimize the mean, but to minimize the combination of the mean and the uncertainty, which is indicated by comparing Fig.5 with Fig.6. In addition, the reduction of uncertainties could also be found from Fig.3, Fig.4 and Fig.6.

V. CONCLUSIONS

The problem of new attributes and the induced uncertainties has been extensively discussed in this paper. The methodology of UMDO has also been extended to spacecraft conceptual design in the presence of new attributes. The application of this methodology on fractionated spacecraft indicates that the proposed method is able to provide useful information under uncertainties induced by new attributes. Future works will be on increasing the optimization efficiency and improving the uncertainty model.

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