

Optimal Aircraft Design Decisions under Uncertainty via Robust Signomial Programming

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Aircraft design benefits greatly from optimization under uncertainty, since design feasibility and performance can have large sensitivities to uncertain parameters. The traditional, mathematically non-rigorous methods of capturing uncertainty do not adequately explain the trade-offs between feasibility and optimality, and require prior engineering knowledge which may not be available for novel aerospace vehicle concepts. This paper proposes a solution method for engineering design optimization problems under uncertainty using robust signomial programs (RSPs). The proposed RSP formulation leverages an existing approximate robust geometric programming (RGP) formulation developed by Saab, and extends it by allowing difference-of-log-convex constraints that appear in many design problems. Signomial programs have demonstrated potential in the solution of multidisciplinary non-convex optimization problems such as aircraft design, and the formulation and solution of robust signomial programs (RSPs) allows for conceptual engineering design that captures parametric uncertainty. The paper details the method which is based on solving a sequence of RGPs, where each RGP is a local approximation of the RSP. Then it explores the trade-off between robustness and optimality rigorously by implementing RSPs on a simple aircraft design problem, and demonstrates the effect of robustness requirements on aircraft design decisions.

Nomenclature

CEG	Convex Engineering Group
GP	geometric program
LHS	left hand side
MDO	multidisciplinary design optimization
NLP	nonlinear program
SP	signomial program
RGP	robust geometric program
RHS	right hand side
RO	robust optimization
RSP	robust signomial program
SO	stochastic optimization

I. Introduction

Aircraft design exists in a niche of design problems where "failure is not an option"^a. This is remarkable since aircraft design problems are rife with uncertainty about technological capabilities, environmental factors, manufacturing quality and the future state of markets and regulatory agencies. **Optimization under**

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^aQuoting Gene Kranz, the mission director of Apollo 13.

uncertainty for aircraft presents low hanging fruit, since the program risk of aircraft design problems is high and the goal of these methods is to be able to provide designs that are robust to realizations of uncertainty in the real world.

Zang et al.[1] succinctly describe the categories of benefits for optimization under uncertainty for aircraft. These are the following:

- *Confidence in analysis tools will increase.* The uptake of new design tools in the aerospace industry has been low due to heavy reliance on legacy design methods and prior experience when faced with risky design propositions, even in the design of novel configurations where understanding of the design tradespaces is lacking. Robustness will increase confidence in analysis tools because of its ability to better capture the effects of technological uncertainty on the potential benefits of new configurations.
- *Design cycle time, cost, and risk will be reduced.* Design cycle costs as well as the engineering hours per aircraft have been increasing [2] precipitously since the 1950's. Aircraft design and development is costly, so the ability to handle uncertainty in the conceptual design process is critical for the long-term success of an aircraft, helping reduce the program risk.
- *System performance will increase while ensuring that reliability requirements are met.* The effectiveness of an aircraft depends heavily on its ability to deliver on performance, which is dependent on assumptions about the current technological environment and the ability to produce vehicles of a certain quality.
- *Designs will be more robust.* The ability to provide designs with feasibility and performance guarantees will mean that designs and products will be more robust to uncertainties in manufacturing quality, environmental factors, technology level and markets, and better able to handle off-nominal operating conditions.

In economics, the idea that risk is related to profit is well understood and leveraged. In aerospace engineering however we often forget that there is no such thing as a free lunch, and that the consequence of risk aversity necessarily is performance that is left on the table. Considering that conceptual design in the aerospace industry hedges against program risk, the Robust Optimization (RO) frameworks proposed in this paper will give aerospace engineers the ability to rigorously trade robustness and the performance penalties that result from it.

I.A. Approaches to optimization under uncertainty

Faced with the challenge of developing general nonlinear programs that can incorporate uncertainty, the aerospace field has developed a number of mathematically non-rigorous methods to design under uncertainty. Oftentimes, aerospace engineers will implement *margins* in the design process to account for uncertainties in parameters that a design's feasibility may be sensitive to, such as material properties or maximum lift coefficient. Another traditional method of adding robustness is through *multi-mission design* [3], which ensures that the aircraft is able to handle multiple kinds of missions in the presence of no uncertainty. This is a type of *finitely adaptive* optimization geared to ensure objective performance in off-nominal operations.

The weaknesses of these non-rigorous methods are many. They provide no quantitative measures of robustness or reliability [1]. They rely on the expertise of an experienced engineer to guide the design process, without explicit knowledge of the trade-off between robustness and optimality [4]. This is a dangerous proposition especially in the conceptual design phase of new configurations, since prior information and expertise is not available. In these scenarios, it is especially important to go back to fundamental physics and use rigorous mathematics to explore the design space [3]. Furthermore, they are often *too conservative*, ruling out potentially beneficial technologies and configurations due to the inability to adequately trade off performance and risk.

There are two rigorous approaches to solving design optimization problems under uncertainty, which are Stochastic Optimization (SO) and RO. Stochastic optimization^b deals with probability distributions of uncertain parameters by propagating these uncertainties through the physics of a design problem to ensure

^bNote that stochastic optimization is an overloaded term, and exists in three contexts in the literature. The first is the solution of deterministic problems with stochastic search space exploration. The second is the solution of simulations, often partial differential equations, with uncertain parameters. The final is the solution of design optimization problems with stochastic parameters. We explore the third category.

constraint feasibility with certain probabilistic guarantees. The goal of SO is predominantly to minimize the expectation of an objective function or to optimize on some desired characteristic of the probability density function of the objective [5]. Robust optimization takes a different approach, instead choosing to make designs immune to uncertainties in parameters as long as the parameter values come from within the defined uncertainty set. As such, RO minimizes the worst-case objective outcome from a defined uncertainty set.

I.B. Advantages of robust over stochastic optimization

The formulation of stochastic models as RO problems has many advantages over general stochastic optimization methods as explored in detail in [6]. These generally fall into three categories, which are tractability, conservativeness and flexibility. RO is more tractable than SO due to the nature of uncertainty propagation. General stochastic methods involve the propagation of uncertainties throughout a model to determine their effects on constraint feasibility and the objective function. This requires the integration of the product of probability distributions with potential outcomes, and since the integration of continuous functions is difficult this is often achieved through a combination of high-dimensional quadrature and discretizations of the uncertainty into possible scenarios. The propagation of parameter scenarios results in a combinatorial explosion of possible outcomes which need to be evaluated to determine constraint satisfaction and the distribution of the objective.

Few problems can be addressed purely through stochastic optimization (eg. the recourse problem as shown in [7],[8], and energy planning problem such as in [9]). It is arguable that the methods used are still limited by the combinatorics and costly system evaluations. RO has to deal with a somewhat related problem, which is the issue of a countably infinite number of possible constraints for a given uncertainty set. However, this is easily tackled by considering the worst case robust counterpart of each constraint, which results in many kinds of optimization problems having tractable robust formulations [6].

Although RO problems solve problems with uncertainty, RO formulations result in solutions that are deterministically immune to all possible realizations of parameters in an uncertainty set [6], which is defined as conservativeness. SO formulations provide no such guarantees. RO also does not require distributional information about uncertain parameters as SO does, and therefore can better address problems where there is a lack of experience or data. It is arguable that RO leaves a lot on the table by not taking advantage of distributional information, however there is a growing body of research on distributionally robust optimization [10] which seeks to leverage existing data.

There is significantly greater flexibility in the formulation of robust versus stochastic models since the methods proposed are more general. It is important to highlight that, although both RO and SO seek to address the problem of optimization under uncertainty, they solve fundamentally different problems. In an ideal world where we have a problem that is tractable and globally optimal for both methods, the two different approaches would result in different solutions.

I.C. Geometric and signomial programming for engineering design

Geometric programming^c is a method of log-convex optimization that has been developed to solve problems in engineering design [11]. Although theory of the Geometric Program (GP) has existed since the 1960's, GPs have recently experienced a resurgence due to the advent of polynomial-time interior point methods [12] and improvements in computing. They have been applied to a range of engineering design problems with success. For a non-exhaustive list of examples, please refer to [13].

GPs have been effective in aircraft conceptual design ([14], [15]). However, the stringent mathematical requirements of a GP limits its application to non-log-convex problems. The Signomial Program (SP) is the difference-of-log-convex extension of the GP which can be applied to solve this larger set of problems, albeit with the loss of some mathematical guarantees compared to the GP [16]. Aircraft pose some of the most challenging design problems [3], and signomial programming has been used to great effect in modeling and designing complex aircraft at a conceptual level quickly and reliably as in [3], [17] and [16]. Other interesting applications for SPs such as in network flow problems are being investigated.

Robust formulations exist for solving geometric programs with parametric uncertainty [18]. We posit that the creation of a robust signomial programming framework to capture uncertainty in engineering design, and

^cProgramming refers to the mathematical formulation of an optimization problem.

specifically aircraft design, will allow us to have more confidence in the results of the conceptual design phase, reduce program risk, and increase overall system performance.

I.D. Contributions

In this paper, we propose a tractable Robust Signomial Program (RSP) which we solve as a sequential Robust Geometric Program (RGP), allowing us to implement robustness in non-log-convex problems such as aircraft design. We extend the RGP framework developed by Saab [18] to SPs. We implement the RSP formulation on a simple aircraft design problem with several hundred variables as defined in [19]. We demonstrate the benefits of robust optimization both in ensuring design feasibility and performance using Monte Carlo (MC) simulations of the uncertain parameters. We further explore the benefits of RO in multiobjective optimization, and propose a goal programming RSP formulation for risk minimization problems.

II. Mathematical Background

II.A. Robust Optimization

Given a general optimization problem under parametric uncertainty, we can define the set of possible realizations of uncertain vector of parameters u in the uncertainty set \mathcal{U} . This allows us to define the problem under uncertainty below.

$$\begin{aligned} \min & f_0(x) \\ \text{s.t.} & f_i(x, u) \leq 0, \forall u \in \mathcal{U}, i = 1, \dots, n \end{aligned}$$

This problem is infinite-dimensional, since it is possible to formulate an infinite number of constraints with the countably infinite number of possible realizations of $u \in \mathcal{U}$. To circumvent this issue, we can define the following robust formulation of the uncertain problem below.

$$\begin{aligned} \min & f_0(x) \\ \text{s.t.} & \max_{u \in \mathcal{U}} f_i(x, u) \leq 0, i = 1, \dots, n \end{aligned}$$

This formulation hedges against the worst-case realization of the uncertainty in the defined uncertainty set. This is often posed by creating an uncertainty set to contain all possible realizations of the uncertainty we are concerned about, usually through a norm,

$$\begin{aligned} \min & f_0(x) \\ \text{s.t.} & \max_u f_i(x, u) \leq 0, i = 1, \dots, n \\ & \|u\| \leq \Gamma \end{aligned} \tag{1}$$

where Γ is defined by the user as an uncertainty bound. The larger the Γ , the greater the size of the uncertainty set that is protected against.

II.B. Geometric Programming

A **geometric program in posynomial form** is a log-convex optimization problem of the form:

$$\begin{aligned} \min & f_0(\mathbf{u}) \\ \text{s.t.} & f_i(\mathbf{u}) \leq 1, i = 1, \dots, m_p \\ & h_i(\mathbf{u}) = 1, i = 1, \dots, m_e \end{aligned} \tag{2}$$

where each f_i is a *posynomial*, each h_i is a *monomial*, m_p is the number of posynomials, and m_e is the number of monomials. A monomial $h(\mathbf{u})$ is a function of the form:

$$h_i(\mathbf{u}) = e^{b_i} \prod_{j=1}^n u_j^{a_{ij}}$$

where a_{ij} is the j^{th} component of a row vector \mathbf{a}_i in \mathbb{R}^n , u_j is the j^{th} component of a column vector \mathbf{u} in \mathbb{R}_+^n , and b_i is in \mathbb{R} . An example of a monomial is the lift equation, $L = \frac{1}{2}\rho V^2 C_L S$. A posynomial $f(\mathbf{u})$ is the sum of $K \in \mathbb{Z}^+$ monomials:

$$f_i(\mathbf{u}) = \sum_{k=1}^K e^{b_{ikj}} \prod_{j=1}^n u_j^{a_{ikj}}$$

where a_{ikj} is the j^{th} component of a row vector \mathbf{a}_{ik} in \mathbb{R}^n , u_j is the j^{th} component of a column vector \mathbf{u} in \mathbb{R}_+^n , and b_{ik} is in \mathbb{R} [13]. The stagnation pressure definition is a good example: $P_t = P + \frac{1}{2}\rho V^2$.

A logarithmic change of the variables $x_j = \log(u_j)$ would turn a monomial into *the exponential of an affine function* and a posynomial into *the sum of exponentials of affine functions*. A transformed monomial $h_i(\mathbf{x})$ is a function of the form:

$$h_i(\mathbf{x}) = e^{\mathbf{a}_i \mathbf{x} + b_i}$$

where \mathbf{x} is a column vector in \mathbb{R}^n . A transformed posynomial $f_i(\mathbf{x})$ is the sum of $K_i \in \mathbb{Z}^+$ monomials:

$$f_i(\mathbf{x}) = \sum_{k=1}^{K_i} e^{\mathbf{a}_{ik} \mathbf{x} + b_{ik}}$$

where \mathbf{x} is a column vector in \mathbb{R}^n . A geometric program with transformed constraints is a **geometric program in exponential form**, and is a convex optimization problem.

The positivity of exponential functions restricts the space spanned by posynomials and limits GPs to certain classes of problems. However, since many engineering problems of interest have purely positive quantities GPs are quite applicable, and certain variable transformations can make problems with negative quantities tractable. The restriction of posynomials to the *less-than-side of inequalities* is a more significant barrier, and motivates the introduction of signomials.

II.C. Signomial Programming

A *signomial* can be defined as the difference between two posynomials. Consequently, a SP is a non-log-convex optimization problem of the form:

$$\begin{aligned} & \text{minimize} && f_0(\mathbf{x}) \\ & \text{subject to} && f_i(\mathbf{x}) - g_i(\mathbf{x}) \leq 0, i = 1, \dots, m \end{aligned} \tag{3}$$

where f_i and g_i are both posynomials, and \mathbf{x} is a column vector in \mathbb{R}^n .

Reliably solving an SP to a local optimum has been described in [13] and [20]. A common solution heuristic involves solving an SP as a sequence of GPs, where each GP is a local approximation of the SP. Although it is a powerful tool, applications involving SPs are usually prone to uncertainties that have a significant effect on the solution.

III. Robust Signomial Programming

As a preview of the following sections, robust signomial programming assumes that parameter uncertainties belong to an uncertainty set, and solves a reformulated design problem to find the best solution, through the process shown in Figure 1. As long as the original optimization problem is SP-compatible, a tractable robust formulation of the problem exists, making this method general. We derive the intractable formulation of a RSP below.

A SP in its **exponential form** is as follows:

$$\begin{aligned} & \min && f_0(\mathbf{x}) \\ & \text{s.t.} && \sum_{k=1}^{K_i} e^{\mathbf{a}_{ik} \mathbf{x} + b_{ik}} - \sum_{k=1}^{G_i} e^{\mathbf{c}_{ik} \mathbf{x} + d_{ik}} \leq 0 \quad \forall i \in 1, \dots, m \end{aligned} \tag{4}$$

where the constraints are represented as difference-of-posynomials in exponential form. Let \mathbf{a}_{ik} and \mathbf{c}_{ik} be the $((i-1) \times m + k)^{th}$ rows of the exponents matrices \mathbf{A} and \mathbf{C} respectively, and b_{ik} and d_{ik} be the $((i-1) \times m + k)^{th}$ elements of the coefficients vectors \mathbf{b} and \mathbf{d} respectively.

Robust Signomial Programming

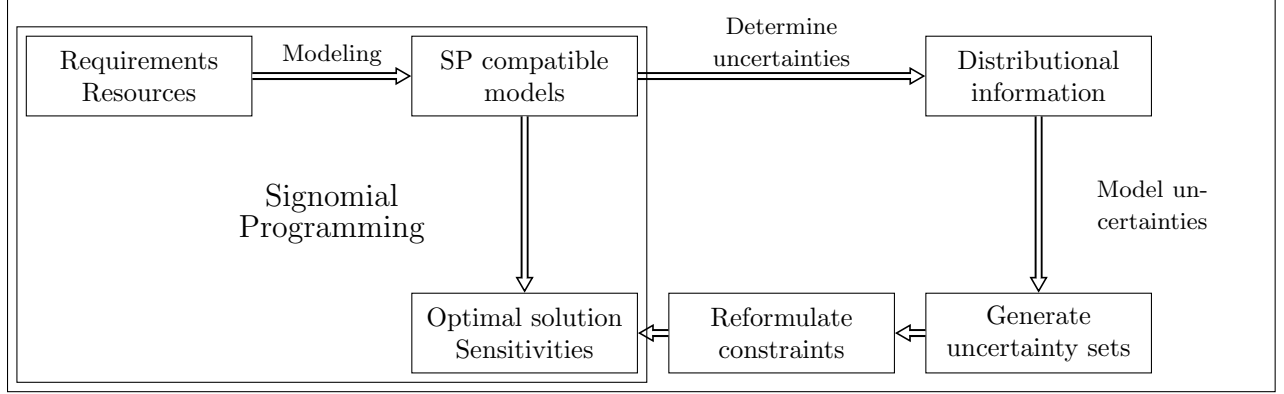


Figure 1: A block diagram showing the difference between the design process using a SP and a RSP.

The data $(\mathbf{A}, \mathbf{C}, \mathbf{b}, \mathbf{d})$ is assumed to be uncertain and living in an uncertainty set \mathcal{U} , where \mathcal{U} is parametrized affinely by a perturbation vector ζ :

$$\mathcal{U} = \left\{ [\mathbf{A}; \mathbf{C}; \mathbf{b}; \mathbf{d}] = [\mathbf{A}^0; \mathbf{C}^0; \mathbf{b}^0; \mathbf{d}^0] + \sum_{l=1}^L \zeta_l [\mathbf{A}^l; \mathbf{C}^l; \mathbf{b}^l; \mathbf{d}^l] \right\} \quad (5)$$

where \mathbf{A}^0 , \mathbf{C}^0 , \mathbf{b}^0 , and \mathbf{d}^0 are the nominal exponents and coefficients, $\{\mathbf{A}^l\}_{l=1}^L$, $\{\mathbf{C}^l\}_{l=1}^L$, $\{\mathbf{b}^l\}_{l=1}^L$, and $\{\mathbf{d}^l\}_{l=1}^L$ are the basic shifts of the exponents and coefficients, and ζ_l is the l^{th} component of ζ belonging to a perturbation set $\mathcal{Z} \in \mathbb{R}^L$ such that

$$\mathcal{Z} = \{\zeta \in \mathbb{R}^L : \|\zeta\| \leq \Gamma\} \quad (6)$$

As mentioned earlier, there should exist a formulation immune to uncertainty in the system's data. Accordingly, the robust counterpart of the uncertain SP in (4) is:

$$\begin{aligned} \min \quad & f_0(\mathbf{x}) \\ \text{subject to} \quad & \max_{\zeta \in \mathcal{Z}} \left\{ \sum_{k=1}^{K_i} e^{\mathbf{a}_{ik}(\zeta)\mathbf{x} + b_{ik}(\zeta)} - \sum_{k=1}^{G_i} e^{\mathbf{c}_{ik}(\zeta)\mathbf{x} + d_{ik}(\zeta)} \right\} \leq 1 \quad \forall i \in 1, \dots, m \end{aligned} \quad (7)$$

The optimization problem in (7) is intractable using current solvers, therefore, a heuristic approach to solving RSPs approximately as a sequential RGP will be presented in the following sections. As our approach is based on robust geometric programming, a brief review of the subject will follow based on [18].

IV. Robust Geometric Programming

This section presents a brief review of the approximation of an RGP as a tractable optimization problem as discussed in [18]. The robust counterpart of an uncertain geometric program is:

$$\begin{aligned} \min \quad & f_0(\mathbf{x}) \\ \text{subject to} \quad & \max_{\zeta \in \mathcal{Z}} \left\{ \sum_{k=1}^{K_i} e^{\mathbf{a}_{ik}(\zeta)\mathbf{x} + b_{ik}(\zeta)} \right\} \leq 1 \quad \forall i \in 1, \dots, m \end{aligned} \quad (8)$$

which is Co-NP hard in its natural posynomial form [21]. We will present three approximate formulations of a RGP.

IV.A. Simple Conservative Formulation

One way to approach the intractability in (8) is to replace each constraint by a tractable approximation. Replacing the max-of-sum in (8) by the sum-of-max will lead to the following formulation

$$\begin{aligned} & \min && f_0(\mathbf{x}) \\ \text{subject to} &&& \sum_{k=1}^{K_i} \max_{\zeta \in \mathcal{Z}} \{e^{\mathbf{a}_{ik}(\zeta)\mathbf{x} + b_{ik}(\zeta)}\} \leq 1 \quad \forall i \in 1, \dots, m \end{aligned} \quad (9)$$

Maximizing a monomial term is equivalent to maximizing an affine function, therefore (9) is tractable.

IV.B. Equivalent Intermediate Formulation

This formulation is equivalent to the formulation in (8), but with smaller, easier to handle posynomial constraints. By the properties of inequalities, the posynomial P in posynomial inequality $M \geq P$ can be divided into an equivalent set of smaller posynomials based on the dependence between its monomial terms. Figure 2 shows how a constraint can be represented as an equivalent set of smaller posynomial constraints.

Figure 2: Partitioning of a large posynomial into smaller posynomials requires the addition of auxiliary variables. S_i are posynomials with independent sets of variables.

The posynomial constraints are categorized into three sets: large posynomials, two-term posynomials and monomials, represented by $S1$, $S2$ and $S3$ respectively. Monomials are tractable, and two-term posynomials can be well approximated using piecewise-linear functions [22]. We implement the following two tractable approximations for large posynomials.

IV.B.1. Linearized Perturbations Formulation

If the exponents are known and certain, then large posynomial constraints can be approximated as signomial constraints. The exponential perturbations in each posynomial are linearized using a modified least squares method, and then the posynomial is robustified using techniques from robust linear programming. The resulting set of constraints is SP compatible, therefore, a robust geometric program can be approximated as a signomial program.

IV.B.2. Best Pairs Formulation

If the exponents are also uncertain, then large posynomials can't be approximated as an SP, and further simplification is needed. This formulation aims to maximize each pair of monomials in each posynomial, while finding the best combination of monomials that gives the least conservative solution. [18] provides a descent algorithm to find locally optimal combinations of the monomials, and shows how the uncertain geometric program can be approximated as a geometric program for polyhedral uncertainty, and a conic optimization problem for elliptical uncertainty with uncertain exponents. For a detailed description of the above formulations refer to [18]. An algorithm for solving an RSP based on the above formulations is provided in the next section.

V. Approach to Solving Robust Signomial Programs

This section presents a heuristic algorithm to solve a RSP based on our previous discussion on robust geometric programming.

V.A. General RSP Solver

As mentioned before, a common heuristic algorithm to solve a SP is by sequentially solving local GP approximations, but the solution is not guaranteed to be globally optimal. Our approach to solve a RSP is based on sequentially solving local RGP approximations. Below we provide a step-by-step algorithm to solve a RSP:

1. Choose an initial guess x_0 .
2. Repeat:
 - (a) Find the local GP approximation of the SP at x_i .
 - (b) Find the RGP formulation of the GP.
 - (c) Solve the RGP to obtain x_{i+1} .
 - (d) If $x_{i+1} \approx x_i$: break

Similar to a SP, a good initial guess will lead to faster convergence and possibly a better solution. The deterministic solution of the uncertain SP is a good candidate x_0 , and is used to speed up convergence.

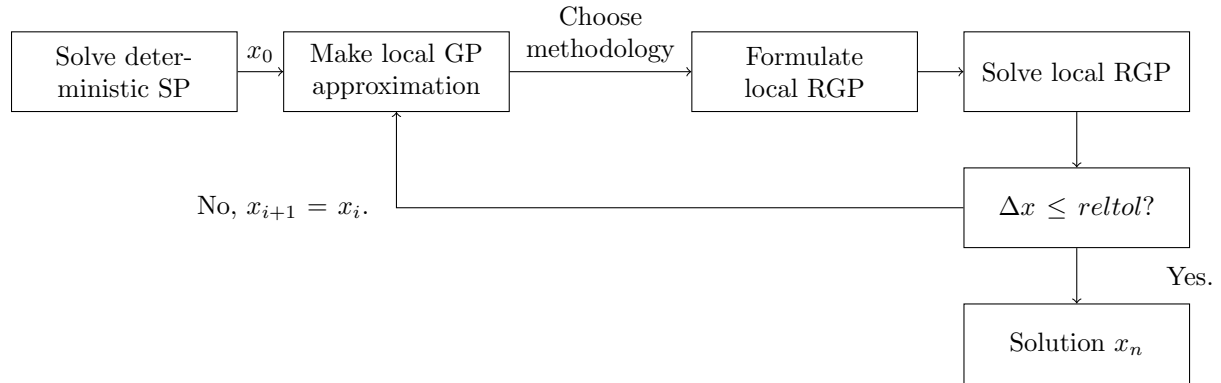


Figure 3: A block diagram showing the steps of solving an RSP.

Any of the previously mentioned methodologies can be used to formulate the local RGP approximation. However, depending on the RGP formulation chosen to solve a RSP, the last formulation and solution blocks in Figure 3 are adjusted for a faster rate of convergence.

V.B. Best Pairs RSP Solver

If the Best Pairs methodology is exploited, then the above algorithm would change so that each iteration would solve the local RGP approximation and choose the best permutation for each large posynomial. The modified algorithm would become as follows:

1. Choose an initial guess x_0 .
2. Repeat:
 - (a) Find the local GP approximation of the SP at x_i .
 - (b) For each large posynomial constraint, select the new permutation ϕ such that ϕ minimizes the robust large constraint evaluated at x_i .
 - (c) Solve the approximate tractable counterparts of the local GP in (8), and let \mathbf{x}_{i+1} be the solution.
 - (d) If $x_{i+1} \approx x_i$: break.

V.C. Linearized Perturbations RSP Solver

On the other hand, if the Linearized Perturbations formulation is to be used, then we can avoid solving a SP at each iteration by first approximating the original SP constraints locally, and in the same loop approximating the robustified possibly signomial constraints locally, thus solving a GP at each iteration instead of an SP. The algorithm would then become as follows:

1. Choose an initial guess x_0 .
2. Repeat:
 - (a) Find the local GP approximation of the SP at x_i .
 - (b) Robustify the constraints of the local GP approximation using the Linearized Perturbations methodology.
 - (c) Find the local GP approximation of the resulting local SP at x_i .
 - (d) Solve the local GP approximation in step c to obtain x_{i+1} .
 - (e) If $x_{i+1} \approx x_i$: break.

VI. Models

We implement the RSP formulation above on a simple unmanned, gas-powered aircraft design problem that is systematically developed in [19]. We optimize a wing, fuselage, and engine given a payload and range requirement. The nominal model has 154 variables and 184 constraints, a common level of sparsity for GP and SP models. A short qualitative overview of the model follows; for more detailed information, please refer to [19]. The uncertainties associated with the parameters will be described in Section VII.

VI.A. Flight Profile

The flight profile models is borrowed from [3]. Within the model, the trajectory of the aircraft is optimized over five steady flight segments, although we are restricted to modeling only climb segments and therefore the stored gravitational potential energy of the aircraft is not captured.

VI.B. Atmosphere

The atmosphere model is taken from [23], and considers changes in density and dynamic viscosity with altitude, for a standard atmosphere.

VI.C. Aircraft

The aircraft is modeled as a wing, fuselage and engine system. The aircraft is assumed to be in steady flight, so that the thrust power is equal to the sum of the drag power and rate of change of potential energy of the aircraft, and the lift is equal to the total weight, ignoring the vertical component of thrust in climb. Its total weight is the sum of its components. The aircraft has to be able to takeoff at specified minimum speed without stalling as well. Aircraft component models are detailed below.

VI.C.1. Wing

Lift is generated by the wing as a function of its geometry and freestream conditions. The wing structure model is based on a simple beam model with a distributed lift load, and a point mass in the center representing the fuselage. Wing fuel volume is modeled as a fraction of the internal volume available in the wing. Its drag is approximated simply as a sum of the induced and profile drags, the latter of which is estimated using a form factor. The weight of the wing is the sum of skin and spar weights.

VI.C.2. Fuselage

The fuselage is assumed to only contain fuel. The fuselage drag is exactly proportional to its frontal area. The fuselage is assumed not to contain any structural members, and so its weight consists only of skin weight, which is based on the minimum gauge of composites.

VI.C.3. Engine

The aircraft is powered by a naturally aspirated piston engine. It is subject to power lapse at lower air densities at higher altitudes. Engine weight is modeled using a posynomial fit of existing engines. brake specific fuel consumption (BSFC) is modeled as a function of maximum thrust at a given altitude.

VI.D. Source of non-log-convexity: fuel volume

We have detailed the fuel models in the wing and fuselage sections, but it is noteworthy that the signomial constraint in the optimization appears in the aircraft total fuel volume constraint, as shown in Equation 10:

$$V_f \leq V_{f_{wing}} + V_{f_{fuse}} \quad (10)$$

The signomial constraints makes the problem non-log-convex, which means that the solution methods detailed by Saab [18] need to be extended to accommodate this optimization problem.

VII. Uncertainties and Sets

As aforementioned in Section I.B, one of the advantages of RO over SO is the fact that it is more effective in absence of data, since the problem has uncertainty set bounds on parameters as inputs instead of complete probability distributions. These uncertainties, given by three times the coefficient of variation (CV)^d, are listed in Table 1. Since for the rest of this work all standard deviations (σ) are normalized by the means of the parameters, we will use 3σ to represent 3CV.

Table 1: Parameters and Uncertainties (increasing order)

Parameters	Description	Value	% Uncert. (3σ)
$S_{wetratio}$	wetted area ratio	2.075	3
e	span efficiency	0.92	3
μ	air viscosity	1.78×10^{-5} kg/(ms)	4
ρ	air density	1.23 kg/m ³	5
$C_{L_{max}}$	stall lift coefficient	1.6	5
k	fuselage form factor	1.17	10
τ	airfoil thickness ratio	0.12	10
N_{ult}	ultimate load factor	3.3	15
V_{min}	takeoff speed	30 m/s	20
W_0	payload weight	6250 N	20
$W_{wcoeff,i}$	wing weight coefficient 1	2×10^{-5} 1/m	20
$W_{wcoeff,ii}$	wing weight coefficient 2	60 N/m ²	20

In this case of a conceptual aircraft design with no prior data, the parameter uncertainties reflect aerospace engineering intuition. The wing weight coefficients $W_{wcoeff,i}$ and $W_{wcoeff,ii}$, and the ultimate load factor N_{ult} have large 3σ s because the build quality of aircraft components is often difficult to quantify with a large degree of certainty. The payload weight (W_0) has a large uncertainty for similar reasons, since it is often developed concurrently with the aircraft. Parameters that engineers take to be physical constants (μ , ρ) and those that can be determined or manufactured with a relatively high degree of accuracy ($S_{wetratio}$, e) have relatively low deviations. Parameters that require testing to determine ($C_{L_{max}}$, V_{min}) have a level of uncertainty that reflects the expected variance of empirical studies. However, note that these quantities are ultimately picked by the designer using prior experience and data, and the level of conservatism in the design will be greatly affected by the chosen 3σ s.

^dThe CV is defined as follows: $CV = \frac{\sigma}{|\mu|}$, where σ is the standard deviation and μ is the mean of the parameter.

VIII. Results

We implement our RSP heuristic algorithm on the aforementioned conceptual aircraft design problem. Our nominal objective function is total fuel consumption, which is to be minimized given a payload and a range requirement.

VIII.A. Mitigation of probability of failure

The problem is solved for different sizes of box and elliptical uncertainty sets, whose sizes are defined by the L1- and L2-norms respectively, by varying the parameter Γ , as defined in Appendix X.A. Mathematically, for box uncertainty, Γ is a scaling of the width of each defined parameter uncertainty. More intuitively, it is the width of the margin provided for each parameter, normalized by its standard deviation.^e For elliptical uncertainty, it is the maximum diameter of the Euclidian norm ball of u_i , which is the number of standard deviations of perturbation of each i th parameter from its nominal value. Intuitively, Γ is a measure of how much risk is being hedged against. $\Gamma = 0$ implies that all of the parameters take their nominal values with zero uncertainty, and larger Γ protects against more parameter uncertainty, where a box uncertainty is more conservative than elliptical uncertainty.

The design variables are then fixed for each solution so that the design can be simulated for different realizations of the uncertain parameters in Table 1 to examine average design performance. In this MC scheme, the random variables are simulated from independent and identically distributed 3σ truncated Gaussians. We simulate from the truncated Gaussian since this makes it possible to confirm mathematically that for $\Gamma = 1$, all simulations of 3σ uncertain parameters are feasible. Designs for each solution in Figure 4 are simulated with the same set of uncertainty realizations for consistency.

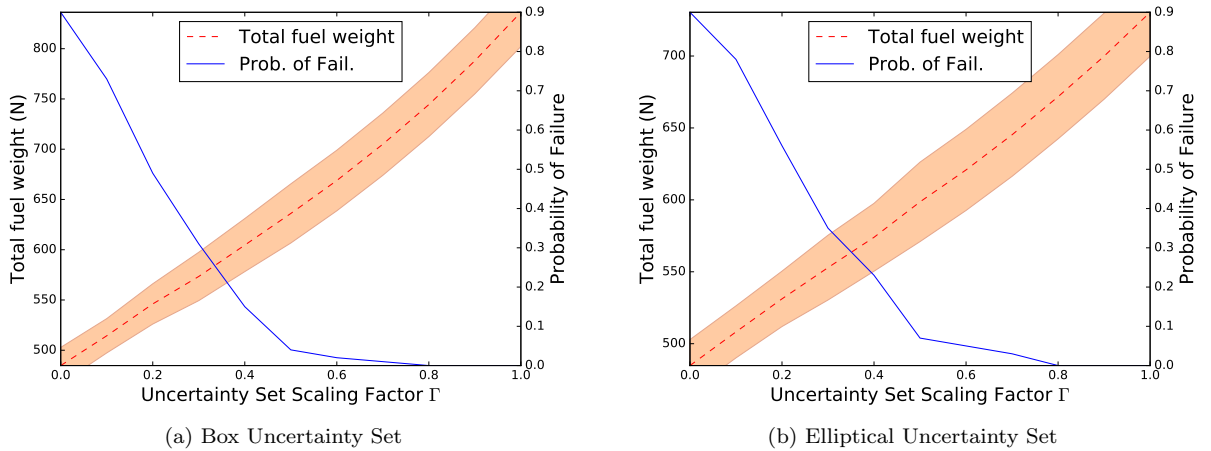


Figure 4: Simulated performance of the optimal robust aircraft, using the Best Pairs formulation, as a function of Γ for different uncertainty sets. The dashed line and the band represent the mean and standard deviation of the performance of aircraft designed for different Γ , and simulated with 100 MC samples of uncertain parameters.

We call the aircraft designed under box uncertainty and under elliptical uncertainty ‘the box aircraft’ and ‘the elliptical aircraft’ respectively. We define the probability of failure of a design as the probability that any constraint in the design optimization problem is violated in a MC simulation. As expected, Figure 4 shows that probability of failure goes to zero as Γ increases, and the probability of failure curve approximates the tail of the inverse cumulative probability distribution of the Gaussian. It is noteworthy that, for the nominal problem ($\Gamma = 0$) only about 10 percent of the realizations of uncertain variables result in feasible solutions. This means that an aircraft designed for the average case would almost surely fail to satisfy the mission requirements, even with equal likelihood of favorable versus unfavorable uncertain outcomes from

^eIt can be easy to assume that using margins and box uncertainty sets will yield the same designs, but they fundamentally function differently. The worst case outcome in box uncertainty can come *from the interior* of the uncertainty set, so the use of box uncertainty is strictly more conservative and more appropriate than the use of margins, which fail to capture the level of conservatism they signal.

the symmetric truncated Gaussian. That being said, depending on the problem, it may necessary to sacrifice performance to achieve a high degree (3σ) of reliability as in the solution for $\Gamma = 1$. As shown by Figure 2, the elliptical aircraft spends 74% more fuel in the worst case than the aircraft designed for the nominal case, but it is also completely robust to all uncertain outcomes in the 3σ set.

Table 2: SP Aircraft Optimization Results

Free variable	Units	No Uncert.	Box [$\Gamma = 1.0$]	Elliptical [$\Gamma = 1.0$]
L/D	-	39.6	30.5	33.6
AR	-	21.9	11.1	14.1
Re	-	1.86×10^6	3.91×10^6	3.19×10^6
S	m ²	18.1	43.7	38.1
V	m/s	40.9	39.8	39.0
T_{flight}	hr	20.4	21.0	21.4
W_w	N	2970	5370	4940
$W_{w, strc}$	N	1880	2470	2410
$W_{w, surf}$	N	1090	2900	2530
$V_{f, avail}$	m ³	0.0637	0.129	0.113
$V_{f, fuse}$	m ³	0.00437	0	0
$V_{f, wing}$	m ³	0.0593	0.129	0.113
E[Objective]	Units	No Uncert.	Box [$\Gamma = 1.0$]	Elliptical [$\Gamma = 1.0$]
W_{fuel}	N	511	1016	889
P[failure]		No Uncert.	Box [$\Gamma = 1.0$]	Elliptical [$\Gamma = 1.0$]
%		90	0	0

Moreover, using margins in design is similar to using a box uncertainty set, and therefore will lead to a more conservative solution with inferior performance. This can be seen by the fact that the elliptical aircraft spends 14% lower fuel in the worst case than the box aircraft, although they both protect against the same uncertain outcomes. The significance of this cannot be understated: the use of margins or box uncertainty protects against the same amount of risk as using elliptical uncertainty, with strictly worse performance outcomes.

In absolute terms, the nominal SP under zero uncertainty takes just under 0.9 seconds to solve on a modern personal computer; the authors refer to [24] and [3] for more in-depth SP solution time analyses. We examine briefly in relative terms about how the different RSP methodologies compare in terms of setup and run times in Figure 5. Since the setup time of the nominal problem is minimal, we have normalized the results by the run time of the nominal problem. The bottom axis ranks the methods by their level of conservativeness, Best Pairs and Simple Conservative formulations being the least and most conservative respectively, and where the elliptical formulations are less conservative than the box formulations. For the box uncertainty, solution times are almost identical for different levels of conservativeness, whereas for the elliptical uncertainty they decrease as the method becomes more conservative.

VIII.B. The Effect of Robustness on Multiobjective Performance

One of the benefits of convex and difference-of-convex optimization methods is the ability to optimize for different objectives [3]. As a demonstration, we optimized the aircraft without uncertainty for 7 different objectives, and show the non-dimensionalized results in Table 3. Since the model is physics based, it is able to accommodate a range of objectives, even ones that are not often considered such as aspect ratio. The resulting aircraft also differ drastically with respect to performance and design variables. As the most extreme example, the aircraft optimized for time cost has 150 times the engine weight as the aircraft optimized for total fuel, since a huge amount of power is required to fly fast.

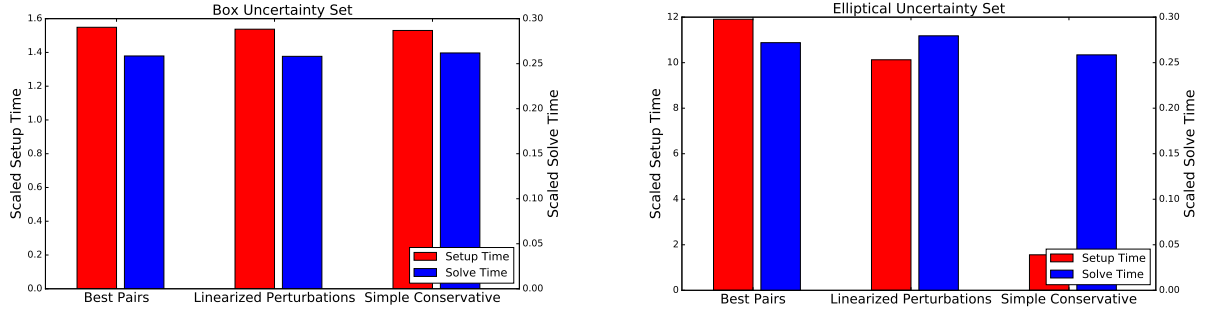


Figure 5: Robust signomial simple aircraft solution and setup times, normalized by the nominal problem solution time, for $\Gamma = 1$. Note that the problems with box uncertainty have much lower setup time costs versus those with elliptical uncertainty, but similar solve times.

Objective	Total fuel	Time cost	Aspect ratio	Engine weight	Wing loading	Total cost	Takeoff weight
Total fuel	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Time cost	9.44	0.3	0.09	152.85	1.0	1.86	2.6
Aspect ratio	4.26	0.46	0.04	25.72	0.94	1.11	1.22
Engine weight	1.09	1.22	1.28	0.8	1.0	1.2	1.15
Wing loading	8.89	1.5	0.28	13.06	0.22	2.76	5.82
Total cost	1.68	0.51	0.39	5.75	1.0	0.71	0.92
Takeoff weight	1.33	0.94	0.33	2.13	1.0	1.01	0.85

Table 3: Non-dimensionalized variations in objective values with respect to the aircraft optimized for different objectives. Objective values were normalized by the total fuel solution.

Aside from this caricature example, we demonstrate the capabilities of RSPs in multiobjective design by considering a more realistic scenario. We perform the optimization of the aircraft with no uncertainty and ellipsoidal uncertainty ($\Gamma = 1$) for 4 different objective functions, and plot the results on spider plots. Spider plots are useful because they allow engineers to see the performance of different designs in a multi-objective environment. One way to envision the multi-objective performance of the aircraft is to consider the area contained within the web defined by the aircraft's performance as the figure of merit; the smaller the web area the better. Due to the large disparities in the potential values of design variables depending on objective as shown in Table 3, we chose to demonstrate this using four objective functions that would be expected to have a high degree of correlation and therefore could yield a nuanced comparative analysis. These were total (time and fuel) cost, total fuel, takeoff weight and mid-cruise lift-over-drag (L/D).

Figure 6 shows the effects of robustness on the different worst-case performance metrics of the different aircraft. For the nominal case, it is possible to see that the aircraft designed for total fuel performs the best when all four objectives are considered, assuming that all objectives are weighted equally. As expected, the box uncertainty set is strictly more conservative than the elliptical uncertainty set, for all objectives. Note that the spider plots show the worst-case performance of the vehicles. This analysis could also be performed for the mean performance of the aircraft determined through MC simulation, but this demonstration limits its scope to the worst-case analysis.

One interesting observation is that there is a convergence in the geometry of the aircraft as they are designed to be robust to uncertain outcomes. All of the robust designs eschew the storage of fuel in the fuselage for larger wings that can store more fuel. This is not to say that none of the aircraft will ever have fuselages; one example is a mission where flight time is a much more important objective than fuel weight. We optimize aircraft for a range of Γ with total cost being the objective. In Figure 8, we show that, depending on our willingness to tolerate risk exposure, we may have drastically different opinions about whether or not a fuselage is beneficial to the performance of the aircraft.

Based on these observations, we argue that there could be significant value left on the table if uncertainty is not considered with sufficient mathematical rigor in early phases of the engineering design process. RSPs allow engineers to capture these complex tradeoffs while considering uncertainty, and have the potential

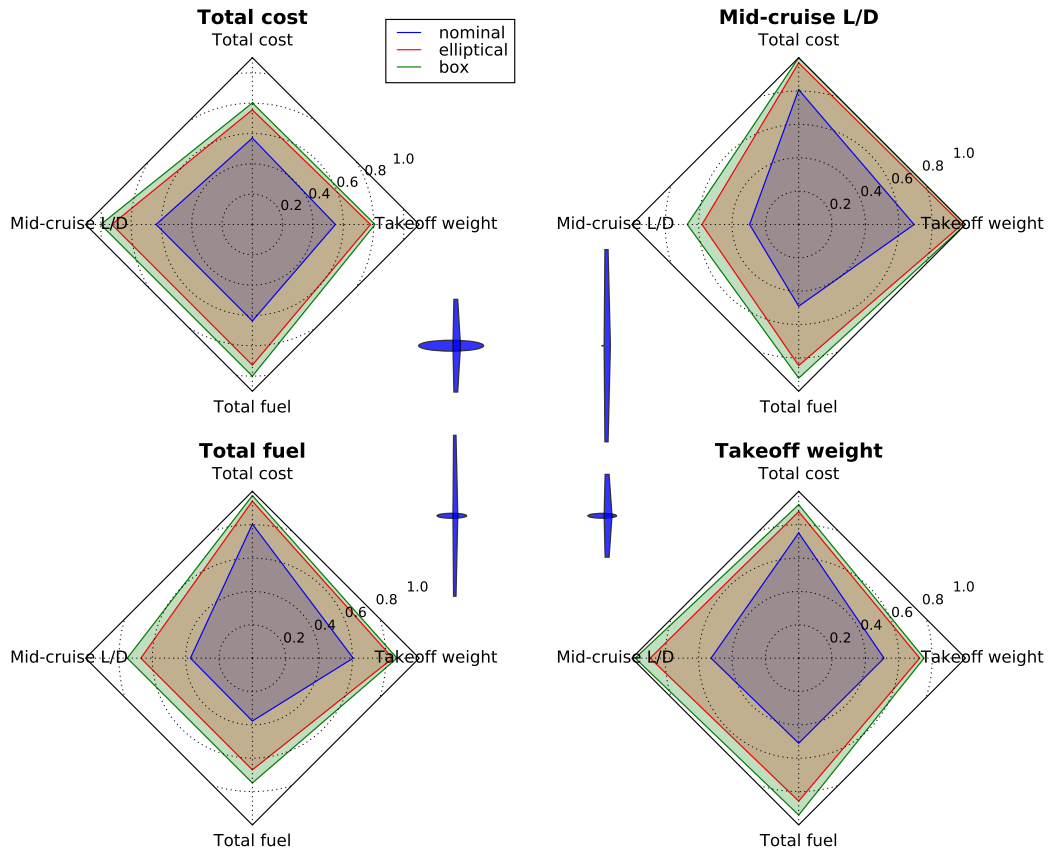


Figure 6: The spider plots of aircraft performance, for aircraft optimized for different objectives. The bolded titles are the design objectives for each plot, whereas the individual spiderwebs show the non-dimensionalized multiobjective performance of the aircraft designed under different uncertainty sets.

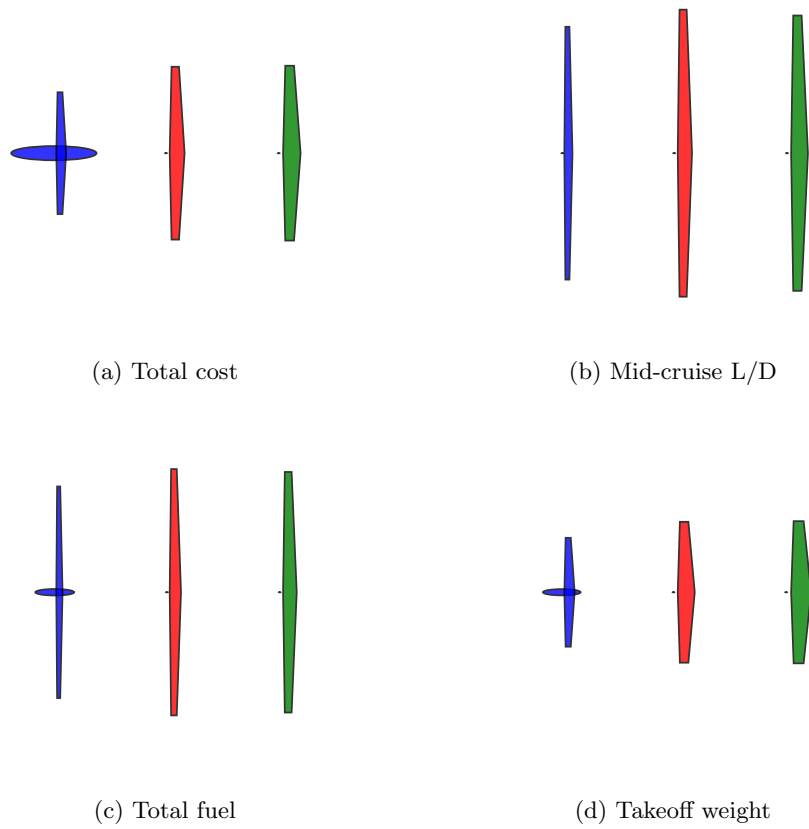


Figure 7: Sketches of the aircraft drawn for corresponding spider plots. Drawn to scale for comparison.

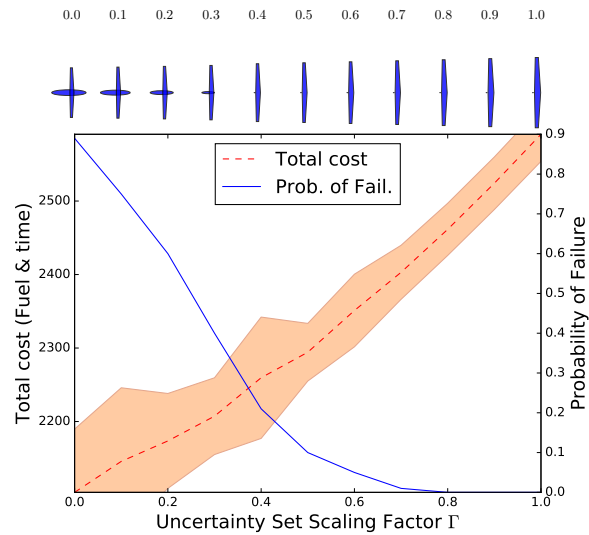


Figure 8: The evolution of aircraft designed for minimum total cost for different Γ s.

to change the mathematically non-rigorous paradigms of design under uncertainty in use in the aerospace industry today.

VIII.C. Risk minimization problems

All of the previous multi-objective analyses have assumed that we have an understanding of exactly the amount of uncertainty we are willing to tolerate. However, minimizing risk can also be the objective of our model. This would suggest the following formulation:

$$\begin{aligned}
& \max \Gamma \\
& \text{s.t. } f_i(x, u) \leq 0, i = 1, \dots, n \\
& \quad \|u\| \leq \Gamma \\
& \quad f_0(x) \leq (1 + \delta)f_0^*, \delta \geq 0
\end{aligned} \tag{a}$$

where f_0^* is the optimum of the nominal problem in Formulation 1, δ is a fractional measure of the objective that we are willing to sacrifice for robustness, which gives $(1 + \delta)f_0^*$ as the upper bound on the objective value. Intuitively, this is a form of goal programming, where we specify the exact maximum worst-case value of an objective we can tolerate so that the program risk is acceptable, but in the meanwhile maximize the total size of the uncertainty we can handle. We call the method of minimizing an objective for a given uncertainty set *the Γ method*, while we call the goal programming approach, which maximizes Γ for a set δ objective penalty tolerance, *the δ method*.

The problem in Formulation a is clearly not equivalent to the problem in Formulation 1, but should yield similar results. As a proof of concept, we will use the objective values from the study shown in Figure4 as the δ inputs to the goal programming model, and compare the results. If we are able to obtain globally optimal solutions, we would expect that Γ and δ from both problems are identical. The results are tabulated in Table 4. Note that the two methods were evaluated MC runs using the same 100 realizations of the uncertainty, for consistency in probability of failure results.

Table 4: Results of original RO formulation versus goal program in terms of size of uncertainty set Γ , objective penalty δ , and probability of failure. Note that the Γ and δ values obtained by the models match, but the probabilities of failure differ.

RO form	Γ	δ	PoF	Goal form	δ	Γ	PoF
	0.00	9×10^{-5}	0.9		-	-	-
	0.10	0.053	0.78		-	-	-
	0.20	0.113	0.56		0.113	0.20	0.66
	0.30	0.176	0.35		0.176	0.30	0.41
	0.40	0.245	0.23		0.245	0.40	0.24
	0.50	0.317	0.07		0.317	0.50	0.06
	0.60	0.395	0.05		0.395	0.60	0.03
	0.70	0.479	0.03		0.479	0.70	0.01
	0.80	0.570	0.00		0.570	0.80	0.00
	0.90	0.669	0.00		0.669	0.90	0.00
	1.00	0.775	0.00		0.775	1.0	0.00

Firstly, note that there are no results reported for the two smallest uncertainty sets $\Gamma = [0.00, 0.10]$. This is because the feasible set of the two problems was small enough that the signomial program solution heuristic was unable to find an interior point from which to explore the solution space, and reported infeasible. Otherwise, the Γ values found by the δ method match with the original RO method, confirming that the two methods produce equivalent results. This was also confirmed by examining the physical dimensions of the aircraft.

However, there were discrepancies found in the probability of failure. This is likely because of how numerical precision affects the solution of the feasibility problem solved as part of the MC scheme. Although

both methods are conservative, since some of the solutions are likely on the border of feasibility, the design could fall in or out of the feasible set depending on the piecewise-linear approximations made. Based on these observations, it was not possible to confirm which method is more conservative, but the probability of failure of the resulting aircraft is consistent with our expectations, being monotonic with the size of the uncertainty set and similar between the two methods.

We can also expand this framework to perform multivariate goal programming, by changing (a) in the formulation a to include all objectives we are interested in.

$$f_{0,j}(x) \leq (1 + \delta_j)f_{0,j}^*, \delta_j \geq 0, j = 1, \dots, m$$

The benefit of goal programming is that it allows us to explore multidisciplinary tradeoffs without having to enumerate the design space along each objective direction. In design it is not obvious whether an objective should in fact be a constraint instead. The most fundamental choice that an engineer can make in design is what the objective function is, and it is often the case that there are many potential objectives that are conflicting. The term multiobjective optimization is misleading because you can only optimize for one objective at once, and the design is going to be influenced by how engineers weigh different objectives. But risk is ubiquitous in engineering design problems, so goal programming allows risk to be used as a global design variable against which all objectives can be weighed.

IX. Potential Future Work or Studies

There are a myriad of potential extensions to signomial programming under uncertainty. In the spirit of helping reduce program risk in aerospace design, the authors make a few observations and recommendations.

In this study, we do not discriminate between the kinds of constraints violated. However, it would be possible to rank the severity of constraint violations so as to penalize some (eg. structural safety) more heavily than others (maximum range constraint). This would inject further realism into the design under uncertainty since some violations contribute to program risk more strongly than others.

Another potentially valuable extension to the proposed framework is the concurrent implementation of multiple sets to contain the uncertain parameters, with the purpose of restricting uncertain outcomes further. One example of this would be to impose an L1-norm on the integer number of uncertain parameters as well as an L2-norm on the overall size of uncertainty set. This method can be used to set the total size of the uncertainty set in a Euclidian sense, but then also to restrict the stochasticity to a subset of all of the uncertain parameters, thereby somewhat restricting nature. This also turns the problem into an integer robust optimization problem which poses interesting computational challenges.

With respect to interesting studies, RO opens up the possibility to discover and analyze the benefits of adaptable architectures in aircraft design versus more traditional point designs with mathematical rigor. Some examples of these are modular designs, morphing designs, adaptively manufactured designs and aircraft families. It is likely that these types of engineered robustness become more effective at reducing program risk in presence of uncertainty, since they are more likely to deliver value under adverse stochastic outcomes.

In situations where there is data available to aid design, RO can help explore the design space while taking into account the stochasticity and noise in the data. This opens up an array of potential trade studies where engineers can learn about the exposure of designs to the sparsity and spread of data and attempt to gather data which best reduces the uncertainty in the performance of optimal designs.

X. Conclusion

In this paper we have motivated the use of robust optimization in conceptual engineering design, in lieu of the mathematically non-rigorous methods of optimization under uncertainty widely used in the aerospace industry today. We have developed a tractable RSP formulation in response to a need to optimize over uncertain parameters, extending the tractable approximate RGP framework developed by Saab [18] to non-log-convex problems. This RSP formulation is a valuable contribution to the fields of robust optimization and difference-of-convex programming.

RSPs have a wide variety of potential applications in engineering design. We demonstrated using a simple aircraft design problem that using RO, and specifically RSPs in conceptual aircraft design will result in systems that are more robust with respect to uncertainties in operational parameters, such as payload

mass and range, as well as uncertain environmental and manufacturing parameters. By making designs immune to realizations of uncertainty in a set, engineers can use robust signomial programming to trade off robustness and optimality within engineered systems in a tractable manner.

RO has the potential to change current aerospace design paradigms by introducing mathematical rigor to design under uncertainty. Current aerospace conceptual design practices still rely heavily on the expertise of established engineers even in absence of prior experience exploring the design space. RSPs are compatible for use alongside physics based models that are deprived of or lacking in data, and so can bring quantitative measures of design reliability to the table and steer the field of aerospace design towards physics-based tools and methods.

Appendix

X.A. Robust Linear Programming: A Quick Review

As mentioned earlier, robust linear programming will be used to formulate an approximate robust geometric program.

Consider the system of linear constraints

$$\mathbf{A}\mathbf{x} + \mathbf{b} \leq 0$$

where

$$\mathbf{A} \text{ is } m \times n$$

$$\mathbf{x} \text{ is } n \times 1$$

$$\mathbf{b} \text{ is } m \times 1$$

where that data is uncertain and is given by equations (5) and (6).

X.A.1. Box Uncertainty Set

If the perturbation set \mathcal{Z} given in equation (6) is a box uncertainty set, i.e. $\|\zeta\|_\infty \leq \Gamma$, then the robust formulation of the i^{th} constraint is equivalent to

$$\Gamma \sum_{l=1}^L | -b_i^l - \mathbf{a}_i^l \mathbf{x} | + \mathbf{a}_i^0 \mathbf{x} + b_i^0 \leq 0 \quad (11)$$

If only b is uncertain, i.e. $A^l = 0 \quad \forall l = 1, 2, \dots, L$, then equation (11) will become

$$\sum_{l=1}^L \mathbf{a}_i^0 \mathbf{x} + b_i^0 + \Gamma \sum_{l=1}^L |b_i^l| \leq 0 \quad (12)$$

which is a linear constraint

On the other hand, if A is uncertain, then equation (11) is equivalent to the following set of linear constraints

$$\begin{aligned} \Gamma \sum_{l=1}^L w_i^l + \mathbf{a}_i^0 \mathbf{x} + b_i^0 &\leq 0 \\ -b_i^l - \mathbf{a}_i^l \mathbf{x} &\leq w_i^l \quad \forall l \in 1, \dots, L \\ b_i^l + \mathbf{a}_i^l \mathbf{x} &\leq w_i^l \quad \forall l \in 1, \dots, L \end{aligned} \quad (13)$$

X.A.2. Elliptical Uncertainty Set

Briefly, if the perturbation set \mathcal{Z} is an elliptical, i.e. $\sum_{l=1}^L \frac{\zeta_l^2}{\sigma_l^2} \leq \Gamma^2$, then the robust formulation of the i^{th} constraint is equivalent to

$$\Gamma \sqrt{\sum_{l=1}^L \sigma_l^2 (-b_i^l - \mathbf{a}_i^l \mathbf{x})^2} + \mathbf{a}_i^0 \mathbf{x} + b_i^0 \leq 0 \quad (14)$$

which is a second order conic constraint.

If only b is uncertain, i.e. $A^l = 0 \quad \forall l = 1, 2, \dots, L$, then equation (14) will become

$$\sum_{l=1}^L \mathbf{a}_i^0 \mathbf{x} + b_i^0 + \Gamma \sqrt{\sum_{l=1}^L \sigma_l^2 (b_i^l)^2} \leq 0 \quad (15)$$

which is a linear constraint.

X.A.3. Norm-1 Uncertainty Sets

Briefly, if the perturbation set represented by \mathcal{Z} is a norm-1 uncertainty set, i.e. $\|\zeta\|_1 \leq \Gamma$, then the robust constraint is

$$\sum_{l=1}^L \mathbf{a}_i^0 \mathbf{x} + b_i^0 + \Gamma \max_{l=1, \dots, L} |b_i^l| \leq 0 \quad (16)$$

when $\mathbb{A}^l = 0$, and

$$\begin{aligned} \Gamma w_i + \mathbf{a}_i^0 \mathbf{x} + b_i^0 &\leq 0 \\ -b_i^l - \mathbf{a}_i^l \mathbf{x} &\leq w_i \quad \forall l \in 1, \dots, L \\ b_i^l + \mathbf{a}_i^l \mathbf{x} &\leq w_i \quad \forall l \in 1, \dots, L \end{aligned} \quad (17)$$

if $\mathbb{A}^l \neq 0$

Note that for this type of uncertainty, the robust constraints are linear.

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