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Spacecraft Reliability-Based Design Optimization Under Uncertainty Including Discrete Variables

Rania Hassan* and William Crossley†
Purdue University, West Lafayette, Indiana 47907

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High reliability is a primary design goal in commercial communication satellite systems because they require large capital investment and are inaccessible after launch. Spacecraft system reliability is typically computed using standard parallel-series combination techniques based upon component and subsystem failure rates provided by suppliers. Component failure rates are empirically determined and, as such, are nondeterministic parameters. Treating these failure rates as uncertain parameters in spacecraft design may avoid unnecessary high redundancy. However, probabilistic methods in reliability evaluation are often ignored because handling uncertain parameters associated with discrete or categorical design variables, such as technology choices and redundancy levels, requires computationally expensive sampling techniques. The computational cost of optimization approaches becomes prohibitive when considering discrete technology and redundancy choices as variables. This work presents a genetic algorithm with Monte Carlo sampling for probabilistic reliability-based design optimization of satellite systems. In this approach, confidence-level constraints ensure that system reliability requirements are met with high probability. The genetic algorithm–Monte Carlo sampling approach is compared to a deterministic margin-based approach that enforces margins or safety factors on the reliability of individual components. The comparison shows that the genetic algorithm–Monte Carlo sampling approach produces satellite designs that have low launch mass (a surrogate for cost) while achieving reliability requirements at specified high confidence levels, while the genetic algorithm–deterministic margin-based approach produces heavy satellite designs with excessive redundancy. Based on this work, extensions of a genetic algorithm-based approach for discrete optimization under uncertainty that may require less computational effort appear possible.

Nomenclature

c	=	penalty multiplier
$E()$	=	expected value of
f	=	fitness function
G	=	uncertain inequality constraint
g	=	inequality constraint
M	=	mass
N_{samples}	=	number of samples
$P()$	=	probability of
R	=	reliability
$\mathbf{x}$	=	design vector
λ	=	failure rate
μ	=	mean
$\boldsymbol{\xi}$	=	uncertain parameters vector
σ	=	standard deviation
Φ	=	Gaussian probability density function
ϕ	=	objective function

I. Introduction

RELIABILITY of a system can be defined as the ability of the system to perform its required functions under stated conditions for a specified period of time [1]. Because of the uncertainties associated with failure rates of components and subsystems, predictions of total system reliability cannot be guaranteed. Therefore, system reliability should be measured in terms of probability of success, and correspondingly, system risk in terms of probability of failure. However, designers commonly use deterministic margin-based (DMB) approaches to account for uncertainties instead of probabilistic approaches to estimate system reliability from distributions of component and subsystem reliability values. DMB approaches are much simpler than probabilistic approaches, but can only provide point estimates for system performance. Probabilistic approaches provide interval estimates and the probabilities (also known as confidence levels) that system performance estimates lie within these intervals. When applying DMB approaches, designers tend to be overly conservative to compensate for excluding design uncertainties when estimating system performance metrics. This is evident in engineering practice. Researchers from several engineering disciplines have demonstrated that probabilistic approaches allow designers to avoid excessively conservative safety factors, hence, unnecessary oversizing (for example, see [2–5]). Specifically, the structural design community has been at the forefront of this research topic. References [6–10] provide examples of the advantages of probabilistic approaches in structural design.

Because there is a tradeoff between system reliability and system cost, especially in spacecraft design [11], DMB approaches typically yield costly products that are believed to be reliable because of the large margins applied to the design. Additionally, engineering predictions often appear without providing any data about confidence levels in system reliability estimates. System risk cannot be completely eliminated, and designing systems with near 100% probability of success is exceptionally costly. Therefore, accurate estimates of system risk should be sought and used in system design and trade studies. Probabilistic analysis in reliability calculations directly and quantitatively accounts for design uncertainties. This is a useful framework for incorporating risk assessment in the decision-making process in engineering design [12].

The contribution of this paper is an investigation of a system design optimization problem under uncertainty with discrete variables. This paper compares a probabilistic approach that uses sampling methods to account for uncertainty and a deterministic

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*Ph.D. Student, School of Aeronautics and Astronautics; currently Postdoctoral Associate, Aeronautics and Astronautics and Engineering Systems, Massachusetts Institute of Technology, E60-275, 77 Massachusetts Avenue, Cambridge, MA 02139; rhassan@mit.edu. Member AIAA.

†Associate Professor, School of Aeronautics and Astronautics, 315 North Grant Street; crossley@purdue.edu. Associate Fellow AIAA.

approach that incorporates a traditional design margin or safety factor approach. The design application investigated here is a commercial communication geosynchronous satellite, which is dominated by categorical (e.g., technology choices) and ordinal (e.g., levels of redundancy) discrete variables. There have been few applications of design under uncertainty applied to small discrete optimization problems, and there appears to be significant potential for probabilistic approaches in satellite systems reliability-based design optimization.

II. Reliability Considerations in Spacecraft Design Optimization

Spacecraft systems typically involve a combination of approaches to achieve reliability including both fault avoidance and fault tolerance. Fault avoidance means selecting highly reliable technologies for spacecraft components and subsystems, which may be oversized, to avoid failure. Fault tolerance employs redundancy to allow the mission to continue despite failures of some components. For example, in commercial communication satellites, it is customary to use 50% redundancy levels in repeater design and full, duplicate redundancy in most of the bus subsystems. Employing both fault avoidance and fault tolerance increases the chances for mission success, but this may be excessive and produce oversized (and therefore expensive) spacecraft. Binckes [13] indicates that most spacecraft reliability models are relatively pessimistic compared to actual on-orbit performance. One of the reasons system designers oversize spacecraft systems is that they often distrust published failure data. This is because failure rates are empirically determined; hence, they are uncertain parameters. Binckes [13] suggests that modeling the uncertainties associated with failure rates in a probabilistic approach would significantly improve reliability models and avoid system oversizing. However, to accurately estimate a system-level uncertain performance metric, like spacecraft reliability, from a set of uncertain design parameters, like failure rates, requires a large number of samples or spacecraft system analyses, given a fixed set of component and subsystem technologies and redundancy levels.

III. Genetic Algorithm for Optimization Under Uncertainty

When optimization is sought for spacecraft system design, probabilistic approaches may become computationally expensive, because accurate estimation of each candidate solution's reliability value requires a large number of system analyses. These reliability estimates are uncertain, so constraints enforce limits on the probability that reliability goals are met; these constraints do not allow for gradients used in calculus-based optimization. During an optimization run, the algorithm evaluates a large number of candidate solutions before converging on the best design. The spacecraft design optimization problem pursued here involves a large number of discrete design variables representing decisions related to technology choices and redundancies for the spacecraft components and subsystems. Because spacecraft analysis models are nonlinear, the design problem involves discrete variables, and the constraints involve probability estimates, a global search method that can address these issues, namely, the genetic algorithm (GA), is used to solve this problem—even with the high computational cost. A subsequent section of this paper discusses other published efforts that employ a GA for design under uncertainty.

The genetic algorithm is modeled after Darwin's theory of *natural selection*; it employs the principal of survival of the fittest in its search process and has been applied successfully to the design of many complex engineering systems. The GA differs from conventional optimization methods in four different ways (adapted from [14]). First, the GA works with a coding for the design variables that allows for a combination of discrete and continuous variables in one problem statement. Second, the GA needs only fitness or objective function values; no derivatives are needed. This feature allows for discontinuous objective and constraint functions. Additionally, this property means that the GA provides no information about optimality of the solution. Third, the GA employs a combination of random choices and deterministic rules to find new points with likely improvement. This random component of the search direction ensures that the GA is likely to search across the entire design space; it will not become trapped in local minima. Fourth, the GA is a population-based search technique, which results in multiple designs with good performance after each run of the GA, rather than only one solution. This feature allows for a global search, but makes the GA an expensive approach compared to gradient-based methods. Additionally, the GA uses a randomly generated initial population. Therefore, the GA can start its search without requiring system designers to predetermine feasible solutions. This is one of the advantages of the GA for use in the conceptual design stage.

Given that the GA evaluates many candidate designs during its run, when combined with traditional sampling approaches like Monte Carlo sampling (MCS), a probabilistic design optimization approach with a GA becomes extremely expensive. This is because each function evaluation in the GA run requires many samples. The focus of this paper, however, is on the comparison between the GA-DMB and the GA-MCS approaches to investigate the advantage of implementing a probabilistic design optimization approach over a deterministic one in spacecraft design without giving much consideration to the computational cost issue. The increased information available via the probabilistic design approach should motivate additional efforts to reduce the computational cost associated with using the GA for discrete optimization under uncertainty.

IV. Spacecraft Models

This section describes the models that evaluate the performance of candidate spacecraft solutions. These include a sizing model that predicts system mass, power, and size based on payload requirements, technology choices and redundancy levels, and the choice of the launch vehicle. Additionally, a spacecraft reliability model predicts system reliability based on technology choices and redundancy levels.

A. Spacecraft Sizing Model

Few computational tools are readily available to predict spacecraft system-level parameters such as mass, power, and size. There were no publicly available sizing tools for the design of commercial communication geosynchronous satellites; consequently, the first author developed a sizing tool largely based on her industrial experience and on the basic approach outlined in *Space Mission Analysis and Design* [15]. The satellite sizing tool is coded into MATLAB™ scripts. In many of the model design estimating relationships, scaling factors are used to correlate a basic prediction to actual values from a database of existing satellites (e.g., repeater mass as a function of repeater bandwidth). Much of the known satellite data are proprietary; therefore, the scaling factors used do not appear in this publication.

A communication satellite acts as repeater that receives a signal from Earth, amplifies it, and changes its frequency before sending it back to Earth. A communication satellite consists of payload and bus. The payload consists of antennas for the reception and transmission of signals, and repeaters for power amplification and frequency conversion. The bus supports the payload by providing orbit and attitude control, electric power, mechanical and structural support, thermal control, and a two-way data link to ground control stations.

The satellite design mission example used here is based on an existing satellite that provides telecommunication services in C and Ku frequency bands common for voice and video services. The existing satellite employs traveling wave tube amplifiers (TWTAs) for the Ku-band repeater and a mix of TWTAs and solid state power amplifiers (SSPAs) for the C-band repeaters. The existing satellite bus uses nickel hydrogen batteries, deployable silicon solar arrays, and North/South (N/S) thermal coupling. The satellite employs bipropellant thruster technology for transfer orbit, N/S stationkeeping (STK), East/West (E/W) STK, and attitude control. This existing

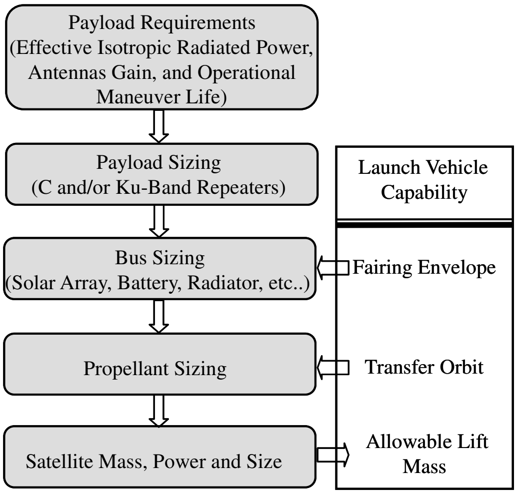

Fig. 1 Flowchart for the spacecraft sizing model.

design provides a baseline for comparison with designs generated by the margin-based and probabilistic optimization.

The input to the spacecraft sizing model is a set of payload requirements as well as technology choices and redundancy levels for the payload and bus subsystems. The choice of the launch vehicle is incorporated in the spacecraft sizing model to provide a set of constraints on the maximum spacecraft size and wet mass. Additionally, the choice of the launch vehicle determines the ΔV requirement for the spacecraft to move from the transfer orbit to the geosynchronous orbit. The spacecraft sizing model uses the above pieces of information to estimate the power, mass, and size of the spacecraft as shown in Fig. 1 using both analytical, physics-based relationships such as the link equation and the rocket equation, and parametric models based on a historical database of spacecraft components and subsystems masses. More details on the spacecraft sizing model are provided in [11,16].

B. Spacecraft Reliability Model

Standard approaches implemented via MATLAB scripts allowed computation of satellite reliability values. The reliability model calculates the reliability of each subsystem based on the type of technology it uses and the level of redundancy implemented. The reliability model first calculates payload reliability and bus subsystem reliabilities, and then computes overall system reliability. Because the spacecraft problem includes the launch vehicle selection as a discrete variable, launch vehicle reliability is also calculated and a constraint imposes a lower limit on its value.

A study by Goddard Space Flight Center [17] showed an average of 1.7 failures per spacecraft during the first 30 days compared to an average of less than 0.2 failures per spacecraft per month afterward. The high failure probability in the early stage of operation indicates that design problems are more likely to become apparent in the early phase of operation. The failure of any component or subsystem in the spacecraft during launch or orbit insertion has a much larger effect on the rest of the mission than failures in later phases of the mission. Therefore, in this research, reliability values at the end of the 30th day of on-orbit operation are computed and used to impose constraints in the spacecraft design problem formulation. Other constraints, such as imposing a lower limit on the end of life reliability values, could be implemented if desired. Additionally, a multipoint formulation with different reliability constraints at different times could be used. Component reliability values used in system reliability calculations for this paper are computed as shown in Eq. (1),

$$R_{\text{component}}(t) = e^{-\lambda t} \tag{1}$$

where $\lambda =$ component failure rate and $t = 30$ days.

Equation (1) assumes that component and subsystem failure rates are constant over the lifetime of the spacecraft. Previous research [18] indicates that constant failure rates do not appropriately model the reliability of spacecraft components and that the concept of reliability bathtub curve better models the failure rates of spacecraft components. The reliability bathtub curve consists of three key periods: infant mortality where failure rates decrease as a function of time, normal life or useful life where failure rates remain low and constant over time, and lastly end of life wear-out with failure rates increasing over time. This research uses constant failure rates due to lack of publicly available information regarding reliability bathtub curves for spacecraft components and subsystems. Additionally, constant failure rates are implemented because the design problem formulation in this research uses reliability values at a single point in the spacecraft lifetime.

The spacecraft reliability model implements calculations for parallel, series, and M-out-of-N combinations as shown in Eqs. (2–4) to calculate subsystem reliabilities from component reliabilities at the end of the 30th day of operation.

Series combination:

$$R_{\text{subsystem}} = \prod_{i=1}^{N} R_{\text{component}_i} \tag{2}$$

Parallel combination:

$$R_{\text{subsystem}} = 1 - \prod_{i=1}^{N} (1 - R_{\text{component}_i}) \tag{3}$$

M active out of N available:

$$R_{\text{subsystem}} = \sum_{i=M}^{N} \binom{N}{i} R^{i}_{\text{component}} (1 - R_{\text{component}})^{N-i} \tag{4}$$

Subsystem reliabilities are then used to calculate overall payload and bus reliability values. Payload reliability includes repeater and antenna reliabilities as shown in Eq. (5). The spacecraft bus reliability includes the reliabilities of six major subsystems and the bus harness as shown in Eq. (6). The bus subsystems include the structures subsystem, the attitude determination and control subsystem (ADCS), the telemetry, command, and ranging (TCR) subsystem, the electric power subsystem (EPS), the thermal protection subsystem, and the propulsion subsystem. Equation (7) shows the combined payload and bus reliabilities to evaluate total system reliability.

$$R_{\text{payload}} = R_{\text{antennas}} R_{\text{repeaters}} \tag{5}$$

$$R_{\text{bus}} = R_{\text{structure}} R_{\text{ADCS}} R_{\text{TCR}} R_{\text{EPS}} R_{\text{thermal}} R_{\text{propulsion}} R_{\text{harness}} \tag{6}$$

$$R_{\text{spacecraft}} = R_{\text{payload}} R_{\text{bus}} \tag{7}$$

The failure rates provided by manufacturers for the different spacecraft components represent the outcomes of multiple component tests. As a result, these values are not deterministic; they follow some sort of probability density functions (PDFs). The objective of this paper is to demonstrate an approach incorporating uncertainties associated with component and subsystem reliability values in total satellite design reliability calculations that can be used in an optimization problem to avoid high safety margins and spacecraft oversizing.

The distributions of component failure rates should be available from the manufacturer's quality control records; however, these distributions are not generally available in the open literature. As a result of this limited data, all uncertain reliability values in this paper are assumed to follow Gaussian (normal) distributions using the published failure rate values as the mean of the distribution and 0.5% of the published value as the standard deviation. The approach developed in this paper is not limited to Gaussian distributions; if other distributions are available or deemed more appropriate, the approach can accommodate them.

The Gaussian distribution may not be the best choice for reliability PDF distributions, because it is unbounded. Therefore, if a reliability value of greater than 1 is sampled from its Gaussian distribution, the sampled value is discarded and another value is sampled. This procedure makes sure that no reliability value is greater than 1, but skews the PDF from a true Gaussian distribution. Better PDF characteristics should be used if they can be obtained from component manufacturers. Using different distributions does not change the basic approach for design under uncertainty. Additional specifics about the reliability model are contained in [11,16].

V. Spacecraft Design Optimization Problem Statement

The literature includes few publications that discuss spacecraft system design optimization. Most notably, the problem statement in this paper is somewhat similar to problem statements presented by Pullen [18] and Mosher [19] in the sense that these approaches couple integrated spacecraft models with nongradient search methods to find the best design concept. However, the work presented here differs from these two previous researchers' work in a number of ways. First, while Pullen [18] and Mosher [19] focused on the design optimization of the bus subsystems, this research integrates bus design with payload design allowing tradeoffs to be directly related to high-level design requirements and, hence, to customer/stakeholder needs. Second, both Pullen [18] and Mosher [19] investigated space science missions; here, the application of interest is commercial communication satellites. To the authors' knowledge, the system design of geosynchronous communication satellites (payload and bus) within an optimization context has not been published previously. Third, both Pullen [18] and Mosher [19] investigated one type of design variable in their problem formulations; Pullen [18] optimized redundancy levels of the bus subsystems whereas Mosher [19] optimized the technology choices of the bus subsystems. The work presented in this paper integrates both categorical (technology choices) and ordinal (redundancy levels) discrete design variables for both the payload and the bus. Fourth, with 27 discrete design variables and a design space that includes 2.2×10^{12} possible combinations, the problem size here is significantly larger than Pullen's or Mosher's spacecraft design optimization problems. Finally, as with this research, Pullen's work [18] accounts for uncertainties via a probabilistic approach whereas Mosher [19] uses a deterministic approach.

It is important to note that the spacecraft design problem formulation in this research does not match the exact practice of any given design team. However, the method presented should be able to handle other objectives, constraints, or variables where the problem has the same basic features of the discrete problem presented as an example in this paper.

A. Objective and Fitness Functions

In this case study, the objective is to minimize the satellite launch mass as expressed in Eq. (8):

$$\text{minimize } \phi(\mathbf{x}) = M_{\text{spacecraft}} \tag{8}$$

The launch mass is considered a surrogate for cost, because cost models for commercial communication satellites are not readily available. However, it is common to describe satellite launch costs in terms of cost per kilogram of mass. In 1998, the estimated cost of launching 1 kg of payload into its orbital position ranged from \$22,500 to \$30,000 [20]. Launch insurance typically costs 25% of launch cost. Additionally, the cost of launching a medium size commercial satellite exceeds 50% of its total cost, including design, manufacturing, assembly, testing, and launching. Often, satellite designers work with a fixed satellite launch mass based on the choice of a launch vehicle and try to maximize payload. The probabilistic approach presented here is applicable in this maximum payload scenario, although the problem formulation would be slightly different.

Three deterministic inequality constraints limit spacecraft geometry and launch mass based on the choice of the launch vehicle. In this problem, the launch vehicle is a categorical variable, for which eight options are provided. There are also three inequality constraints imposed on the spacecraft, payload, and launch vehicle reliability values. These reliability values are uncertain parameters. The spacecraft reliability is a function of payload reliability and bus subsystem reliabilities. Here, a separate constraint limits payload reliability to emphasize the importance of this reliability for commercial communication satellites.

To formulate the single objective function needed for the GA optimization, a linear exterior penalty function handles the three deterministic inequality constraints as Eq. (9) shows. The second set of inequality constraints are uncertain and will be addressed differently via two approaches: the DMB and the MCS approaches,

$$f(\mathbf{x}) = \phi(\mathbf{x}) + \sum_{i=1}^{3} c_i \max[0, g_i(\mathbf{x})] \tag{9}$$

B. Design Variables

There are 27 design variables that describe the satellite payload and bus subsystems, and the choice of the launch vehicle. Spacecraft designers may have different views of what variables are important to the problem and which components should be considered for redundancy. The purpose of this study is to demonstrate the usefulness of probabilistic approaches for reliability-based design of spacecraft systems. System designers can use the methodology this paper presents and couple it with more realistic spacecraft models and problem formulations. Table 1 summarizes the design variables used in this problem statement. The first design variable describes the choice of the launch vehicle. The second set of design variables, with indices 2 to 14, describes technology choices for components and subsystems whereas the last set of design variables, 15 to 27, describes component and subsystem redundancy levels.

When decoded from the GA binary chromosome, each of the 27 design variables represents a deterministic design variable. The 14 design variables representing component and subsystem technology choices and the choice of the launch vehicle have associated uncertainties. For example, the second to the ninth design variables represent the type of high power amplifier (HPA) technology used in each of the satellite's 8 C-band repeaters. Here, the failure rate of a TWTA has a different published failure rate than that of a SSPA; as a result, the PDF describing reliability of the TWTA will have a different mean and standard deviation than that of the SSPA. The calculation of total spacecraft reliability uses samples from each probability distribution associated with the technology choice for each of the design variables 2 to 14. Table 2 presents the values used as the means of the distributions for these technology choices. A few of these mean reliability values are calculated from component failure rates reported in the literature and the rest are estimated or assumed values for lack of better information.

Table 3 lists data used for launch vehicle reliability calculations. Each launch vehicle has a figure of merit representing its reliability based on the number of successful launches out of the overall number of launches until 1999 [23]. Launch vehicles that have less than 50 successful launches were penalized an additional 25% below the 1999 published success rate. This somewhat arbitrary strategy was used to discriminate against launchers that have a high success rate with a low number of launches.

The launch vehicle data set shown in Table 3 is used because it is taken from a single source [23]. The data might not reflect the most current reliability metrics used in practice today. Additionally, the launch vehicle selections may not reflect all choices currently considered by satellite companies. However, including other reliability values or other launch vehicles as discrete choices for launch vehicle or removing some of the vehicles listed in Table 3 does not change the approach for discrete optimization under uncertainty.

The redundancy levels described by the last 13 design variables in Table 1 determine whether the series, parallel or M-out-of-N reliability calculation is needed. Finally, these are combined to compute values for payload reliability and total spacecraft reliability.

Table 1 Satellite problem design variables

Index	Design variable	Discrete values
1	Launch vehicle choice from eight options	Ariane 4, Ariane 5, Proton, Delta, Atlas, Long March, Sea Launch, or H2A
2–9	HPA type for the eight C-band Txs[a]	TWTA or SSPA
10	Solar array cell type	GaAs single junction, GaAs multijunction, Si thin, Si normal, or hybrids of Si and GaAs
11	Battery cell type	NiCd or NiH_2
12	N/S thermal radiator panels coupling	Yes or no
13	N/S STK thruster technology	Xenon plasma, arcjets, bipropellant, or hydrazine
14	E/W STK thruster technology	Bipropellant or hydrazine
15	Redundancy level for the Ku-band Tx	0, 1, 2, or 4 redundant HPAs for 12 active HPAs
16–22	Redundancy level for seven C-band Txs	0, 1, 2, or 4 redundant HPAs for 12 active HPAs
23	Redundancy level for last C-band Tx	0 or 12 redundant HPAs for two active HPAs
24	Propulsion subsystem redundancy level	No redundancy or duplicate redundancy
25	ADCS redundancy level	No redundancy or duplicate redundancy
26	TCR subsystem redundancy level	No redundancy or duplicate redundancy
27	Solar array redundancy level	0, 2, 4, or 6% of solar array area

[a]Transponders.

Table 2 Components and subsystems mean reliability values

Subsystem	Component	Mean reliability
Payload	Repeater TWTA	99.95% [21]
	Repeater SSPA	99.94% [21]
	Antennas	100%[a]
Structure and mechanisms		99.00%[a]
Harness (wiring)		99.90%[a]
Attitude determination and control subsystem (ADCS)		99.00%[a]
Telemetry, command, and ranging (TCR) subsystem		99.00%[a]
Electric power subsystem (EPS)	Solar array Si cells	99.00%[a]
	Solar array GaAs cells	98.50%[a]
	Battery NiH_2	99.00%[a]
	Battery NiCd	98.00%[a]
Thermal subsystem	No coupling	99.30% [22]
	N/S coupling	97.37% [22]
Propulsion subsystem	Bipropellant thrusters	99.93%[b]
	Hydrazine thrusters	99.50%[a]
	Arcjets	99.00%[a]
	Plasma thrusters	98.50%[a]

[a]Assumed.
[b]Proprietary source.

Constraints that place a minimum limit on reliability are then used to calculate the fitness of the design solution. Because reliability values are uncertain, the constraint functions and the fitness function are also uncertain values that follow probability distributions. However, the probability distributions of the constraint and fitness functions are difficult to predict a priori because they are aggregate uncertain functions with 27 discrete design variables and 14 uncertain parameters.

Each of the 27 variables has between two to eight possible discrete values as indicated in Table 1, corresponding to a chromosome length of 41 binary bits in the GA representation. Those 27 design variables correspond to 2^{41} different possible designs.

Table 3 Reliability data for launch vehicles [23]

Launch vehicle	Successful launches/ total launches	Success rate	Mean reliability value
Ariane 5	1/3	33%	8%
Ariane 4	83/86	97%	97%
Sea Launch	1/1	100%	75%
Proton	229/260	88%	88%
Delta	78/80	98%	98%
Atlas	41/41	100%	75%
Long March	46/54	85%	85%
H2A	5/6	83%	58%

C. Constraints

There are six constraints imposed on the spacecraft design problem. The first and second constraints ensure that the solar array panel length and the radiator panel height do not exceed the height of the fairing of the launch vehicle as expressed mathematically in Eqs. (10) and (11), respectively, and as shown schematically in Fig. 2. The maximum allowable lift mass of the launch vehicle is used as a constraint on the satellite total wet mass (launch mass), which is expressed in Eq. (12). These deterministic constraints are not affected by the uncertain parameters,

$$g_1(\mathbf{x}) = \frac{\text{solar array panel length}}{\text{fairing height}} - 1 \leq 0 \tag{10}$$

$$g_2(\mathbf{x}) = \frac{\text{radiator height}}{\text{fairing height}} - 1 \leq 0 \tag{11}$$

$$g_3(\mathbf{x}) = \frac{M_{\text{spacecraft}}}{\text{allowable lift mass}} - 1 \leq 0 \tag{12}$$

Three constraints are imposed on the reliabilities of the satellite, payload, and the launch vehicle. The reliability of the launch vehicle, based on the number of successful launches out of the total number of launches, was included because this is generally a mission requirement. A minimum launch vehicle reliability of 90% is imposed. Additionally, payload reliability is specified to be greater than 99%. This reliability limit is added because high payload

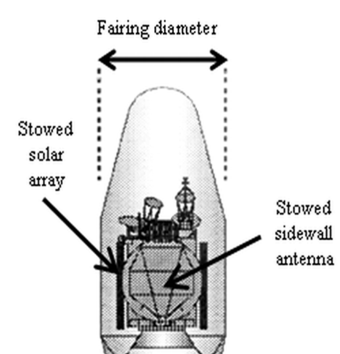

Fig. 2 Stowed satellite configuration inside launch vehicle fairing.

reliability translates into high link availability, which is required for market competitiveness. Finally, a limit is imposed on the overall spacecraft reliability, which combines payload and bus reliability. The minimum limit chosen for the spacecraft reliability is 95%. A design is considered feasible if the computed reliabilities exceed these launch vehicle, spacecraft, and payload reliability limits. These limit values for reliability were chosen based upon the authors' experience and engineering intuition; other values could be chosen.

In this probabilistic design formulation, the three reliability metrics with minimum required limits are uncertain functions, because each involves uncertain reliability parameters. As represented in Eqs. (13–15), these reliability measures are functions of deterministic design variables, $\mathbf{x}$, and uncertain parameters, $\boldsymbol{\xi}$,

$$g_4(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{R_{\text{launcher}}(\mathbf{x}, \boldsymbol{\xi})}{90\%} \tag{13}$$

$$g_5(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{R_{\text{payload}}(\mathbf{x}, \boldsymbol{\xi})}{99\%} \tag{14}$$

$$g_6(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{R_{\text{spacecraft}}(\mathbf{x}, \boldsymbol{\xi})}{95\%} \tag{15}$$

These three equations look similar to traditional constraint functions that are negative valued when satisfied; however, these three equations cannot be used directly as design constraints in an optimization formulation because each can have different values for the uncertain design parameters, $\boldsymbol{\xi}$, when describing the same satellite design concept (same values for the 27 discrete design variables) represented by $\mathbf{x}$. This formulation would not allow the search method to converge to an optimal design solution. A reformulation of the constraints on the uncertain reliability measures is needed to allow for an optimization approach. The three constraints on the uncertain reliability measures are handled differently for the two solution approaches, GA-DMB and GA-MCS, compared in this study.

VI. Uncertain Constraint Handling Approaches

This section presents two methods that allow for the evaluation of overall system reliability while incorporating uncertainties associated with component and subsystem failure rates. The first method is the classic Monte Carlo sampling method. The second method is a margin-based approach that accounts for the uncertainties in system reliability by imposing a safety factor or design margin on each component's published reliability value.

A. Monte Carlo Sampling Approach

Most probabilistic design problems employ MCS or other reduced sampling methods for reliability prediction [24]. In an optimization formulation involving many uncertain variables, MCS will require millions of function evaluations to give accurate results, which can be very expensive computationally. Additionally, using MCS does not provide for function continuity, so calculus-based optimization cannot rely on MCS for function evaluations. However, the GA, like other zero-order methods, has no restrictions on function continuity and could use MCS for function evaluations.

For the GA with MCS, evaluation of each individual design uses a large number of samples from the probability density functions representing the uncertain parameters. In this manner, constraint and objective functions can explicitly use uncertain values. Interval estimates for the uncertain performance metric, rather than point estimates, are obtained via the MCS approach. The main assumption is that the distribution of an aggregate uncertain performance function that is being sampled is a normal distribution because it involves repeated measurement of the same quantity with different sample values. When the sample size is small, the t distribution should be used instead to describe the distributions of aggregate uncertain functions. According to several references (see, for example, [25]), when the number of samples is sufficiently large (greater than 30), the normal distribution can be used to approximate the t distribution in the prediction of the accuracy of the estimate. In the satellite design problem, the prediction of the performance of each design generated in the optimization run will use 500 sample sets. The accuracy of predictions made via MCS is inversely proportional to the square root of the number of samples, N_{samples}, used in performance prediction as shown in Eq. (16):

$$\mu_m \pm \text{accuracy} = \mu_m \pm \Phi^{-1}(\text{confidence level}) \frac{\sigma_m}{\sqrt{N_{\text{samples}}}} \tag{16}$$

Here, μ_m is the mean of the uncertain performance metric, for instance, satellite reliability, measured from a sample size equal to N_{samples}. σ_m is the sample standard deviation, and Φ^{-1} is the inverse normal density function. For example, for a confidence level of 99%, Φ^{-1} is equal to 2.575. For a given number of samples, the accuracy of prediction increases (the interval width is decreased) when the selected confidence level is decreased.

In a population-based optimization approach such as the GA, which evaluates many designs each generation, MCS can become prohibitively expensive because it uses N_{samples} function evaluations to assess each candidate solution, whether it has good or poor fitness. Nonetheless, a quick survey of published literature showed that both engineering and nonengineering applications of the GA for optimization under uncertainty have generally implemented the expensive MCS approach or other stratified sampling methods. Table 4 summarizes a selected set of these research efforts in chronological order. This list is not exhaustive but presents applications from several disciplines that combine MCS with the GA. Based on this literature summary, using MCS for each function evaluation appears to be the state of the practice, if not the state of the art, for optimization under uncertainty using GAs. This also presents the opportunity for methods with similar capabilities for discrete optimization under uncertainty but with lower computational cost.

Using MCS within an optimization formulation, the literature reports two approaches to enforce constraints on uncertain responses similar to the reliabilities in Eqs. (13–15). These two approaches are as follows: enforcing the expected value of the uncertain response to be greater than (or less than) a specified limit [e.g., $E(f(\mathbf{x}, \boldsymbol{\xi})) \geq k$], or enforcing the probability that the uncertain response satisfies a performance constraint to exceed some confidence limit [e.g., $P(f(\mathbf{x}, \boldsymbol{\xi}) \geq k) \geq 0.99$]. The first constraint type is an "expected value constraint," and the second, a "confidence-level constraint."

In the expected value formulation, many samples are used to estimate the expected values of the uncertain aggregate reliability functions as shown in Eqs. (17–19). The expected values can then be substituted in the constraint functions as expressed in Eqs. (20–22):

$$E(R_{\text{launcher}}) = \sum_{i=1}^{N_{\text{samples}}} R_{\text{launcher}}(\mathbf{x}, \boldsymbol{\xi})/N_{\text{samples}} \tag{17}$$

$$E(R_{\text{payload}}) = \sum_{i=1}^{N_{\text{samples}}} R_{\text{payload}}(\mathbf{x}, \boldsymbol{\xi})/N_{\text{samples}} \tag{18}$$

$$E(R_{\text{spacecraft}}) = \sum_{i=1}^{N_{\text{samples}}} R_{\text{spacecraft}}(\mathbf{x}, \boldsymbol{\xi})/N_{\text{samples}} \tag{19}$$

$$G_4(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{E(R_{\text{launcher}})}{90\%} \leq 0 \tag{20}$$

Table 4 Summary of selected research efforts implementing traditional sampling approaches with heuristic search methods for design optimization under uncertainty

Publication year [Ref. no.]	Application	Optimization method	Sampling method
1995 [33]	Personal computer reliability	GA	LHS[a]
1996 [18]	Spacecraft bus reliability	SA[b]	MCS
1998 [26]	Communication network reliability	GA	MCS
2000 [27]	Plant layout with uncertain economic and safety metrics	GA	MCS
2000 [28]	Water quality reliability	GA	MCS
2001 [29]	Supply chain with stochastic demand	GA	MCS
2001 [30]	Energy market stochastic bidding	GA	MCS
2002 [31]	Aircraft engine technology risk	GA	MCS
2002 [32]	Workspace design with uncertain robot configurations	GA	MCS

[a]Latin hypercube sampling.
[b]Simulated annealing.

$$G_5(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{E(R_{\text{payload}})}{99\%} \le 0 \tag{21}$$

$$G_6(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{E(R_{\text{spacecraft}})}{95\%} \le 0 \tag{22}$$

If two different instances of the same design variables, $\mathbf{x}$, are encountered, they will have a different set of uncertain sampled parameters, $\boldsymbol{\xi}$. If the expected value calculations use a large number of samples, the expected values associated with these two instances of the same $\mathbf{x}$ will be nearly the same. Hence, the constraint values and the fitness values will also be nearly the same for designs with the same design variables encountered in the optimization run. This allows the GA to converge toward the optimal design. In this expected value constraint formulation, the constraints enforce limits on the expected reliability values. This means that if the estimated expected reliability values for a given design exceed the constraint limits, then this design is considered feasible. Several studies that use the GA for design under uncertainty (see, for example, [18,26–32]) enforce constraints on expected values of uncertain aggregate metrics using MCS.

The confidence-level constraint formulation enforces constraints limiting the probabilities associated with the estimated uncertain values (see, for example, [33,34]). This is because it is not sufficient to obtain a design solution with a high expected reliability value. It is also crucial that the confidence level in the solution be sufficiently large to consider a solution feasible. A confidence level is the probability of success of an estimate or a predicted value; here, the estimates are those of aggregate reliability values. These confidence-level constraint formulations appear in Eqs. (23–25),

$$G_4(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{P(R_{\text{launcher}}(\mathbf{x}, \boldsymbol{\xi}) \ge 0.90)}{\text{confidence level}} \le 0 \tag{23}$$

$$G_5(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{P(R_{\text{payload}}(\mathbf{x}, \boldsymbol{\xi}) \ge 0.99)}{\text{confidence level}} \le 0 \tag{24}$$

$$G_6(\mathbf{x}, \boldsymbol{\xi}) = 1 - \frac{P(R_{\text{spacecraft}}(\mathbf{x}, \boldsymbol{\xi}) \ge 0.95)}{\text{confidence level}} \le 0 \tag{25}$$

For a chosen confidence-level limit, say 99%, a feasible solution that satisfies Eqs. (23–25) will have at least a 99% chance that its expected reliability values exceed the minimum required 90, 99, and 95% limits on launcher, payload, and spacecraft reliabilities, respectively. In other words, if 100 copies of this spacecraft are built, 99 of the 100 should satisfy the required reliability limits.

The idea of using a confidence-level constraint formulation in the spacecraft design problem matches the objective of obtaining high reliability design solutions at high confidence levels. This is because satellite system engineers have to demonstrate high system reliability at high confidence levels to obtain good insurance rates—one of the reasons commercial satellite designs incorporate high levels of redundancies. Therefore, the confidence-level constraint formulation shown in Eqs. (23–25) is preferred over the expected value formulation shown in Eqs. (20–22).

The fitness function of each design appears in Eq. (26) where g_i represent the deterministic constraints described in Eqs. (10–12), and G_j represent the confidence-level constraints described in Eqs. (23–25):

$$f(\mathbf{x}, \boldsymbol{\xi}) = \phi(\mathbf{x}) + \sum_{i=1}^{3} c_i \max[0, g_i(\mathbf{x})] + \sum_{j=4}^{6} c_j \max[0, G_j(\mathbf{x}, \boldsymbol{\xi})] \tag{26}$$

The GA employed in this investigation uses Gray coding, uniform crossover, and tournament selection. The chromosome string length for this communication satellite problem is 41 bits (the sum of all the bits representing the 27 design variables shown in Table 1). A constant population size of 164 ($4 \times$ chromosome length) individuals is used as suggested by previous empirical studies [35]. The implemented mutation probability is 0.3% $[(41 + 1)/(2 \times 164 \times 41)]$; this is again suggested by empirical studies [35]. Because conducting MCS for each fitness evaluation is very expensive computationally, each function evaluation used only 500 samples. Here, the GA stops its run if the minimum fitness value does not change for more than ± 0.01 kg for 10 consecutive generations.

The GA with MCS was run at five different confidence levels. At the largest confidence level of 99%, the serial GA converged on average over 10 runs in 61 generations, 5,116,800 function evaluations, and required about 11.8 h to converge running a MATLAB code on Pentium 4 processors. Based on these runs, it is predicted that the code would require an estimated 108 h (4.5 days) to converge if 5000 samples were used. Because of limited access to computational resources, only runs using 500 samples were used for this effort; however, a parallel, worker-manager GA could reduce the elapsed time and/or allow for more samples per individual design. To assess the reliability estimates, postprocessing of the GA-generated optimal solution used 50,000 sample sets to compute its reliability with greater accuracy than the estimates from the optimization runs.

B. Deterministic Margin-Based Approach

The DMB approach to the spacecraft reliability-based design optimization problem provides a comparison of solution quality (e.g., launch mass and reliability values) and computational cost with the probabilistic MCS approach. The DMB approach represents the practice of applying design margins or safety factors in reliability evaluation.

Because probabilities of predicted aggregate reliability values are not computed in a deterministic approach, a constraint that is comparable to the confidence-level constraint can be enforced on aggregate system reliability only by enforcing confidence-level constraints on the reliability values of each individual subsystem or component. For example, to be 99% confident that a feasible design obtained by the GA has an aggregate spacecraft reliability value greater than the required 95% limit, each component or subsystem reliability value used in the computation of the spacecraft reliability must belong to the lower 1% of its probability distribution.

A TWTA, one of the technology choices available to the payload repeaters' HPAs, provides an example of how component or subsystem reliability values are implemented in the DMB approach using a confidence-level formulation. The published TWTA reliability value is 99.95%; this value is assumed to be the mean, $\mu_{\text{component}}$, of a normal distribution that represents the uncertainty associated with the TWTA reliability. The standard deviation, $\sigma_{\text{component}}$, of the reliability distribution is assumed to be 0.5% of the published reliability value; here, this is equal to 0.0049. The subscript "component" indicates that this procedure is applicable to all components and subsystems.

To avoid sampling and probabilistic calculations while still accounting for uncertainty, the published reliability value of each component used in the calculation of spacecraft reliability is modified in a margin-based-like procedure. The value of TWTA reliability used in the spacecraft reliability calculations needs to be less than the published value, which is assumed to be the mean of the distribution of reliability values. To provide an analog to the 99% confidence-level constraint, the TWTA reliability used in the calculations should correspond to a value for which 99% of the distribution is to the right of this value.

With the assumption that the component reliability follows a normal distribution, the modified TWTA reliability value can be calculated using the inverse normal distribution, Φ^{-1}. For 99% of the distribution to lie to the right of the modified value, $\Phi^{-1}(0.99) = 2.33$. Figure 3 illustrates this calculation where the hashed area represents 99% of the probability distribution. Therefore, at a confidence level of 99%, the modified TWTA reliability value used in the spacecraft reliability calculation is found using Eq. (27). For this example, using a 98.79% reliability value for the TWTA in place of the mean (published) 99.95% value provides a margin of 1.16% for this component. This is analogous to the concept of safety factors used in structural design in which a published value for yield strength is modified (reduced) to produce an allowable stress level for use in a constraint:

$$R_{\text{TWTA}}(\text{DMB approach, 99\% confidence level}) = 0.9995 - 2.33 \times 0.0049 = 0.9879 \tag{27}$$

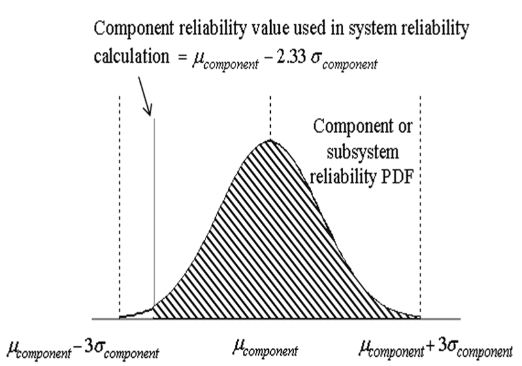

Fig. 3 Modified component reliability value corresponding to a confidence level of 99%.

If a modified component reliability value corresponding to a 99% confidence level is used for every component and subsystem to calculate system reliability and if the 95% limit on system reliability is satisfied using these modified reliability values, it can be inferred that the 95% system reliability requirement is satisfied at a 99% confidence level. This concept is described mathematically in Eq. (28) for any given confidence level. This same concept applies to the aggregate payload reliability constraint.

$$\begin{aligned} &\text{if } \forall_i\ R_{\text{component}_i} \le \mu_{\text{component}_i} - \Phi^{-1}(\text{confidence level})\sigma_{\text{component}_i} \\ &\text{for } i = 1, 2, \ldots, \text{no. of components} \quad \text{and} \quad R_{\text{spacecraft}} \ge 95\% \\ &\quad \therefore P(R_{\text{spacecraft}} \ge 95\%) \ge \text{ confidence level} \Rightarrow G_6 \le 0 \end{aligned} \tag{28}$$

The major advantage of the DMB approach is that it allows for imposing confidence-level constraints without the use of expensive sampling approaches. However, the disadvantage is that the DMB approach may assign large safety margins at high confidence levels.

In this deterministic problem formulation, the same GA settings used for the GA-MCS approach generates solutions.

VII. Comparison of Satellite Designs Produced by the MCS and DMB Approaches

This section compares spacecraft designs produced by the GA-DMB and the GA-MCS approaches. The comparison establishes the advantage of using the nondeterministic MCS approach over the margin-based approach in terms of solution quality (spacecraft mass and feasibility with respect to reliability constraints) and provides an assessment of the computational cost (number of function evaluations).

In both the MCS and the DMB problem formulations, the GA was run with constraints formulated at five different confidence-level limits: 70, 80, 90, 92.5, and 99%. A confidence level assigns margins to component reliability values in the DMB approach and allows for probabilistic constraints in the MCS approach. For each approach, the GA was run 10 times at each of the five confidence levels to assess repeatability of the results.

At each confidence level, the mean spacecraft launch mass values obtained from 10 runs are plotted for both approaches in Fig. 4. Additionally, the minimum, mean, and maximum spacecraft mass values appear in Table 5. Table 5 shows that the variations in the resulting best spacecraft mass from all 10 runs are very small at each confidence level. For example, the 10 runs conducted using a confidence level of 90% had a minimum of 3669.5 kg and a maximum of 3670.8 kg for the DMB approach, and a minimum of 3580.3 kg and a maximum of 3596.6 kg for the MCS approach. At other confidence levels, there was a similar narrow range of spacecraft mass. The consistency of the results suggests that the GA

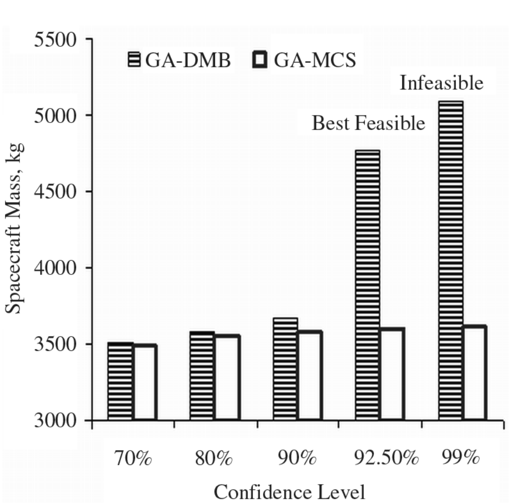

Fig. 4 Mean mass of spacecraft design solutions found by GA-DMB and GA-MCS at various confidence levels.

Table 5 Comparison of solution quality of minimum mass spacecraft produced by the GA-DMB and GA-MCS approaches

Confidence level	GA-DMB min	GA-DMB mean	GA-DMB max	GA-MCS min	GA-MCS mean	GA-MCS max
70%	3488.2	3508.0	3532.4	3488.2	3488.2	3488.2
80%	3570.7	3572.9	3592.3	3535.0	3551.5	3574.2
90%	3669.5	3669.6	3670.8	3570.8	3582.4	3596.6
92.5%	4719.5	4766.8	4820.3	3587.4	3602.9	3625.7
99%	5085.0	5085.0	5085.0	3602.8	3614.9	3624.4

may have arrived at the global optimal solutions in all those runs; however, proof of global optimality does not exist for this discrete problem without enumeration.

Figure 4 also shows that at high confidence levels, the DMB approach generates very heavy launch mass designs compared to those generated by the MCS approach. The results in Table 5 show that in the DMB approach, the average value of minimum spacecraft mass of the 10 runs at each confidence level increases from 3508.0 to 5085.0 kg with the increase of the confidence level from 70 to 99%. In comparison, for the MCS approach, the average minimum spacecraft mass ranges from 3488.2 to 3614.9 kg over the same range of confidence-level limits. Both approaches produce similar designs at confidence levels less than or equal to 90%. However, at high confidence levels, the DMB approach generates spacecraft design solutions that are much heavier than the solutions generated by the MCS approach. Additionally, at the highest confidence level of 99%, the DMB approach was unable to find any feasible solution. The highest confidence level at which the deterministic approach was able to find a feasible solution is 92.5%; this best design (the minimum mass from 10 runs) has a spacecraft launch mass of 4719.5 kg. Comparatively, at this confidence level of 92.5%, the MCS approach found a feasible spacecraft, that is, a design that satisfies the confidence-level constraints on the reliability requirements, with a mass of only 3602.8 kg.

Table 6 compares the values of the design variables of the minimum mass designs (lowest mass of the 10 runs) obtained by MCS and DMB at a confidence level of 92.5%. Table 6 shows that there are two main reasons for the oversizing of the spacecraft design found by the DMB approach. First, the 4719.5 kg design obtained by the DMB approach has significantly higher payload redundancy than that of the 3602.8 kg design obtained by the MCS approach. The 4719.5 kg design obtained by DMB has a total of 27 redundant HPAs for a total 98 active (operating) HPAs, whereas the 3602.8 kg design obtained by MCS has a total of 10 redundant HPAs only. It is important to note that a slightly larger payload mass results in a significantly larger satellite mass, because the payload mass drives the sizing of all bus subsystems. Second, while the MCS spacecraft design solution uses electric propulsion for N/S stationkeeping operations, the DMB solution uses chemical propulsion, which has considerably higher mean reliability than electric propulsion (99.9 and 98.5%, respectively), but also increases the required propellant mass and propulsion subsystem significantly. The DMB solution uses chemical propulsion, because at the required confidence level of 92.5%, the GA chooses subsystem designs with highest reliability values to satisfy the reliability requirements when using a reliability margin on each component or subsystem in the design.

Following the DMB approach at a confidence-level limit of 92.5%, the computed reliability of the minimum mass spacecraft design is 95.0%, using the margin-based approach to reduce the effective component reliability values. To provide a more accurate estimate of the actual reliability of this DMB-generated design, it was postprocessed and evaluated using MCS with 50,000 samples. The MCS estimate for the spacecraft reliability of this DMB-generated design is 97.6%. This could be interpreted as the following: using a confidence-level constraint of 92.5% to modify reliability values of the components and subsystems in the DMB formulation has the net result of assigning a total of 2.6% margin to the aggregate spacecraft reliability value.

For comparison, the expected value of spacecraft reliability of the design generated by the MCS approach is 97.2% using 500 samples. Out of the 500 sample sets used at the 92.5% confidence level, 494 sample sets produced feasible reliability values, that is, greater than the required payload, spacecraft, and launch vehicle reliability limits. Therefore, in comparison with the imposed 92.5% confidence-level constraint, the computed probability of success, or probability of meeting the reliability requirements, for this design is 98.8% (494/500). Additionally, when this MCS-generated design was reevaluated in a postprocessing run with 50,000 samples to provide more accurate estimates, the spacecraft reliability was estimated as 97.2% with 49,531 out of the 50,000 samples producing feasible designs. Therefore, the computed probability of success, or probability of meeting the reliability requirements, for this design is 99.1% (49,531/50,000).

Figure 5 shows the mean computational cost from 10 runs for both the DMB and MCS approaches at each of the five confidence levels; Fig. 5 uses a logarithmic scale for the number of function evaluations. Table 7 shows that the variation in the computational cost of the GA runs represented by the difference in minimum and maximum values is more obvious than the variation in the mass values in Table 5. The variation in the computational cost is a known characteristic of the GA (and other similar, heuristic search methods).

For the DMB approach, the average computational cost varies from 7052 to 9659 function evaluations at the different confidence levels. The computational time for a serial GA run varied from 42 s to 2 min on average for the DMB approach on a Pentium 4 processor at the different confidence levels. In comparison, for the MCS approach, the computational cost varies from an average of 4.3×10^6 to 6.4×10^6 function evaluations at the different confidence levels. The average computational time corresponding to these serial GA

Table 6 Description of design variables of minimum mass solutions obtained by DMB and MCS approaches using a confidence level of 92.5%

Design variable	Discrete values DMB (4719.5 kg)	Discrete values MCS (3602.8 kg)
1 launch vehicle choice from eight options	Delta	Same
2–9 HPA type for the eight C-band Txs	SSPAs for the 1st and 3rd–8th Txs and TWTAs for the 2nd Tx	Same
10 solar array cell type	Si cells	Same
11 battery cell type	NiH_2	Same
12 N/S thermal radiator panels coupling	No	Same
13 N/S STK thruster technology	Bipropellant	Plasma
14 E/W^f STK thruster technology	Bipropellant	Bipropellant
15–23 Ku- and C-band Txs redundancy level	98 active out of 125 available (a total of 27 redundant HPAs)	98 active out of 108 available (a total of 10 redundant HPAs)
24 propulsion subsystem redundancy level	Duplicate redundancy	Same
25 ADCS redundancy level	Duplicate redundancy	Same
26 TCR subsystem redundancy level	Duplicate redundancy	Same
27 solar array redundancy level	6% of solar array area	Same

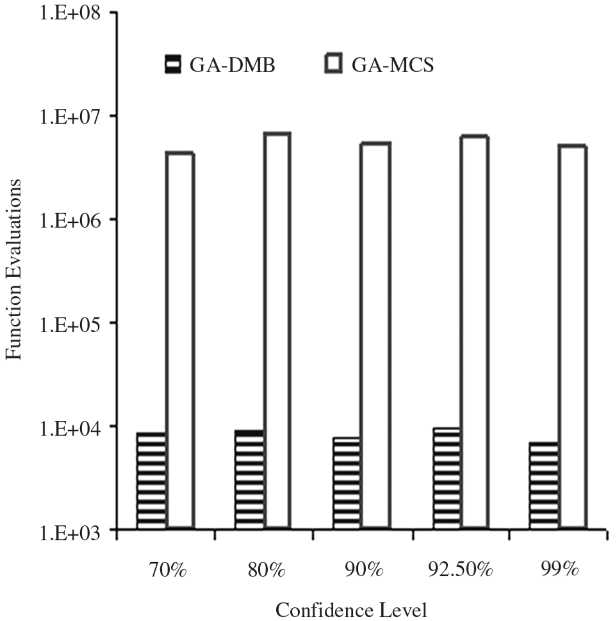

Fig. 5 Comparison of computational cost of DMB and MCS at various confidence levels.

runs varied from 9.8 to 15.4 h on the same computer used for the DMB runs. The main message from Fig. 5 is that to obtain low mass spacecraft designs that satisfy reliability requirements at high confidence levels using the probabilistic MCS approach, a computational price has to be paid. Figure 5 shows that while the GA-DMB approach converges quickly with only thousands of function evaluations and in few minutes, the GA-MCS approach requires a computational cost that is 3 orders of magnitude greater than the DMB approach and converges in half a day on average. Although half a day of computational time might be acceptable, in a design setting where higher fidelity spacecraft models are available, the computational cost of the MCS approach may become prohibitive. At the same time, although the DMB approach is simple to implement and requires little computational time, it produces oversized spacecraft that would be very expensive to build and launch.

VIII. Future Work

The results presented in this work suggest that although the GA-MCS approach is computationally expensive compared to the GA-DMB approach, it generates results that appear to make the computational effort worthwhile. Other methods such as importance sampling, Latin hypercubes, and the adaptive ordinal approach [36] reduce the computational cost but are still relatively expensive. Additionally, these methods and others need modifications to address the discrete variable problem presented in this research.

The genetic algorithm has potential to make use of its population-based search to add samples without the need for hundreds of analyses for each fitness evaluation. The GA starts its search from a randomly generated population. As the search progresses via the GA operators, the GA starts to converge to areas of good fitness in the design space. Designs with good fitness values reappear in future generations until convergence. Copies of good designs from all generations in a GA run can serve as samples to evaluate the uncertain fitness values of these designs, while designs with poor fitness receive very little, if any, copies or samples. In this sense, the population-based search starts as a deterministic search during the initial generations and becomes more of a nondeterministic search near the end. The authors have developed a GA population-based sampling approach that significantly reduces the computational cost for optimization with discrete and uncertain variables; this approach appears in [37].

IX. Conclusions

The research presented in this paper couples integrated spacecraft models with a genetic algorithm for the conceptual design of commercial communication satellite systems. A reliability-based design optimization formulation is proposed for the spacecraft design problem. The objective is to minimize the spacecraft launch mass, a surrogate for cost, given minimum constraints on payload and total spacecraft reliabilities. The spacecraft conceptual design problem includes a set of discrete design variables representing components and subsystem technology choices and redundancy levels, hence, the use of the GA, a heuristic global search method based on evolution theory. The GA can handle discrete design optimization problems that involve both categorical and ordinal variables. Using an optimization formulation for the conceptual design of spacecraft systems allows system architects to explore more design variable combinations than what they can handle manually, and hence, avoid design fixation. This process leads to optimal design concepts, including concepts that the designers may not have considered.

The uncertainties associated with components and subsystem failure rates—hence their reliability values—are modeled. The objective is to evaluate system reliability in a probabilistic approach to quantify the uncertainty associated with aggregate payload and spacecraft reliability metrics. This approach is meant to aid system architects make informed risk-based decisions using quantitative probabilistic analysis rather than the traditional deterministic margin-based or safety factor approaches. A probabilistic design approach can prevent system oversizing and the inclusion of large amounts of redundancies, which appears to be the current practice in spacecraft design.

The spacecraft design optimization problem was solved using a deterministic margin-based approach and a Monte Carlo sampling approach to compare the quality of the optimal solutions obtained by both methods as well as the required computational cost. The quality of a spacecraft design solution is defined in this work as the launch mass of the spacecraft given that the design solution is feasible with respect to confidence-level constraints that are imposed on aggregate reliability requirements. In the MCS approach, probabilities of achieving reliability requirements are calculated from a large number of samples and are used in the confidence-level constraints evaluation. In the DMB approach, confidence-level constraints are imposed on the component level to assign reliability margins. Both approaches, GA-MCS and GA-DMB, were run at five different confidence levels. Additionally, 10 runs were carried out for each approach at each confidence level to assess the repeatability of the

Table 7 Comparison computational cost in terms of number of function evaluations of the GA-DMB and GA-MCS approaches

	GA-DMB			GA-MCS		
Confidence level	min	mean	max	min	mean	max
70%	7872	8643	9,348	3,198,000	4,264,000	4,756,000
80%	8036	8758	9,348	4,100,000	6,412,400	12,054,000
90%	6560	7626	8,692	3,444,000	5,239,800	12,136,000
92.5%	6724	9659	12,628	4,346,000	6,133,600	13,448,000
99%	6724	7052	7,708	4,018,000	5,116,800	7,052,000

GA results. The best design description found in each of these 10 runs was very consistent, suggesting that the results are repeatable.

The results show that, at low confidence levels, the two approaches provide similar spacecraft designs (i.e., similar launch mass values) that are feasible with respect to the imposed confidence-level constraints. However, at high confidence levels, the DMB approach provides heavy spacecraft designs with high redundancy and high reliability technology choices, for all components and subsystems even if the choice has low performance or high mass. Additionally, at the largest confidence-level constraint of 99%, the DMB approach could not find any feasible solution. In comparison, at high confidence levels, the MCS approach finds low launch mass spacecraft design solutions that satisfy the confidence-level constraints on the aggregate reliability metrics by mixing reasonable amounts of redundancies with a balanced set of technology choices that maximizes performance and reliability values.

Using a probabilistic design approach, such as MCS, can generate lower mass spacecraft designs that satisfy the reliability constraints at high confidence levels, as compared to designs generated by a deterministic approach for reliability-based design. However, in the MCS approach, or other reduced sampling methods, a large number of samples is needed to accurately calculate an estimated reliability value. This becomes very expensive in an optimization formulation where each function evaluation requires many performance analyses for the sampling. A literature survey revealed that, in the past few years, several engineering and nonengineering applications have combined MCS with the GA for the probabilistic design optimization of complex systems. Although the GA-MCS approach appears to be state of the art, its large computational cost may discourage practitioners from using it in design problems where high fidelity models for spacecraft design are available. A separate paper by the authors presents a population-based sampling (PBS) approach that allows for design optimization under uncertainty in a fraction of the computational cost required by the GA-MCS approach.

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O. de Weck
Associate Editor