

# A Heuristic for Including Black Box Analysis Tools into a Geometric Programming Formulation

by

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## Abstract

Recently, geometric programming has been proposed as a powerful tool for enhancing aircraft conceptual design. While geometric programming has shown promise in early studies, current formulations preclude the designer from using black box analysis codes which are prolific in the aircraft design community. Previous work has shown the ability to fit data from these black box codes prior to the optimization run, however, this is often a time consuming and computationally expensive process that does not scale well to higher dimensional black boxes. Based upon existing iterative optimization methods, we propose a heuristic for including black box analysis codes in a geometric programming framework by utilizing sequential geometric programming (SGP). We demonstrate a heuristic SGP method and apply it to a solar powered aircraft using a black boxed GP compatible profile drag function. Using this heuristic algorithm, we achieve less than a 1% difference in the objective function between a direct implementation of the constraint and a black box implementation of the constraint.

Thesis Supervisor: Warren W. Hoburg

Title: Boeing Assistant Professor



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# Chapter 1

## Importance of Conceptual Design

### 1.1 The Three-Phase Aircraft Design Process

Nevil Shute has a unique position in history as both successful aeronautical engineer and a successful author. In his book *No Highway*, Shute describes the design process from the perspective of a young engineer:

“A beautiful aircraft is the expression of the genius of a great engineer who is also a great artist. But it is impossible for that man to carry out the whole of the design himself; he works through a design office staffed by a hundred draughtsmen or more. A hundred minds, each with their own ideas, are striving to improve the chief designer’s original conception.”

-Nevil Shute, *No Highway*

As Shute alludes to, designing a new aircraft can be a massive undertaking, requiring hundreds of engineers, or “draughtsmen,” to bring the design from an initial concept to a detailed design that is ready for production. Given the magnitude of this task, aircraft design is typically separated into three phases: conceptual, preliminary and detailed.

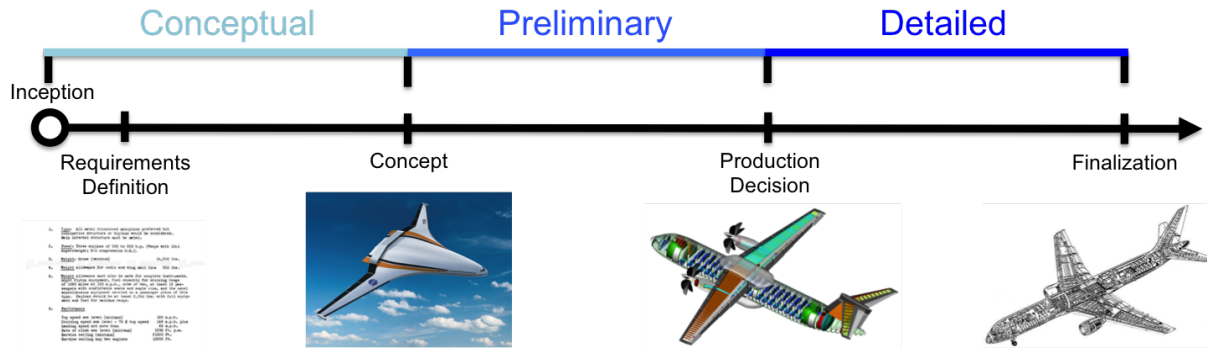


Figure 1-1: Three phases of aircraft design

In most cases, the inception of an aircraft, as indicated in Figure 1-1, and the requirements definition occur simultaneously, and so the purview of conceptual design is to develop a rough geometry and concept of operations from a set of requirements. Conceptual design is fundamentally a creative process [5], linking the function of the concept (the requirements) to the form of the concept (the geometry) [6]. Traditionally, aerodynamics, propulsion, and weights are the disciplines considered in conceptual design.

Preliminary design picks up at the end of conceptual design and brings the aircraft to the point where a production decision will be made. Generally, preliminary design is the phase of the design where 2D geometric representations will be replaced with 3D representations, however, this paradigm has changed in recent years [7, 8]. This 3D geometry then enables high fidelity analysis such as computational fluid dynamics (CFD) and finite element analysis (FEA). Preliminary design traditionally adds stability and control as well as structures to the discipline list. However, as computational tools have become more prolific, the line between conceptual and preliminary design has become less defined, particularly in regard to the classical discipline split.

Detailed design is the final process of creating a production ready design. As Anderson [9] states, detailed design is literally the “nuts and bolts” phase of the design. Transitioning to this phase of the design requires a significant increase in manpower, cost and complexity, and so only the best aircraft designs make it to this phase. Important considerations in



this phase include maintenance, supply chains and ease of manufacture.

Each phase of design has its own unique set of challenges, but conceptual design is perhaps the most crucial for a successful aircraft program. The importance of conceptual design is made apparent by Blanchard and Fabrycky [1]:

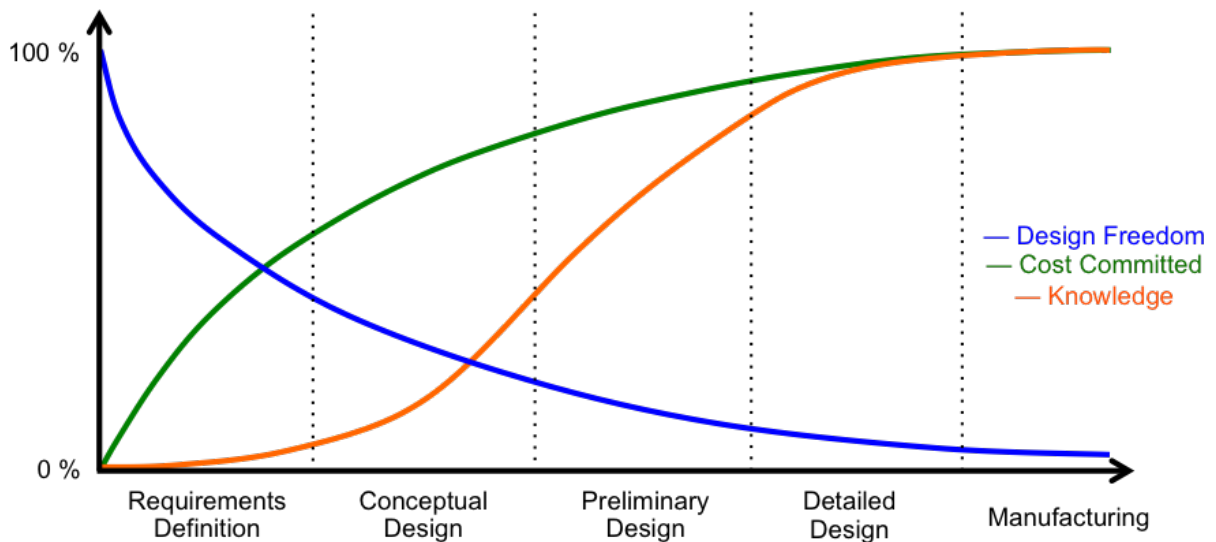


Figure 1-2: Knowledge, cost committed and design freedom in the design process [1]

By the end of conceptual design, decisions have been made that account for a high percentage of the cost and severely limit the design freedom, however the design is still poorly understood until it progresses through the remaining phases of the design process. Given the critical role of conceptual design, this work will primarily focus on this phase.

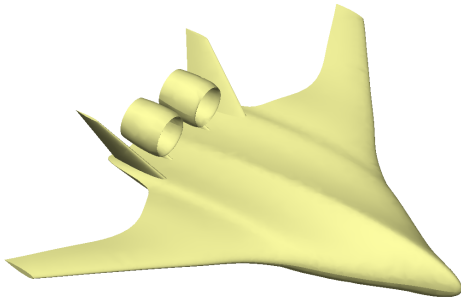
## 1.2 Conceptual Aircraft Design

In conceptual design, a designer seeks to develop a concept that is feasible, robust and optimal. Each of these three goals can be captured in a specific question the designer must answer [9]:

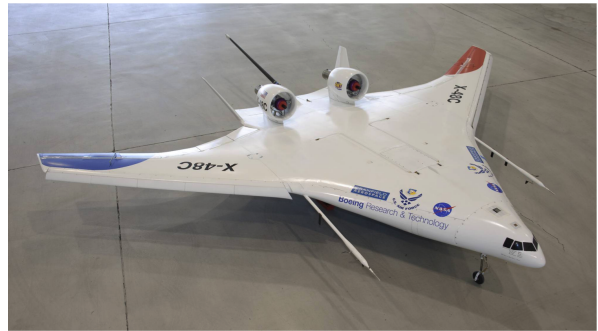
1. Feasibility—Is there a concept that meets or exceeds the requirements and constraints?

2. Robustness—How close is the concept to not meeting the requirements and constraints?
3. Optimality—What is the best concept that meets the requirements and constraints?

For an aircraft designer, the term *concept* typically refers to a layout of the major components of the aircraft, along with their relative positions and sizes [9]. Figure 1-3 shows just such a layout, along with the actual experimental aircraft this concept became:



(a) Concept Generated in Engineering Sketch Pad [8]



(b) X-48C blended wing body experimental aircraft [10]

Figure 1-3: Aircraft concept and experimental airplane

To generate a concept such as the one in Figure 1-3, a large number of design variables had to be considered, traded and eventually finalized. This set of design variables is frequently referred to as the *design space* for the aircraft concept. Choosing the variables that will make up the design space is often one of the most crucial steps in conceptual design. A poor selection may lead to an intractable optimization problem, while a good selection will capture the features important to the design and create clarity in how the design moves through the design space. Parameters for defining the geometry generally comprise the majority of the space, but performance parameters such as the range of the aircraft, the cruise altitude, or maximum velocity, are also often included as a part of the design space. A general design space could have thousands of dimensions and be infinitely large, but selection of the final concept is governed by three sets of criteria: constraints, objectives and requirements.

Constraints are typically bounds imposed by physics on the design space, for example, the maximum stress in a material cannot be exceeded. A constraint is often treated as a hard cutoff for the design, and is frequently given considerable margin, since exceeding a physical constraint can sometimes have catastrophic consequences.

Objectives are measures of the value or cost of the aircraft, for example, the range the aircraft can fly or the time it takes to manufacture the airplane in the factory. When taken together, these objectives often form an *objective function* which will be maximized or minimized by selecting the correct concept in the design space.

Requirements are the genesis of an aircraft program, typically a list of tasks the aircraft should perform and specifications to which the aircraft is expected to conform. In this way, requirements are a superset of the objectives, with the important distinction that requirements are bounded, while objectives are unbounded. Due to this bounding, system level requirements flow down into secondary subsystem requirements. In practice, requirements are essentially treated as constraints in the design problem, however unlike physical constraints, requirements are often flexible and iterated on between the designer and the customer. This negotiation ensures maximum value is obtained from the new aircraft concept.

The role of the concept is to link together the requirements, constraints and objectives, as shown in Figure 1-4 below.

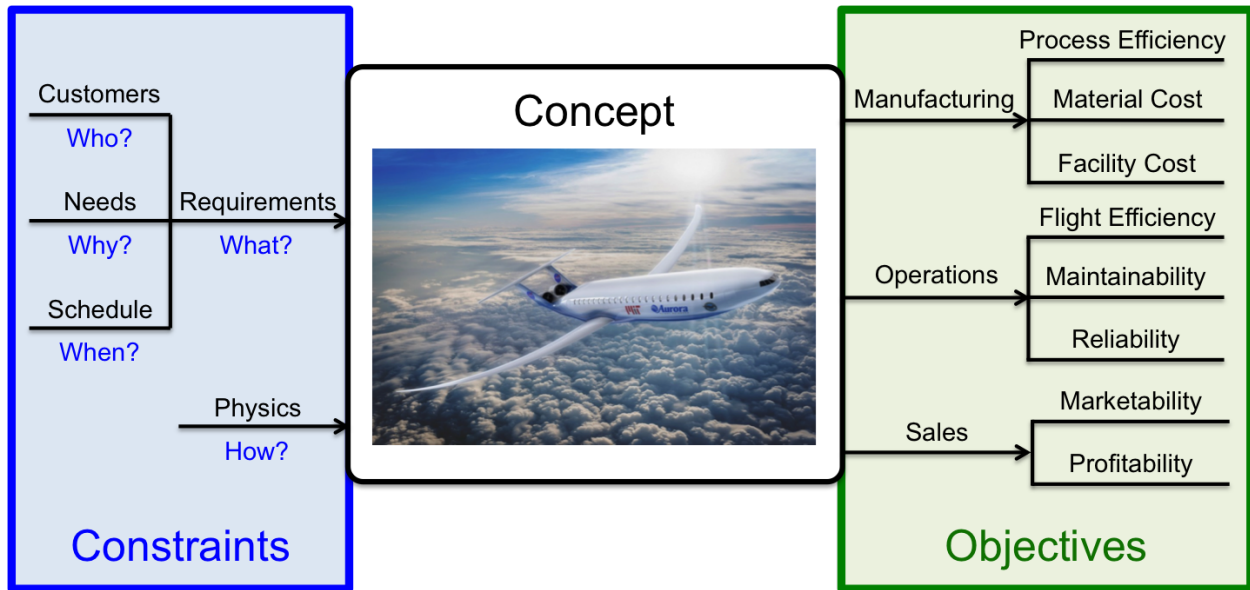


Figure 1-4: Aircraft concept linking requirements, constraints and objectives [2] (Adapted from [3])

Searching a design space is often a daunting task, and the conceptual designer's tool of choice is the trade study. During a trade study, the designer will take a subset of design variables, sweep over the range between some minimum and maximum value, and study the corresponding values of the objectives. This process allows the designer to see how changes in the design variables affect the performance of a concept, providing insight into the best selections for the design variables, along with the sensitivity of the performance of the concept to these selections.

Trade studies have traditionally been performed using empirical or historical methods such as those compiled by Raymer [11], Torenbeek [5], Roskam [12], Shevell [13], Schaufele [14] and Anderson [9], however, advances in high performance computing have altered the landscape in a few ways. First, integrated design tools have enabled trade studies to explore larger design spaces by merging design variables from multiple areas of aircraft design. These tools have relied extensively on the development of Multidisciplinary Analysis and Optimization (MDAO), which will be discussed in Chapter 2. Additionally, physics based analysis methods, which had typically reserved for preliminary and detailed design, have

become available for use in conceptual design. Physics based methods in particular have opened conceptual design to concepts for which no historical or empirical data exists, leading to exciting advances such as the D8 [15] and the blended wing body [16].

### **1.3 Trend of Increasing Design Time**

Despite the role integrated tools and physics based models have played in conceptual design, perhaps the most significant advance in recent years has been the implementation of numerical optimization, enabled by advances in computing technology. Optimization can be used to save the designer time and effort by intelligently searching the space of design variables for the concept which maximizes the objective function, ensuring feasibility, robustness, and optimality.

Numerical optimization has become standard in all aspects of the design community. Tools such as PASS [17], WingMOD [18], SUAVE [19], CEASIOM [20], and TASOPT [21] are just a few examples of tools which have achieved recognition in the aircraft design community. However, despite advances in numerical optimization and increases in computational speed, there is an alarming upward trend in development time for modern aircraft, as shown by Figure 1-5:

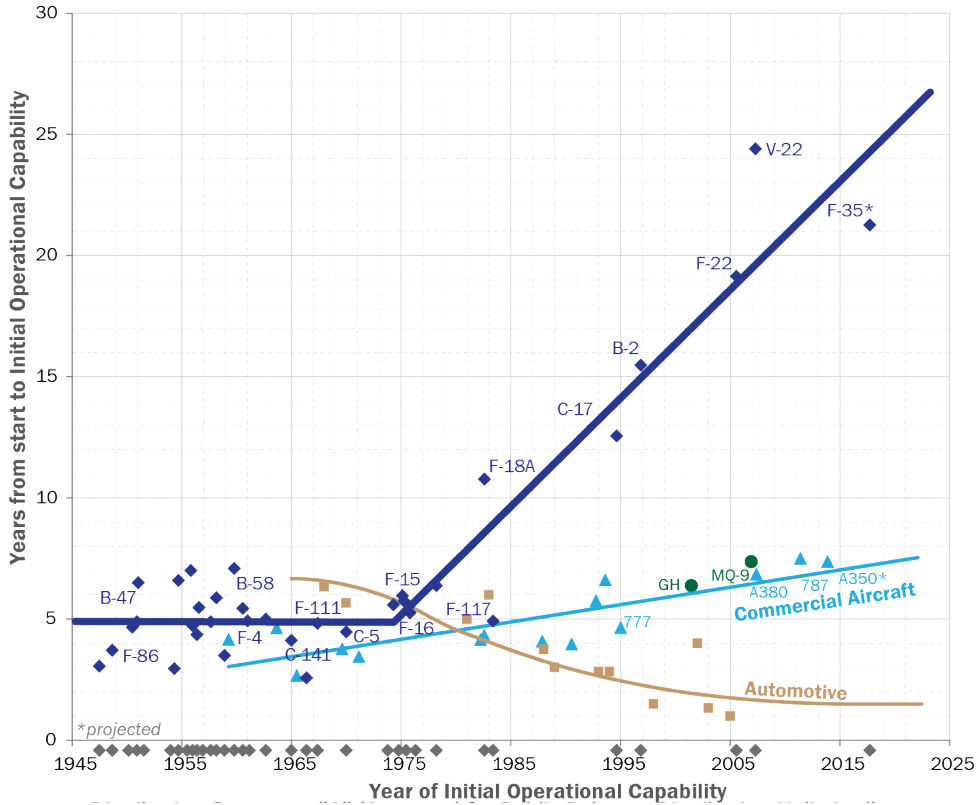


Figure 1-5: Increasing development time of modern aircraft [4]

Simply put, the proliferation of high performance computing does not seem to have resulted in the more rapid development of aircraft. This increasing trend has no single cause and is by no means easy to diagnose, but one major takeaway from this trend is that computational tools must be made as efficient as possible. At time of writing, many tools still can take hours, and in extreme cases weeks or months to run. Thus, the pursuit of efficiency has led to numerous proposals for algorithms, architectures and methods that make the process simpler and more effective. This pursuit is the main goal of the field of Multidisciplinary Analysis and Optimization (MDAO).

# Chapter 2

## MDAO in Aircraft Design

### 2.1 Overview

Multidisciplinary Analysis and Optimization (MDAO)<sup>1</sup> is an active field of research focused on the design and optimization of complex systems. Complex system design problems are typically separated into multiple disciplines, or smaller sub-problems, for teams or individuals to address. Individual disciplines have historically been analyzed in isolation, with system level interactions being handled on a case by case basis or via some hierarchy. However, as high performance computation has become more widely available, design teams have been able to consider multiple disciplines simultaneously, giving rise to the field of MDAO. The earliest examples of MDAO came out of attempts to perform coupled aerostructural optimization [22], but it has evolved into a large and diverse field. In this chapter, we will discuss key concepts in MDAO, namely the definition of a discipline, the role of analysis, and methods of optimization.

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<sup>1</sup>MDAO is alternatively known as Multidisciplinary Design Optimization (MDO) or simply Multidisciplinary Optimization (MDO)

## 2.2 Definition of a Discipline

Full scale piloted aircraft can be incredibly complex machines: millions of parts, functioning together in unison. As such, there is no feasible way for a single individual or team to keep track of each detail associated with the airplane. While there are many different ways of decomposing complex systems, two of the most prevalent are physical decomposition and functional decomposition (Figure 2-1).

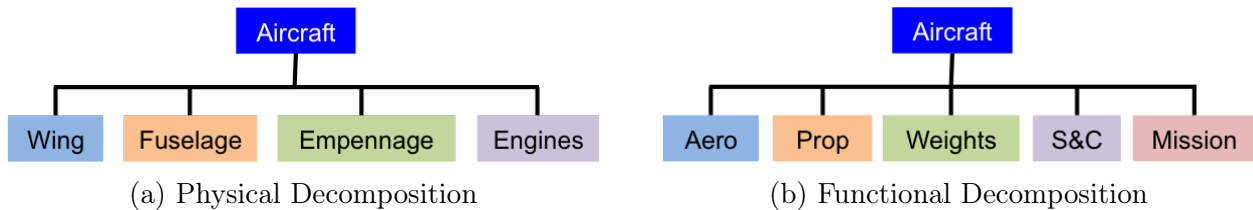


Figure 2-1: Methods for system decomposition

In a physical decomposition<sup>2</sup>, components of the aircraft are separated according to their physical location. In contrast, a functional decomposition separates specific tasks on the aircraft and includes all components which address this task. For most aircraft, a functional decomposition is used for the high level systems problem, but physical decompositions tend to be used within functional groups. A functional decomposition also makes the most sense from a project management standpoint, as it is most likely that a subject matter expert in one area will likely be able to apply his or her knowledge to the entire aircraft. One notable exception is aircraft engines, which are typically designed and manufactured by separate companies and then mounted by the airframing company. A functional decomposition leads to the predominant disciplines (or sub tasks) in aircraft design: Aerodynamics, Weights and Structures, Propulsion, Stability and Control, and Performance and Mission Analysis.

While the exact roles of discipline teams can vary widely between organizations, a general breakdown with high level goals and objectives is provided here for the reader. An experienced professional in aircraft design may skip to Section 2.3 without loss of

---

<sup>2</sup>alternatively a component decomposition



continuity.

### 2.2.1 Performance and Mission Analysis

The goal of the performance discipline is to compute how well an aircraft performs in the measures defined by the objectives. In this way, performance is the “hub” that ties all of the other disciplines together. Traditionally, the core of the performance discipline has focused on mission analysis, captured best by the Breguet Range Equation<sup>3</sup>:

$$R = \frac{V}{SFC} \frac{L}{D} \ln \left( \frac{W_i}{W_{i+1}} \right) \quad (2.1)$$

which relates several of the major variables of interest. It is immediately apparent how the disciplines tie together:  $\frac{VL}{D}$  from aerodynamics,  $SFC$  from propulsion, and  $\frac{W_i}{W_{i+1}}$  from weights.

While the Breguet Range Equation is incredibly useful for initial sizing, other metrics of classical performance are also of interest, such as takeoff and landing distances, climb performance, and trim. These metrics require a more detailed analysis, leading to a simple mission simulation where the aircraft is treated as a rigid body and simulated over a 2D mission profile, requiring additional data from aerodynamics and propulsion. These higher fidelity calculations enable predictions for those parameters of interest that cannot be captured in the Breguet Range Equation. Eventually, full 6 DOF simulations can be developed using these same principles.

While the focus of the performance discipline has historically been on mission analysis, many aircraft programs are interested in performance metrics beyond flight profiles. Performance metrics such as noise, emissions, observability, maintenance, and

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<sup>3</sup>Provided here for jet powered aircraft

manufacturing have become increasingly critical for a wide variety of aircraft programs and will likely receive increased attention in coming years.

### **2.2.2 Aerodynamics**

The aerodynamics discipline is primarily concerned with how the aircraft interacts with the fluid it is traveling through. From the Breguet Range Equation, it is apparent that the main role of the aerodynamics discipline is determining the best  $\frac{VL}{D}$  for the aircraft at both nominal and off nominal flight states. However, a secondary objective is to determine the stability and control derivatives over a wide range of flight states. This aero database is necessary for determining control surface effectiveness, trim states, and controllability of the aircraft and typically involves extensive crossover with the Stability and Control discipline.

### **2.2.3 Propulsion**

The propulsion discipline is responsible for all analyses pertaining to the engine. The propulsion discipline must provide an estimate of thrust specific fuel consumption, *SFC*, which is the weight of fuel consumed per unit of thrust generated in a unit of time. When considering the mission simulation approach to performance, the broader and more useful goal becomes providing engine maps: curves of engine *SFC* and thrust as a function of throttle setting (or sometimes spool speed), flight speed and altitude.

### **2.2.4 Weights and Structures**

The weights and structures discipline spans all analyses concerning the prediction of the aircraft weight and design of the detailed structural layout. In conceptual design, it is more common to think of this discipline as weight prediction, rather than detailed structures

design, which becomes more prevalent in preliminary and detailed design. While empty weight prediction occupies much of the attention of the weights discipline, an equally vital task is predicting the location of the center of gravity for the aircraft under a variety of loading cases. This CG excursion analysis is crucial for determining both the aerodynamic stability derivatives and the trim state the airplane, which can significantly impact performance.

### **2.2.5 Stability and Control**

The stability and control (S&C) group is primarily responsible for sizing the aircraft empennage and control surfaces, working in conjunction with the aerodynamics group. An additional function of the S&C group is to provide the first high level control scheme that will eventually be perfected in a flight control system during the detailed design process. This responsibility includes sizing control actuators, along with predicting dynamic performance of the aircraft, and performing eigenmode analysis.

## **2.3 Analysis**

As was alluded to in the discussion of each of the disciplines, a discipline will typically receive a set of inputs from the system problem and then provide a set of outputs back. The mathematical mapping from inputs to outputs is referred to as *analysis*. The field of analysis is exceedingly complex, having multiple levels and requiring advanced understanding of the discipline in question. In addition, the analysis step is the most expensive step by far in terms of cost, manpower and time.

### 2.3.1 Notion of Fidelity

Each discipline group in aircraft design has a number of tools at their disposal. For example, an aerodynamics team might have a wide variety of analytical and testing options including basic aerodynamic analysis, various computational methods, or flight testing. Any one of these options will produce the required data (or outputs to the systems problem), however, some of these methods will be trusted to provide a more accurate number as compared to physical reality than others. This degree of accuracy is often referred to as the “fidelity” of the analysis method, however it may also be referred to as the “order” of the analysis. Increasing fidelity results in a higher degree of confidence (less uncertainty) in the final result, but at the cost of increased expense, either computationally or monetarily. These analysis methods can be organized into a so-called “fidelity tree” (Figure 2-2)<sup>4</sup>, shown here for the Aerodynamics discipline.

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<sup>4</sup>While most designers or design groups hold to this type of tree, the methods are rarely written in order of trust like this, as trust in a tool or method will be highly dependent on personal experience

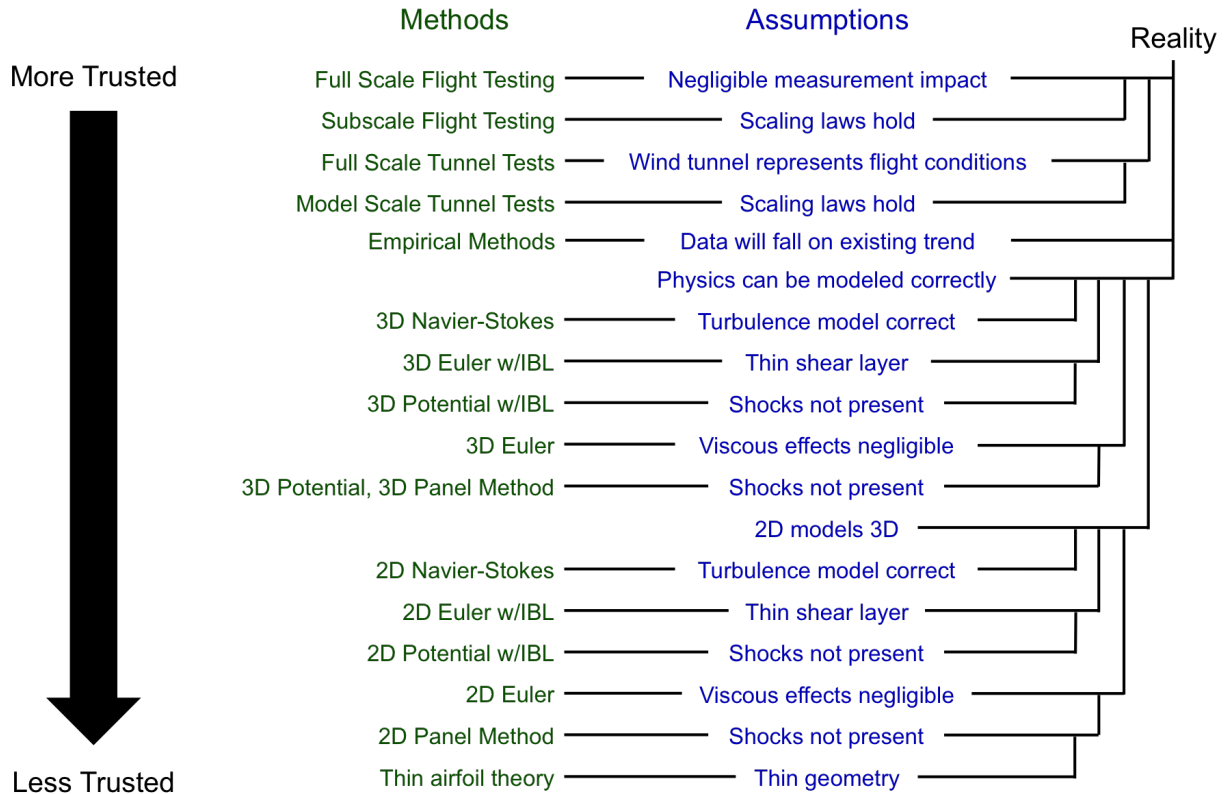


Figure 2-2: Aerodynamics fidelity tree

This tree describes the assumptions that must be made to “trust” the result from an analysis method, with each assumption moving the method further away from the true physics of the problem. Assumptions go down the middle of the tree, with the analysis methods listed on the left hand side. As an example, only one assumption is required on this fidelity tree to reach full scale flight test, but five assumptions are required to reach Thin Airfoil Theory, meaning that in general, the data from flight testing is considered more trustworthy than the predictions from Thin Airfoil Theory. This particular tree has been set up such that methods at the top of the tree are generally considered to be more “trusted”, and therefore of higher fidelity than tools lower on the chart. Fidelity trees can be set up for any discipline, but a survey is beyond scope here. Price [23] provides a “Nickol chart” which is a compilation of these fidelity trees for a variety of disciplines.

### 2.3.2 High Fidelity “Black Box” Analyses

In practice, each branch of a fidelity tree corresponds to a different tool or method that the discipline team is capable of utilizing. Testing is often too expensive to be practical for development and is therefore reserved for validation. Thus, computational methods dominate conceptual design, and a wide variety of these methods are available depending on the application. For example, when a 2D full potential code with an integrated boundary layer correction is required, XFOIL is commonly used, whereas 3D viscous flow will require a CFD code like OVERFLOW. Writing an analysis tool or method is a large undertaking, requiring detailed expertise and coming at the price of a large development cost. As a result, the tendency is to treat an existing method as a “black box”. The term “black box” refers to the fact that the user is unaware of the inner workings of the analysis code, but can simply be trained on how to feed in inputs and interpret outputs. These black boxes are prolific in the aircraft industry across all disciplines and, at the time of this writing, are critical components of all three phases of the design process. In fact, many black box codes used to this day are decades old legacy codes that are highly trusted and would be costly to replace. Thus, a major focus of the MDAO community has been studying how to make these discipline black boxes communicate with each other in the most effective way possible for the purposes of design and optimization. Many of these approaches are outlined by Martins and Lambe [22], but a full discussion of MDAO methods is beyond scope here.

## 2.4 Optimization

To this point, all that has been discussed is the *analysis* element of the design process. In other words, if a design is reached, it can be fed into these cascading analyses and a performance evaluation can be output. A designer must close this loop, taking the performance outputs and using them to inform changes in the design. As was stated in

Chapter 1, the set of design variables that collectively describe the aircraft design is often referred to as the *design space* of the aircraft. The greatest challenge for the designer is deciding which design in this design space is the best one, and in this pursuit, the designer’s most powerful tool is optimization. At its best, optimization can be thought of as a series of automated and simultaneous trade studies, capable of evaluating multiple trades and arriving at the best design. In practice, optimization falls well short of this goal, but is still incredibly useful in finding the “best” design near a designer’s informed guess, determining the ways in which the designer should manipulate the current design, and guiding the designer away from dangerous regions in the design space.

### 2.4.1 Formulating Mathematical Optimization Problems

Chapter 1 discussed the role optimization plays in the aircraft design process, but how does one turn aircraft design into a mathematical optimization problem? The first step is to write an objective function, which generally serves as a surrogate for the value of the aircraft being designed.<sup>5</sup> Example objective functions are as follows:

$$\frac{W_{MTO}}{V} \frac{SFC}{L/D} \quad (2.2)$$

$$N_{eng}W_{engine} + W_{fuselage} + W_{wing} + W_{avionics} + W_{empennage}$$

Additionally, constraint functions are written which bound the space of feasible solutions. As discussed in Chapter 1, constraints can come from underlying physics or from imposed requirements. In numerical optimization, constraints take the form of equalities and

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<sup>5</sup>A more detailed discussion of aircraft objectives is located in Chapter 1

inequalities, such as the following:

$$\begin{aligned} L &= \frac{1}{2}\rho V^2 C_L S \\ \sigma_{y_{AI}} &\leq 55 \text{ MPa} \end{aligned} \tag{2.3}$$

With these two concepts of mathematical objectives and constraints, we can introduce the form of a mathematical optimization problem [24]:

$$\begin{aligned} &\text{minimize} && f_0(\mathbf{x}) \\ &\text{subject to} && f_i(\mathbf{x}) \leq b_i, \quad i = 1, \dots, m \end{aligned} \tag{2.4}$$

where  $f_0$  is the objective function and the  $f_i$  are the constraints which are constrained to be less than or equal to a constant  $b_i$ <sup>6</sup>. A simple example of minimizing the drag of a wing

---

<sup>6</sup>Note that any inequality can be manipulated into this form



is as follows [25]:

$$\begin{aligned}
& \text{minimize} && D \\
& \text{subject to} && C_{D_{fuse}} = \frac{(CDA0)}{S} \\
& && C_{D_{ind}} = \frac{C_L^2}{A\pi e} \\
& && Re \leq \frac{\rho V}{\mu} \left( \frac{S}{A} \right)^{0.5} \\
& && C_f \geq \frac{0.074}{Re^{0.2}} \\
& && C_{D_p} = \left( \frac{S}{S_{wet}} \right) C_f k \\
& && C_D \geq C_{D_p} + C_{D_{fuse}} + C_{D_{ind}} \\
& && W_w \geq SW_{W_{coeff2}} + \frac{A^{1.5} N_{ult} S^{0.5} W^{0.5} W_0^{0.5} W_{W_{coeff1}}}{\tau} \\
& && W \leq \frac{1}{2} \rho V^2 C_L S \\
& && W \leq \frac{1}{2} \rho V_{min}^2 C_{L,max} S \\
& && W \geq W_0 + W_w \\
& && D \geq \frac{1}{2} \rho V^2 C_D S
\end{aligned} \tag{2.5}$$

## 2.5 Takeaways from MDAO

MDAO represents the state of the art of aircraft design, and in fact all complex system design. It is therefore crucial that any design or optimization work understand the main takeaways from this community. First, black box analysis codes are critical to real system design. The development cost and time that is required to develop new methods is simply too high for practicing design teams. Second, and perhaps more crucial here, is the fact that a vast majority of MDAO takes an analysis first approach, focusing on intelligent ways to wire the black box codes together into large analysis codes, and then complex optimization algorithms are used to solve the problem. However, a recent development is

the optimization first approach taken by Hoburg [25]. His proposal is that rather than focus on the analysis, emphasis should be placed on highly efficient optimization, for example Geometric Programs (GPs), and analysis methods should be integrated into this highly efficient framework. The geometric programming approach will be introduced in the next chapter.

# Chapter 3

## Convex Optimization and Geometric Programs

### 3.1 Convex Optimization

Hoburg [25] has recently proposed a paradigm shift in conceptual design, that efficient optimization be utilized and models developed to fit this new optimization framework. At the core of this proposal is the notion of convex optimization. Floudas [26] defines the notion of convexity using Jensen's Inequality:

$$f[(1 - \lambda)\mathbf{x}_1 + \lambda\mathbf{x}_2] \leq (1 - \lambda)f(\mathbf{x}_1) + \lambda f(\mathbf{x}_2) \quad (3.1)$$

As a result of this mathematical property, convex optimizations can be solved quickly and efficiently. A convex optimization problem as defined by Boyd [24] is one where the objective and constraint functions are convex. By sticking to this form, we obtain a number of benefits over a general non-linear programs (NLPs). First, NLPs make no guarantees on global optimality, where as the Jensen Inequality ensures that any optimum

of a convex function is global. Second, convex optimization problems do not require initial guesses to converge to the global optimum as any initial guess is guaranteed to converge to the optimum. Finally, convex optimization problems can be solved very rapidly utilizing interior point methods [24].

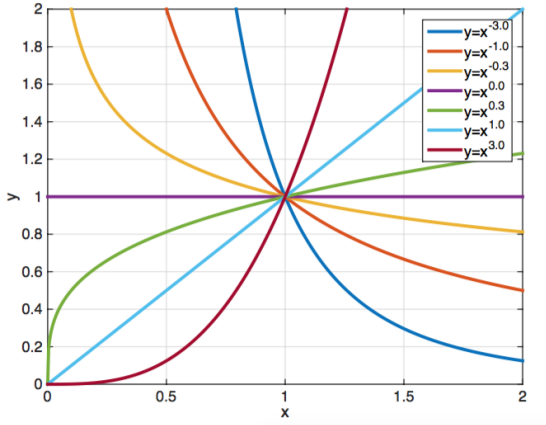
Despite the many advantages of convex optimization, a potential drawback is that, by definition, all objectives and constraints must be convex. However, work pioneered by Hoberg [25] has demonstrated that by utilizing a geometric programming formulation, this is not a serious limitation in the case of aircraft conceptual design through the use of Geometric Programming (GP).

## 3.2 The Geometric Programming Formulation

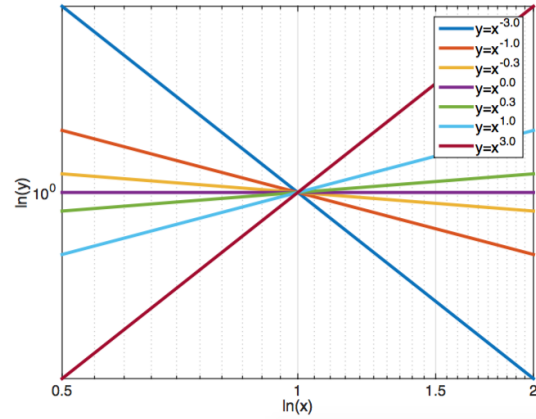
A geometric program (GP) is an optimization problem that is convex when transformed into logspace [27]. In order for this condition to be true, the objectives and constraints must take a special form, specifically that of a monomial or posynomial function. A monomial function takes the form:

$$f(\mathbf{x}) = cx_1^{a_1}x_2^{a_2}\dots x_n^{a_n} \quad (3.2)$$

where  $\mathbf{x}$  is a vector of  $n$  decision variables,  $c$  is a positive scalar, and the exponents  $a_i$  are real numbers. A family of monomials ( $c = 1$ ) is plotted below (Figure 3-2), along with the transformation to logspace.



(a) Monomials in standard coordinates



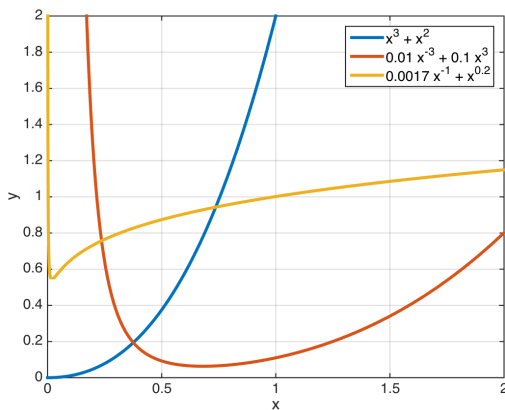
(b) Monomials transformed into logspace

Figure 3-1: Example of a monomial family

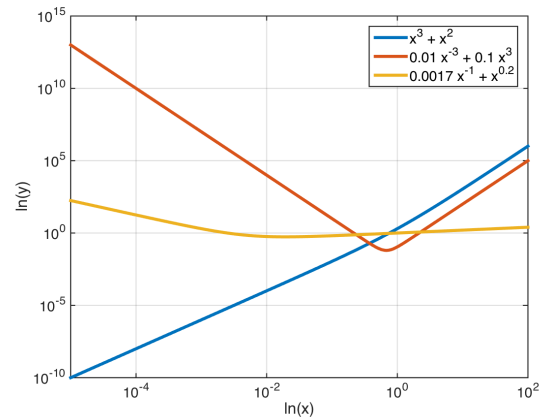
Note that all monomial functions become *affine* or *linear* upon transformation, meaning that any function that can be written in monomial form can be converted into an affine function in logspace. A posynomial is then defined as the sum of one or more monomial functions:

$$g(\mathbf{x}) = \sum_{k=1}^K c x_1^{a_{1k}} x_2^{a_{2k}} \dots x_n^{a_{nk}} \quad (3.3)$$

Given this form, a few examples are plotted below:



(a) Posynomials in standard coordinates



(b) Posynomials transformed into logspace

Figure 3-2: Some posynomial examples

Note that posynomials need not be convex in regular space, but after transformation do indeed become convex. Therefore, any set of objectives that can be written as monomials and posynomials is *convex* in logspace. With these definitions, we can define the standard form of a GP [27]:

$$\begin{aligned}
 & \text{minimize} && g_0(\mathbf{x}) \\
 & \text{subject to} && f_i(\mathbf{x}) = 1, \quad i = 1, \dots, m \\
 & && g_i(\mathbf{x}) \leq 1, \quad i = 1, \dots, p
 \end{aligned} \tag{3.4}$$

where  $f_i$  are monomial functions and  $g_i$  are posynomial functions. Boyd [27] provides the following example GP:

$$\begin{aligned}
 & \text{minimize} && x^{-1}y^{-1/2}z^{-1} + 2.3xz + 4xyz \\
 & \text{subject to} && (1/3)x^{-2}y^{-2} + (4/3)y^{1/2}z^{-1} \leq 1 \\
 & && x + 2y + 3z \leq 1 \\
 & && (1/2)xy = 1
 \end{aligned} \tag{3.5}$$

When a problem is written in this form, we say that it is *GP compatible* and can be solved by commercial off the shelf codes.

### 3.3 Geometric Programming for Conceptual Design

Hoburg's [25] breakthrough was that many problems of interest to the aircraft design community fit into this monomial and posynomial form. By reviewing Equation 2.5, this

becomes evident:

$$\begin{aligned}
& \text{minimize} && \frac{1}{2}\rho V^2 C_D S \\
& \text{subject to} && 1 \geq \frac{0.074}{C_f Re^{0.2}} \\
& && 1 \geq \frac{(CDA_0)}{C_D S} + \frac{kC_f S_{wet}}{C_D S} + \frac{C_L^2}{C_D \pi e AR} \\
& && 1 \geq \frac{2W}{\rho V^2 C_L S} \\
& && 1 \geq \frac{W_0}{W} + \frac{W_w}{W} \\
& && 1 \geq 45.42 \frac{S}{W_w} + 8.71 \times 10^{-5} \frac{N_{lift} A^{3/2} \sqrt{W_0 W S}}{W_w \tau} \\
& && 1 \geq \frac{2W}{\rho V_{min}^2 C_{L_{max}} S} \\
& && 1 = \frac{\rho V}{\mu Re} \sqrt{\frac{S}{A}}
\end{aligned} \tag{3.6}$$

Hoburg goes on to develop models for propulsion, loads, structures, and aerodynamics. Using the GP formulation, Hoburg demonstrated the ability to perform conceptual design of aircraft in fractions of a second, significantly expanding the ability of the designer to study the design space.

### 3.4 Advantages of the Geometric Programming Approach to Conceptual Design

Many advantages come from taking a geometric programming approach to aircraft design. First, the mathematics of conceptual design tend to be GP compatible, which is convenient to implement. Second, since objectives and constraints take the same form (monomial and posynomial) requirements can quickly be swapped out as either the objective of the optimization or a constraint in the problem. Third, since GP is a convex formulation,

designs are arrived at rapidly and guarantee global optimality. In the context of MDAO, GP has an additional advantage. GP is referred to as a Simultaneous Analysis and Design (SAND) architecture. SAND architectures are the least expensive computationally [28] and are therefore attractive for conceptual design, but a SAND approach requires that all discipline analysis equations be treated explicitly as constraints in the formulation [22], requiring a great deal of effort on the part of the designer to implement. GP keeps the computational benefit of a SAND architecture, and since most equations of interest are directly GP compatible, the impracticality of implementation is significantly reduced. In fact, by utilizing GPkit [29], implementation of a GP is as simple as transcribing the equations of interest.

### 3.5 Geometric Programs and Black Boxes

As was discussed in Chapter 2, black boxed analysis codes play a critical role in the design process, and therefore a key drawback of the GP formulation is the exclusion of these black boxes. There is no way for a GP to solve with a constraint that is not GP compatible, and thus to incorporate a general black box, one of three approaches must be taken. First, all of the mathematics of the black box can be rewritten into a GP compatible analysis code and implemented directly as constraints in the GP formulation. This method works well for small problems and low fidelity analyses, however quickly becomes impractical. In addition, many analysis, such as high fidelity aerodynamics, are inherently not GP compatible and could not be implemented in this form.

Second, the black box can be pre-sampled and fit with an explicit GP compatible mathematical function. This is the approach taken by Hoburg [30], enabled by GPfit [31]. This approach solves the key problem in a direct implementation approach in that the mathematics of the black box itself do not have to be convex, only the relation between inputs and outputs. For example, this relationship tends to hold true for relationships



between  $C_L$  and  $C_D$ , but the mathematics required to estimate a  $C_D$  for a given  $C_L$  are not inherently GP compatible beyond the lowest levels of fidelity. The limit to this approach is the number of design variables considered by the black box, as the computational time to sweep over the black box increases with the number of inputs to the black box (unless parallelization is available). This limitation makes this approach challenging, perhaps even infeasible, for black boxes with many inputs and outputs.

Finally, an iterative optimization algorithm can be implemented where the black box analysis is called as the algorithm iterates. This approach sacrifices the guarantees inherited from the GP, including rapid convergence and global optimality, but provides the most flexibility, enabling general black box integration without the curse of dimensionality that arises when pre-computing all the data. To further investigate this idea, inspiration is drawn from existing iterative optimization methods that will be discussed in Chapter 4.



# Chapter 4

## Iterative Optimization Methods

### 4.1 Sequential Quadratic Programs

The primary issue raised in Chapter 3 is that the GP formulation does not naturally lend itself to the use of black box analyses. However, in the past, iterative optimization algorithms have been utilized in order to incorporate black boxes, with sequential quadratic programs (SQPs) being among the most common in the aircraft design community [17, 32], due to their effectiveness, simplicity, and flexibility. A sequential quadratic program is a generic non-linear solution algorithm that approximates the design space as a quadratic program (QP) local to the current design point, and then iterates until convergence is reached.

A quadratic program (QP) takes the form [33]:

$$\begin{aligned} \text{minimize} \quad & q(x) = \frac{1}{2}x^T Gx + x^T c \\ \text{subject to} \quad & a_i^T x = b_i, \quad i \in \mathcal{E} \\ & a_i^T x \geq b_i, \quad i \in \mathcal{I} \end{aligned} \tag{4.1}$$

Note here that the objective is a quadratic function of  $x$ , and the constraints are linear in  $x$ .

Considering sequential quadratic programs, we seek to solve the generic non-linear optimization problem, or non-linear program (NLP) [34]:

$$\begin{aligned}
 & \text{minimize} && f(\mathbf{x}) \\
 & \text{subject to} && h(\mathbf{x}) = 0 \\
 & && g(\mathbf{x}) \leq 0
 \end{aligned} \tag{4.2}$$

For an SQP algorithm, we take our current design vector  $\mathbf{x}^k$  and approximate the optimization problem locally as a quadratic program [34]:

$$\begin{aligned}
 & \text{minimize} && \nabla f(\mathbf{x}^k)^T d_x + \frac{1}{2} d_x^T \nabla^2 f(\mathbf{x}^k) d_x \\
 & \text{subject to} && \nabla h(\mathbf{x}^k)^T d_x + h(\mathbf{x}^k) = 0 \\
 & && \nabla g(\mathbf{x}^k)^T d_x + g(\mathbf{x}^k) \leq 0 \\
 & && d_k = \mathbf{x} - \mathbf{x}^k
 \end{aligned} \tag{4.3}$$

The SQP algorithm takes the first and second derivatives of the objective and fits the objective locally with a quadratic function. Additionally, the first derivative is taken of all of the constraints, and a local linear fit is performed. This forces the general non-linear program into a QP formulation. Consider the following example:

$$\begin{aligned}
 & \text{minimize} && 100x^{0.8}y^{0.8} + 10x^{0.8}y^{-0.8} + 10y^{0.8}x^{-0.8} + x^{-0.8}y^{-0.8} \\
 & \text{subject to} && 8xy - 1 = 0 \\
 & && 1.1x + 0.2 - (x^2 + y) \leq 0
 \end{aligned} \tag{4.4}$$

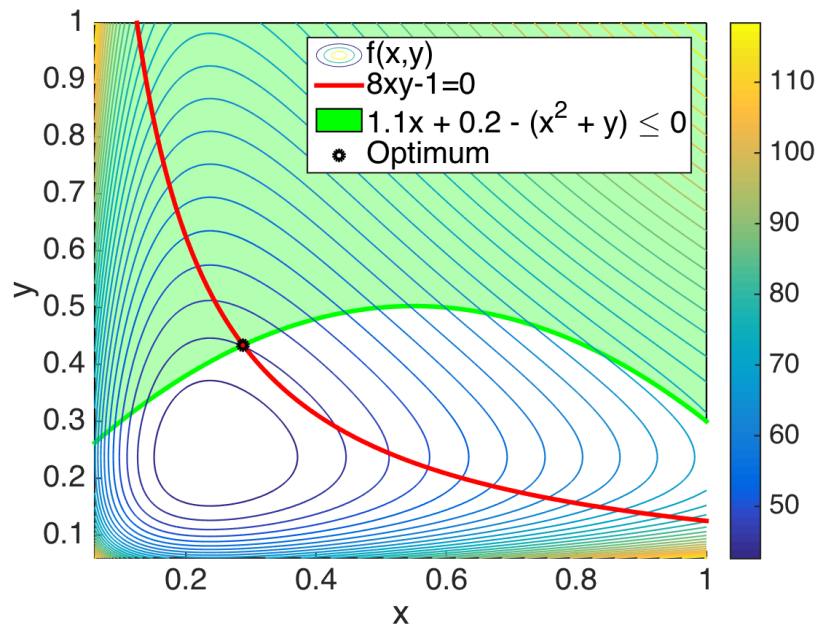


Figure 4-1: Example optimization problem

Applying the SQP algorithm, a graphical solution can be compiled:

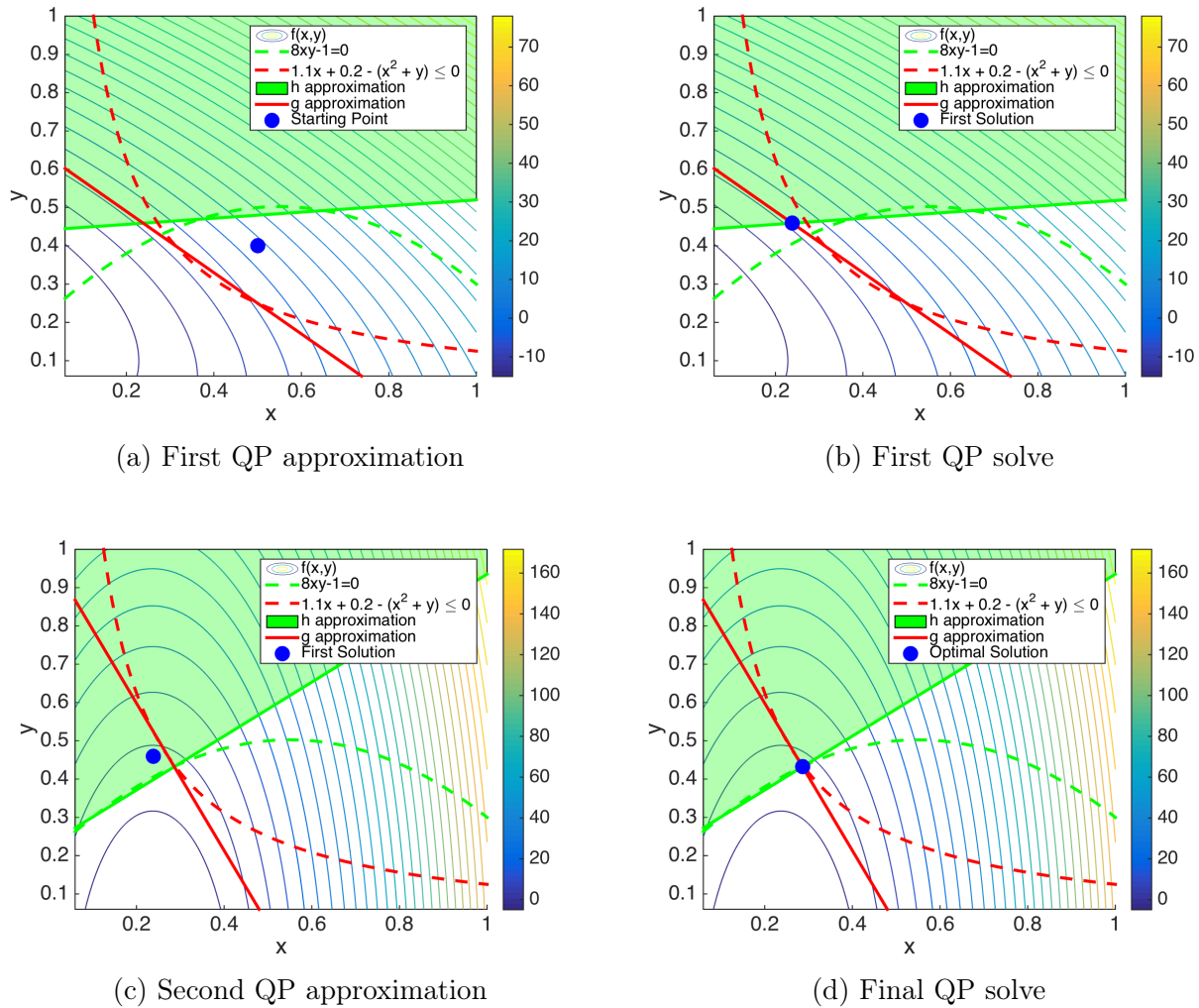


Figure 4-2: The solution of an example sequential quadratic Program

With this algorithm, the objective and constraints are approximated in a QP form that can be solved rapidly by the optimizer. As the algorithm progresses, the approximation becomes closer to the actual underlying mathematics until convergence to a relative tolerance.

The linear form of the constraints in each QP subproblem provides an avenue for incorporating the black box analyses. A linear constraint can be computed for each black box using the derivatives of the output variables with respect to the input variables. These derivatives can be obtained by using finite-differencing, adjoint methods or some other

differentiation scheme, and hence the penalty of calculating the linear constraints equivalent to the penalty of computing the derivatives. But despite the versatility of the SQP algorithm, it does not take full advantage of the GP formulation, and so another approach should be considered.

## 4.2 Signomial Programs

A signomial program (SP) is a geometric program which has been modified to include subtraction of terms. By a rigorous definition, a signomial is defined as the linear combination of monomial terms [24]. By this definition, we can also write a signomial as the difference between two posynomials:

$$h(\mathbf{x}) = \sum_{k=1}^K cx_1^{a_{1k}}x_2^{a_{2k}}\dots x_n^{a_{nk}} - \sum_{l=1}^L dx_1^{a_{1l}}x_2^{a_{2l}}\dots x_n^{a_{nl}} \quad (4.5)$$

A signomial program in standard form can then be defined:[24, 35]

$$\begin{aligned} & \text{minimize} && \frac{p_0(\mathbf{x})}{p_1(\mathbf{x})} \\ & \text{subject to} && h_i(\mathbf{x}) = 0, \quad i = 1, \dots, m \\ & && h_j(\mathbf{x}) \leq 0, \quad j = 1, \dots, p \end{aligned} \quad (4.6)$$

By using the SP formulation, many of the same mathematical advantages of the GP formulation are maintained and the ability to subtract terms in the constraints is also available. The extensibility of the SP formulation to aircraft design has been demonstrated by Kirschen [36]. While SPs can accommodate a broader range of models, they lose all of the guarantees that can be made by GPs due to the non-convexity introduced by the subtraction, however, of interest here is the SP solution method. Consider the same

example from above, but this time plotted in logspace:

$$\begin{aligned}
 &\text{minimize} && 100x^{0.8}y^{0.8} + 10x^{0.8}y^{-0.8} + 10y^{0.8}x^{-0.8} + x^{-0.8}y^{-0.8} \\
 &\text{subject to} && 8xy - 1 = 0 \\
 &&& 1.1x + 0.2 - (x^2 + y) \leq 0
 \end{aligned} \tag{4.7}$$

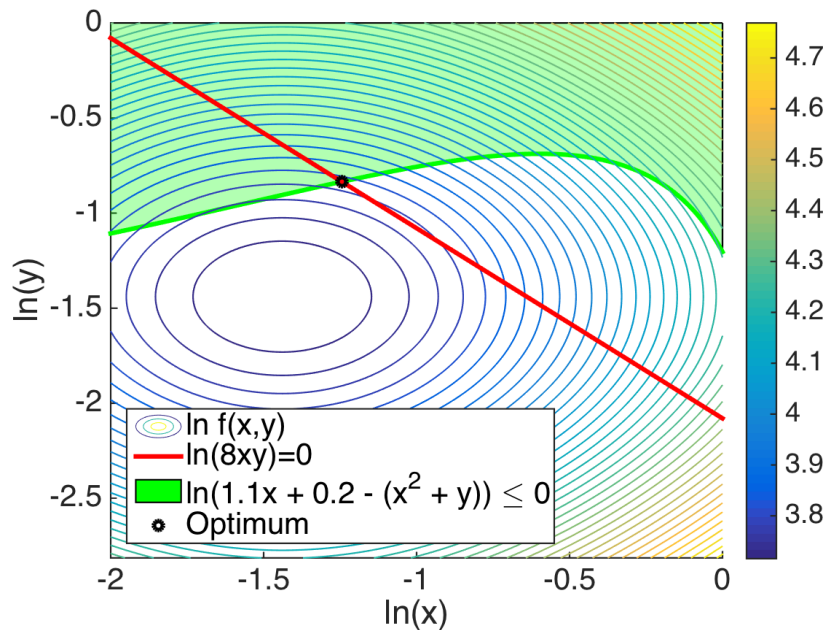
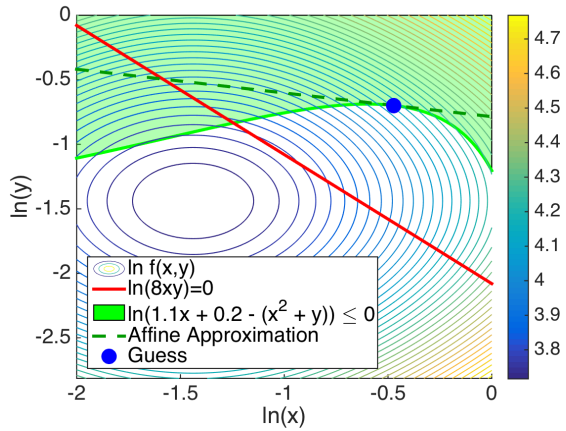


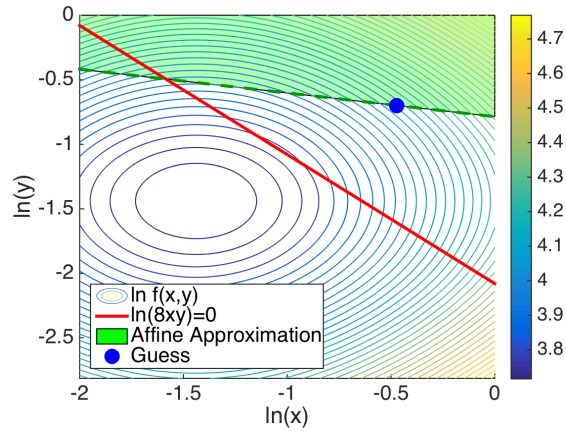
Figure 4-3: An example signomial program

As we can see in Figure 4-3, we have introduced a constraint which is concave in logspace. Now, the best possible GP compatible fit we can make to this constraint is affine in logspace. So, we select an initial point and make this approximation. This GP is then solved, creating a new design point. The linearization and solving process is then repeated until a certain relative tolerance is achieved. The solution process is shown below in Figure 4-4:

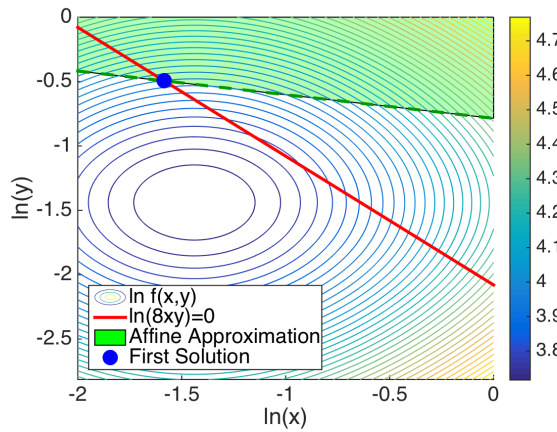




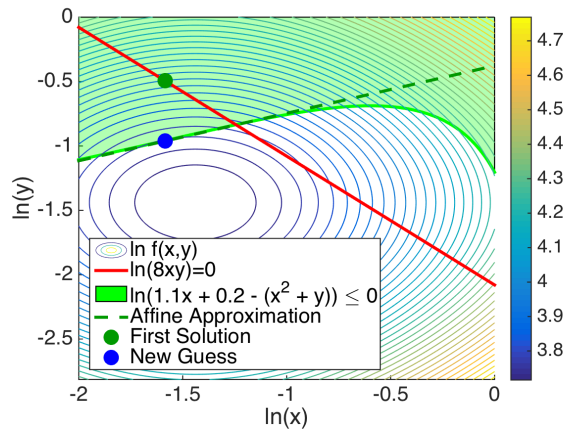
(a) Initial linearization



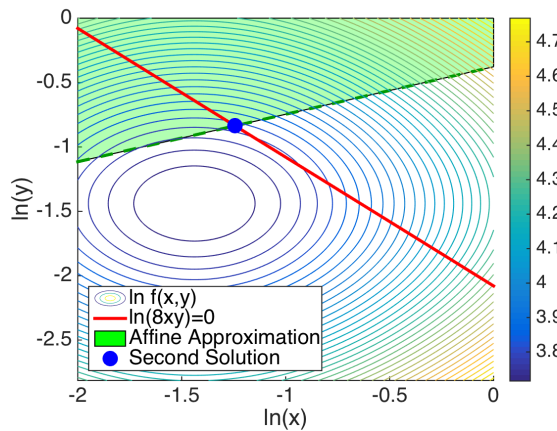
(b) Formulating the GP



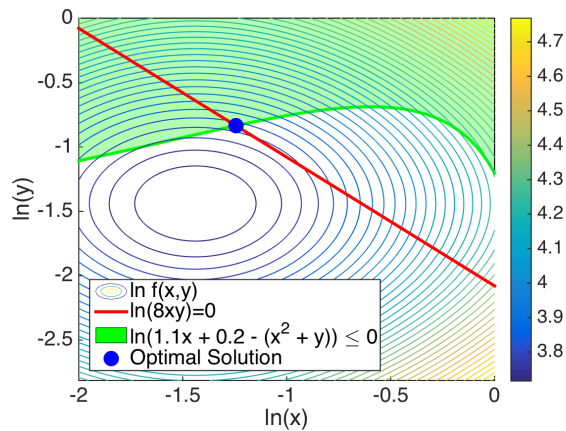
(c) Solving the first GP



(d) Updating to a new GP



(e) Solving the new GP



(f) Converged to final solution

Figure 4-4: The solution of an example signomial program

Signomial programs provide us with an important perspective, demonstrating how geometric programs can be used in an iterative fashion to solve problems which are not GP compatible. However, unlike SQP, there is no longer a convenient way of incorporating black boxes, as the solution algorithm still requires explicit signomial constraints which can be relaxed. Thus, we must take the black box functionality of SQP along with the GP core of SP.

### 4.3 Sequential Convex Programs

Boyd [37] outlines methods for solving a sequence of convex problems. While the SQP algorithm is one example of a sequential convex program (SCP), Boyd primarily discusses the Difference of Convex Programming (DOC) algorithm. A DOC is a superset of signomial programming (SP), where the optimization problem takes the form:

$$\begin{aligned} & \text{minimize} && f_0(\mathbf{x}) - g_0(\mathbf{x}) \\ & \text{subject to} && f_i(\mathbf{x}) - g_i(\mathbf{x}) \leq 0, \quad i = 1, \dots, m \end{aligned} \tag{4.8}$$

where  $f_i$  and  $g_i$  are both convex functions. Difference of convex programs are typically solved using the Convex-Concave Procedure (CCP), where the concave functions  $g_i$  are approximated as linear by [38]:

$$\hat{g}_i(\mathbf{x}; \mathbf{x}_k) = g_i(\mathbf{x}_k) + \nabla g_i(\mathbf{x}_k)^T (\mathbf{x} - \mathbf{x}_k) \tag{4.9}$$

and then a single iteration becomes:

$$\begin{aligned} & \text{minimize} && f_0(\mathbf{x}) - \left( g_0(\mathbf{x}_k) + \nabla g_0(\mathbf{x}_k)^T (\mathbf{x} - \mathbf{x}_k) \right) \\ & \text{subject to} && f_i(\mathbf{x}) - \left( g_i(\mathbf{x}_k) + \nabla g_i(\mathbf{x}_k)^T (\mathbf{x} - \mathbf{x}_k) \right) \leq 0, \quad i = 1, \dots, m \end{aligned} \tag{4.10}$$

which we can now guarantee will be a convex problem. This guarantee can be made because any strictly convex function  $f_i$  in linear combination with a linear (or quasi-convex) function  $\hat{g}_i(\mathbf{x}; \mathbf{x}_k)$  will also be convex [26]. The sub-problem then inherits the various benefits associated with convexity.

Studying the CCP algorithm helps us identify key areas in which general SCP algorithms can be advantageous over SQP algorithms. As discussed by Lipp and Boyd [38], the CCP retains more information about the underlying mathematics of the original problem in each subproblem, especially in the constraints. While the constraints in an SQP must be linear, the constraints in a CCP solve are limited only to be convex and hence contain second derivative information. Additionally, the linear approximation of the concave portion of the problem ensures that this linear approximation is a global overestimation, thus the trust regions that are sometimes required in SQP are not necessary.

### 4.3.1 Sequential Geometric Programming

The term sequential geometric programming (SGP) appears very little in the literature, save one paper [39], and does not seem to have gained widespread acceptance nor developed a standard definition. We define a sequential geometric programming algorithm as a solution method for non-linear programs (NLPs) where several geometric programming approximations are solved sequentially. An SGP algorithm solves the following NLP:

$$\begin{aligned}
 & \text{minimize} && g_0(\mathbf{x}) \\
 & \text{subject to} && f_i(\mathbf{x}) = 1, \quad i = 1, \dots, m \\
 & && g_i(\mathbf{x}) \leq 1, \quad i = 1, \dots, p \\
 & && h_i(\mathbf{x}) \leq 1, \quad i = 1, \dots, q
 \end{aligned} \tag{4.11}$$

where the constraints  $f_i(\mathbf{x})$  and  $g_i(\mathbf{x})$  are GP compatible, while the constraints  $h_i(\mathbf{x})$  are

not and may not even be explicit. Ideally, a general SGP algorithm will mimic the same flexibility of a SQP, and maintain the convex benefits of a GP. We will propose a heuristic algorithm which meets these criteria, but first, let us consider a generalization of iterative methods.

## 4.4 General Iterative Methods with Black Boxes

Based on the SQP algorithm and previous work in iterative GP solution methods, we can extrapolate a generalized sequential optimization algorithm which utilizes calls to a black box analysis, summarized in the flowchart below:

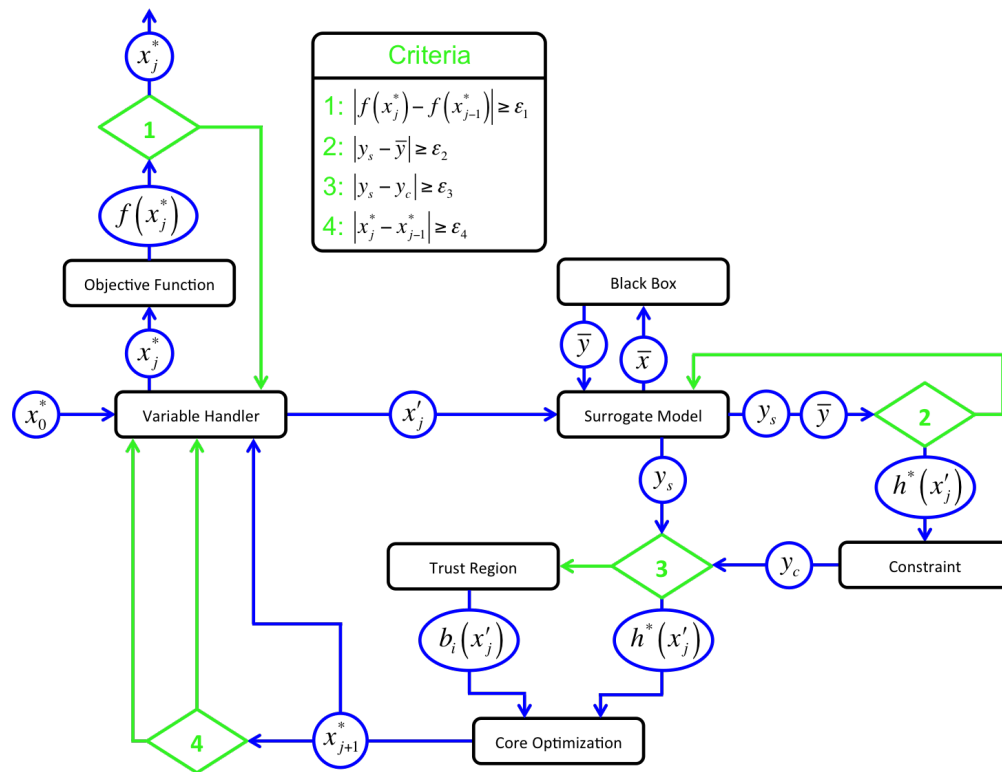


Figure 4-5: Detailed flowchart of iterative optimization methods

A sequential geometric programming algorithm also follows this same flowchart. In the next chapter, we will discuss this flowchart at length and propose a SGP heuristic algorithm.

# Chapter 5

## Proposal for a Heuristic Sequential Geometric Programming Algorithm

### 5.1 Algorithm Introduction

Figure 4-5 outlines a generalized sequential algorithm which utilizes a black boxed constraint, but our interest is specifically the practical implementation of a sequential geometric programming algorithm. In this chapter, we will step through the various nodes in Figure 4-5 and discuss how each node functions in the proposed heuristic algorithm.

The proposed SGP algorithm will follow the same high level architecture outlined in Figure 4-5. An initial guess,  $\mathbf{x}_0^*$ , is passed in and used to create a sampling region for the black box. These samples are then used to create a surrogate model of the black box. The surrogate will then be transformed into a GP compatible constraint,  $h^*(\mathbf{x})$ , and passed into the GP approximation for that iteration. The GP is solved, a new point is generated and then the process continues until convergence is reached.

## 5.2 Initialization

Selecting a good initial guess is crucial to the success of sequential algorithms [37], and therefore must be given special consideration. However, with an SGP algorithm, a standard practice is readily available. Using analysis methods such as those proposed by Hoburg [25], a GP compatible constraint can be used in place of the black boxed constraint and the GP solved. In most cases, this will provide a high quality initial guess for the SGP algorithm to begin. While this approach may require a non-trivial effort in some cases, the ability to readily generate an initial guess through the use of a low fidelity GP is a substantial advantage the SGP algorithm has over others.

## 5.3 Variable Handling

The variable handler cell is a construct of the flow chart and serves as a stand in for some of the logic of the algorithm. At the beginning of each iteration, the entire design vector  $\mathbf{x}_j^*$  will be available for processing. The variable handler takes this design vector and serves as a filter for two downstream steps. First, the handler passes the required design variables into the objective function for evaluation. Second, the handler passes the relevant design values into the appropriate surrogate models. In the case of a single black box constraint, the variable handler will only be responsible for processing one set of variables, however, where multiple black boxes are used, multiple sets will be passed downstream. For this work, we will only utilize a single black box constraint.

## 5.4 Surrogate Modeling

A surrogate model is simply a function which mimics the black box as closely as possible while being less expensive to evaluate. Many options for surrogate models exist, including

simple functions such as posynomials and more complex functions such as Gaussian Process models. The choice of surrogate model and constraint form are inherently coupled, and two extreme options exist for how the two should work together. First, a high fidelity surrogate can be utilized, which captures all of the details of the black box but is not compatible with the underlying optimization. In this case, a procedure must be generated which converts this high fidelity surrogate into a compatible constraint. Using a high fidelity surrogate model ensures the black box is modeled well, but often comes at the price of increased computational expense to call the number of points required to fit the high order surrogate. As a result, this approach should be taken for black box functions that require a high fidelity surrogate to be represented, for example when small perturbation of the inputs result in large changes in the outputs over the region of interest.

Another situation in which high fidelity surrogates should be considered is when the underlying black box itself is thought to be highly incompatible with the core optimization, in this case, when a black box is poorly approximated as GP compatible. In these cases, the convex-concave procedure provides an avenue for solution. For any general black box which can be represented by a Taylor Series, the black box can be equally well represented by a signomial. Then, by the CCP, a signomial program can be relaxed into a GP and solved. This approach will be the subject of future work.

At the other extreme, we can limit ourselves to surrogate models which are compatible with the underlying optimization. A SQP takes this approach to the extreme, using only linear surrogate models for the black box at each iteration. This approach is lightweight computationally, requiring only a few points to be calculated at each iteration, but should only be used with black boxes which are well approximated by GP compatible functions. One additional benefit of this approach is that the surrogate model can directly pass itself into the optimization, eliminating the need to ensure the constraint matches the surrogate, as is required for a high fidelity surrogate model. However, the obvious limitation here is that some black boxes will be poorly approximated by these low fidelity functions and so

convergence may be poor, or the problem may even be infeasible.

For this work, we will be utilizing only black boxes which are well approximated by GP compatible functions, and will thus exclusively use surrogate models which are GP compatible.

## 5.5 Black Box Considerations

Black box analysis codes were covered in some depth in Chapter 2. In the SGP algorithm, the black box receives inputs from the surrogate model and provides outputs back for some number of points contained within a sampling region. A few considerations, first, the black box must be valid over the entire region being considered. For some off the shelf packages, this may require some modification or a wrapper which fills in regions for which the black box is not valid. Alternatively, a black box can also come with a set of constraints to be implemented by the GP.

## 5.6 Creating GP Compatible Constraints

### 5.6.1 Soft-Max Affine (SMA) Functions

To create GP compatible constraints from the surrogate models, we require a mathematical form that is of posynomial construction. Hoburg [30] proposes a few functions which are GP compatible to be used for data fitting: max affine (MA), softmax affine (SMA), and implicit softmax affine (ISMA). For the purpose of this work, we will use the SMA function for all black box fitted constraints. An SMA function can be written as:



$$1 \geq \frac{1}{x_1^\alpha} \sum_{i=1}^M c_i \prod_{j=2}^N x_j^{a_{i,j}} \quad (5.1)$$

As discussed in Section 5.4, in our approach for this work we fit an SMA function directly to the black box data. Thus in practice, the surrogate model and SMA GP compatible constraint act as one object. We therefore must develop methodology for linking the black box with the SMA constraint/surrogate model. There are three considerations for this process: the number of terms used by the SMA function to model the black box, the interval over which to sample, and how to select points within that interval.

### 5.6.2 Number of SMA Terms

An SMA function with  $M$  terms and  $N$  independent variables requires  $M(N + 1) + 1$  data points to be returned from the black box function, and so clearly selecting the correct number of SMA fitting terms has the single largest impact on the number of black box calls made during the run of the algorithm. Given the critical nature of this consideration, we leave it exposed as a setting that can be selected by the designer. In practice, we observe that a good choice is to use a number of terms equal to the number of inputs to the black box. This provides the fitting algorithm with enough flexibility to fit the data, while minimizing the number of calls that must be made.

### 5.6.3 Interval of Sampling

Two extremes exist for selecting a sample interval: a large region which captures the global trends of the black box, or a local region which captures the details near the current design point. Between these two extremes is a continuous spectrum of options, illustrated by the figure below:

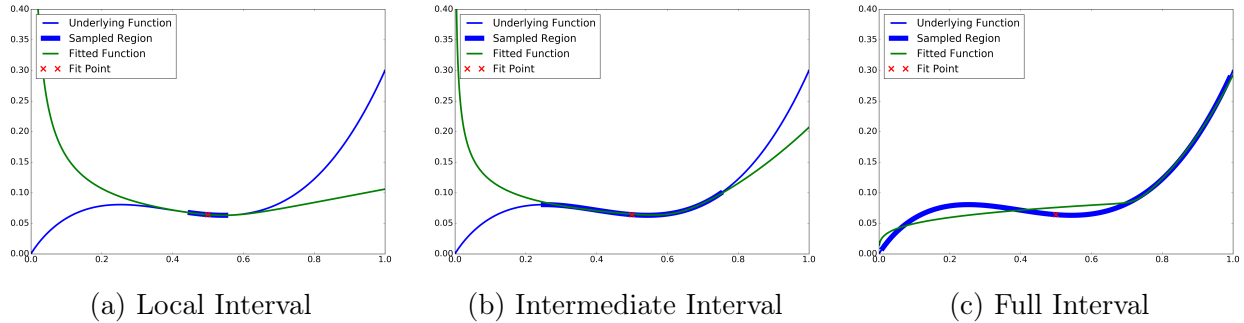


Figure 5-1: Impact of sampling interval on fit

Note that there is a trade-off between local error and global error. As the sampling region approaches the full interval, global error decreases at the cost of local error. Selection on this spectrum is non obvious, even for functions that are well approximated by a SMA function as we have assumed. In the early iterations, we want to capture the global trend of the black box, but when approaching convergence, local error should be driven down. Thus, we propose a mechanism for changing the interval as the algorithm iterates, favoring a global sampling region early and then moving to a local interval.

Two user defined parameters control the interval. First, an initial interval is explicitly defined by the user, as a percentage multiplier and divisor on the initial guess. Second, a parameter is defined that tunes the rate at which the interval decreases in size, slowly progressing to a local sampling region. This value is the percent of the previous interval to be taken in the next iteration.

When approaching final convergence, an SMA fit on a highly local region will still produce local model error at the design point, despite high confidence that the design point is correct. We therefore desire a new fitting function that ensures minimal error at the point under consideration, roughly analogous to using a linear fit at the termination of an iterative algorithm. Boyd [27] provides a general monomial approximation scheme for any function:

$$f(\mathbf{x}) \approx f(\mathbf{x}^*) \prod_{i=1}^n \left( \frac{x_i}{x_i^*} \right)^{a_i} \tag{5.2}$$

$$a_i = \frac{x_i^*}{f(\mathbf{x}^*)} \frac{\partial f}{\partial x_i^*}$$

which ensures minimal error at  $\mathbf{x}^*$  and creates a good local approximation. When the sampling interval decreases in size to a certain user specified value, the algorithm flips into a monomial fitting mode to remove as much local error as possible.

### 5.6.4 Selecting Points in the Interval

A final consideration is how to select points within the interval once it has been defined. Our algorithm simply casts an evenly spaced grid over the  $N$  dimensional interval, and does this with every iteration, saving none of the data from previous iterations. This is an area that could be significantly improved by future work.

## 5.7 Implementing Trust Regions

In cases where the surrogate model diverges from the constraint beyond the local region, trust regions should be used to constrain the optimizer. A trust region is easy to implement in a GP as the percent change of the design variable with respect to the previous value. In this case, trust regions were implemented whenever monomial constraints were used, as monomials can vary widely from the surrogate model beyond the local region of the design variable.

## 5.8 Convergence Criteria

Figure 4-5 outlines four criteria which must be true at convergence:

1. The change in objective between iterations must be small
2. The surrogate model must accurately represent the black box
3. The constraint must accurately represent the surrogate
4. The change in the design variable values must be small

The first criteria compares the value of the objective function at the current design point with the value of the objective function at the previous design point. A common metric for iterative algorithms, when the difference between these two values is large, it indicates that the algorithm has not yet converged to the optimal design point and so the algorithm continues iterating. As the algorithm iterates, this difference will continue to get smaller until the relative tolerance is satisfied and the algorithm then returns the converged design. See Figure 4-2 for a graphical example.

The second criteria compares the outputs variables of the black box with the output variables of the surrogate model for the same set of inputs. In most cases, the surrogate will not match the black box for all points even under the best of circumstances, and so the meaning of this metric will vary on a case by case basis. However, regardless of application the surrogate will have to match the black box at the final design point in order to ensure convergence.

The third criteria compares the dependent variables of the constraint with the dependent variables of the surrogate model. Since this approach utilizes the surrogate directly as a constraint in the GP solve, this error is by definition zero.

The fourth criteria compares the design variables between the current iteration and the last iteration. Similar to the first criteria, when the design values are changing substantially it implies that the optimal design may not have been reached. Thus, we can implement the additional criteria that the relative change in design variables should be small and handle this criteria in the same way as the relative tolerance criteria. In practice, we do not implement any such constraints, but the discussion is included here for comprehensiveness.



# Chapter 6

## Implementation of the Sequential Geometric Programming Algorithm on a Solar Powered Aircraft

### 6.1 Solar Aircraft Test Problem

Recent work by Burton and Hoburg [40] produced a GP compatible model for conceptual design of solar powered HALE aircraft. This model optimizes 166 design variables, and captures trades in a non-intuitive design space. The full results of Burton's GP are included in Appendix A. We selected this problem to test the SGP algorithm on, specifically the profile drag model.

Burton's original model contains a GP compatible equation for profile drag:

$$C_{D_p}^{3.72} \geq 0.0247C_L^{2.49}Re^{-1.11} + 2.03 \times 10^{-7}C_L^{12.7}Re^{-0.338} \\ + 6.35 \times 10^{10}C_L^{-0.243}Re^{-3.43} + 6.49 \times 10^{-6}C_L^{-1.9}Re^{-0.681} \quad (6.1)$$

The first step was to modify this constraint to include  $\tau$ , which is also a critical parameter for airfoil selection. Hoburg [25] previously provided just such a constraint based on fitting a family of NACA 4-series airfoils:

$$\begin{aligned}
1 \geq & 2.56 C_L^{5.88} \tau^{-3.32} Re^{-1.54} C_{D_p}^{-2.62} + 3.8 \times 10^{-9} C_L^{-0.92} \tau^{6.23} Re^{-1.38} C_{D_p}^{-9.57} \\
& + 2.2 \times 10^{-3} C_L^{-0.01} \tau^{0.033} Re^{0.14} C_{D_p}^{-0.73} + 1.19 \\
& \times 10^4 C_L^{9.78} \tau^{1.76} Re^{-1} C_{D_p}^{-0.91} + 6.14 \times 10^{-6} C_L^{6.53} \tau^{-0.52} Re^{-0.99} C_{D_p}^{-5.19}
\end{aligned} \tag{6.2}$$

While a NACA 4-series airfoil would be a poor selection of airfoil for a HALE solar powered aircraft, this constraint provides us with a tested example which relates the variables of interest.

This case is the baseline for our remaining work, an entirely GP model which captures the tradeoffs we are interested in. The full results of this baseline case are included in Appendix A.

While the ultimate goal of this work is to implement a high fidelity black box such as those mentioned in Chapter 2, our immediate goal is to evaluate the performance of the SGP algorithm. Thus, Equation 6.2 was placed into a black box, returning a profile drag for a given set of inputs for  $C_L$ ,  $Re$ , and  $\tau$ . This enables a common comparison between the algorithm and a known GP solution.

In summary, we have two cases to consider:

- Case 1: Equation 6.2 implemented directly as a GP constraint, solved as a GP
- Case 2: Equation 6.2 implemented as a black box, solved as an SGP



## 6.2 User Defined Inputs

Many parameters are available to the user and are summarized here for clarity.

### 6.2.1 Initial Guess Values

*parameters.clguess, parameters.reguess, parameters.tauguess*

These parameters provide an initial guess for the SGP algorithm to begin iterating. Note that initial guesses are not required for all design variables, only those used in the black box constraint.

### 6.2.2 SMA Model Parameters

*parameters.fit\_order*

This value sets the number of terms used in the SMA fitting function. In the current algorithm, this number remains fixed throughout all iterations, but future work may explore allowing this number to be actively controlled by the algorithm.

### 6.2.3 Initial Sampling Interval Parameters

*parameters.cl\_band, parameters.re\_band, parameters.tau\_band*

These values set the initial sampling interval, or “band” for the SGP algorithm. The user specifies these values as a fraction of the initial guess. For example, a value:

```
parameters.cl_band = 0.5
```

corresponds to an initial sampling from  $0.5C_L^*$  to  $1.5C_L^*$ .

## 6.2.4 Sampling Interval Tightening Parameters

*parameters.cltighten, parameters.retighten, parameters.tautighten*

These parameters set the rate at which the sampling interval tightens as percent of the previous interval. For example, a value:

```
parameters.cltighten = 0.9
```

would result in 90% of the previous interval being preserved at the next iteration. Therefore, the first iteration would be 90% of the initial interval, the second 81% and so on.

*parameters.band\_min*

Value sets the limit at which the algorithm switches into monomial mode. A nominal value of 10% of the initial interval has worked well for this work, but future work may study more rigorous selection of this value.

## 6.2.5 Monomial Mode Parameters

*parameters.monomial\_fd\_band*

This value sets the perturbation for the finite differencing scheme as a fraction of the initial guess and is generally set to a small value.

*parameters.trust\_region*

This value sets up the trust region implemented when the algorithm flips to monomial mode. The following constraints are implemented:

$$\begin{aligned}
\frac{C_L}{C_L^*} &\leq 1 + \text{parameters.trust\_region} \\
\frac{C_L}{C_L^*} &\geq 1 - \text{parameters.trust\_region} \\
\frac{Re}{Re^*} &\leq 1 + \text{parameters.trust\_region} \\
\frac{Re}{Re^*} &\geq 1 - \text{parameters.trust\_region} \\
\frac{\tau}{\tau^*} &\leq 1 + \text{parameters.trust\_region} \\
\frac{\tau}{\tau^*} &\geq 1 - \text{parameters.trust\_region}
\end{aligned}
\tag{6.3}$$

*parameters.modelTol*

This value sets the tolerance for Convergence Criteria 2 as outlined in Chapters 4 and 5.



# Chapter 7

## Results of the Sequential Geometric Programming Algorithm

### 7.1 Success Metrics

There are two key success metrics for the algorithm. First, the algorithm should return a result similar to the directly implemented GP model, ie, the algorithm should achieve the optimal design point within a small error. Second, the number of black box calls should be minimized, as calls to the black box are assumed in general to be computationally expensive.

Additionally, we expect that a good algorithm would be robust to various values for the initial guess and the tuning parameters outlined in Chapter 6.2. Thus, we will sweep over these values and recover performance in both metrics to validate a robust algorithm.

## 7.2 Algorithm Performance

Taking the initial guesses for  $C_L$ ,  $Re$  and  $\tau$  to be 90% of their known optimal values and using reasonable tuning parameters (0.4 for band values and 0.65 for tightening values), we see the following results:

Table 7.1: Comparing Solar Aircraft Results

	Case 1	Case 2	Error
Black Box Calls	-	120	-
$W_{total}$ (lbf)	59.5589	59.5598	0.00%
$C_{Dp}$	0.0137	0.0138	0.28%
$C_D$	0.0198	0.0200	0.79%
$C_L$	0.8860	0.8889	0.33%
$\tau$	0.2714	0.2700	-0.51%
$Re$	95233.3337	95620.8497	0.41%
$V$ (m/s)	28.8922	28.8403	-0.18%
$P_{max}$ (W)	265.2127	265.5984	0.15%
$S$ (ft <sup>2</sup> )	55.3864	55.4670	0.15%
$A$	45.5262	44.9616	-1.24%
$MAC$ (ft)	1.1030	1.1107	0.70%
$b$ (ft)	50.2149	49.9388	-0.55%
$W_{wing}$ (lbf)	15.7429	15.7346	-0.05%
$W_{battery}$ (lbf)	24.8680	24.9041	0.15%

The full results of the SGP algorithm are included in Appendix A. Note that the overall objective exhibits less than a one percent error, with the largest design variable error being less than two percent. The algorithm also required only 120 calls to the black box which would be quite reasonable for a black box code such as XFOIL. The convergence of the algorithm is shown in the plot below:

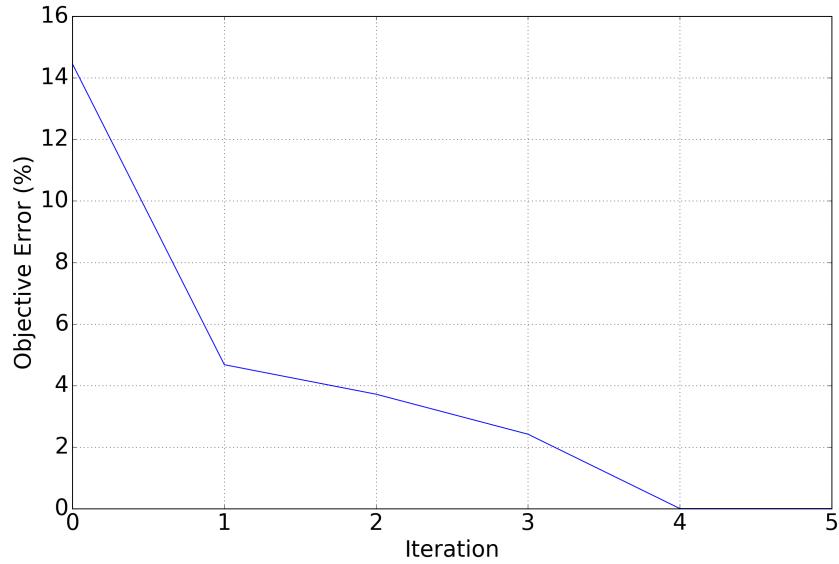
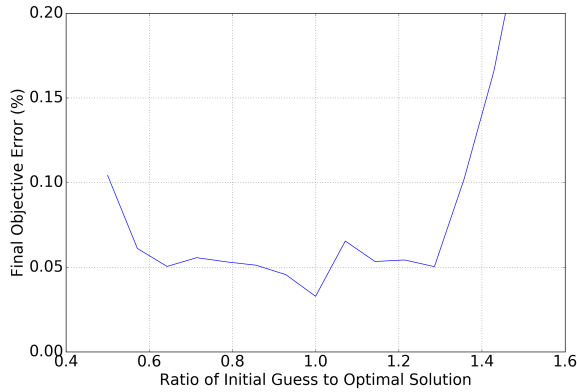


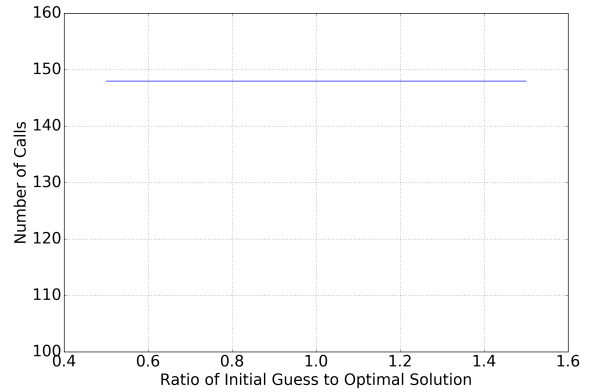
Figure 7-1: Convergence of the SGP Algorithm

Considering algorithm robustness, we swept over three of the user defined inputs mentioned in Chapter 6.2: initial guess, initial interval, and interval tightening. The two parameters not under consideration were fixed during the sweep at well behaving nominal values. Ideally, we would observe that as these user inputs vary, the overall error in the objective function between Case 1 and Case 2 will remain small, and the number of black box calls will also remain low.

Sweeping the initial guess from 50% of the known optimum to 150% of the known optimum, we see the following results:



(a) Error in Objective



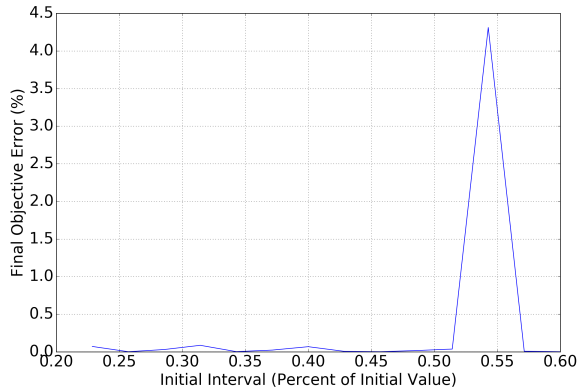
(b) Number of Calls

Figure 7-2: Impact of changing the initial guess of Case 2

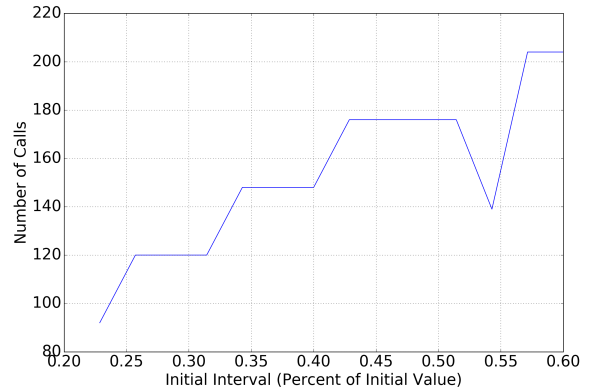
As might be expected, we see a minimum error near an initial guess of exactly the known optimum, and an increasing error as we move away from that best guess. Note that for most of these trials, the absolute error between the objective functions of Case 1 and Case 2 are less than 0.1%. Interesting however is that the number of black box calls stays the same as we sweep over the initial guesses. This is primarily due to the fact that the number of SMA iterations remains the same, as the intervals change in the same way in every case and only one monomial fit is required to reach model tolerance. If the required model tolerance were tightened, we might expect different behavior.

Considering the initial interval, we observe the following results:





(a) Error in Objective

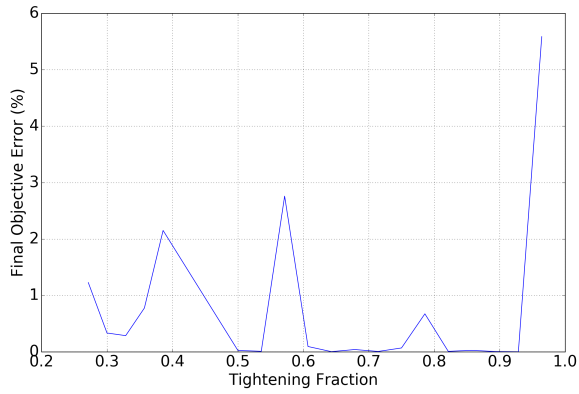


(b) Number of Calls

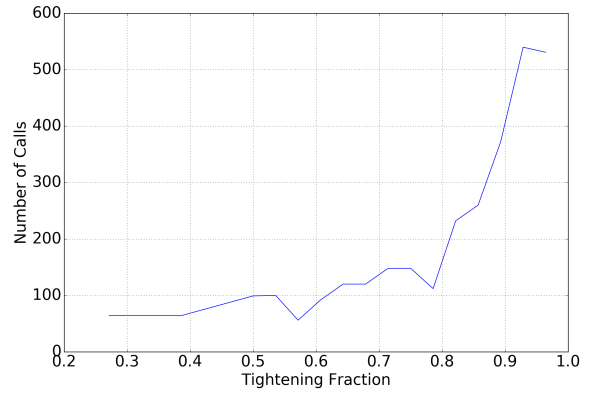
Figure 7-3: Impact of changing the initial interval of Case 2

The x-axis here is the initial band value discussed in Chapter 6.2. These results are quite interesting. First, we observe a spike in error at around 0.55. Coupled with the comparatively low number of black box calls at this point, this error is likely due to an early GPkit termination, however less than 5% error is still observed. Additionally, the stair-step in the number of calls is due to the logic which changes to monomial mode. Each step represents an additional SMA call before the monomial mode is activated, since as the initial interval gets bigger, it takes more steps to reach the fixed value where the mode changes.

Finally, we consider the rate at which we tighten the interval:



(a) Error in Objective



(b) Number of Calls

Figure 7-4: Impact of changing the tightening rate of the interval of Case 2

The x-axis here is the tightening value discussed in Chapter 6.2. Sweeping this parameter results in the most error in the objective, with no discernible trend. However, as expected, the number of calls increases as the ratio of preserved interval increases, resulting in more SMA iterations. Based on these results, a value between 0.6 and 0.8 seems most appropriate.

# Chapter 8

## Conclusions and Future Work

### 8.1 Summary

Geometric programming (GP) has proven a valuable tool in the conceptual aircraft design space, however the GP formulation prevents the use of black box analysis tools that are prolific in the MDAO community. This work extends the GP formulation, enabling a black box drag polar to be utilized during conceptual design. A sequential geometric programming algorithm was developed based on the previous work in sequential convex programming, and applied successfully to a solar powered HALE aircraft with less than 1% error in the final objective. This work lays the groundwork for a new opportunity in GP, bringing it closer to more classical MDAO formulations and expanding its practicality in real design problems.

## 8.2 Future Work

### 8.2.1 Utilizing Signomial Surrogate Models

The next step for this work is to implement a signomial surrogate modeling approach. This would first require a general signomial fitting algorithm which does not yet exist. Once this algorithm has been written, methods for relaxing signomial constraints into posynomials (via similar methods to the CCP) must be developed and the algorithm tested on a new test problem.

A more long term vision for surrogate models would be to implement something like a Gaussian Process which could incorporate a measure of uncertainty quantification in addition to the deterministic values provided by a SMA or signomial fit. This type of method could significantly reduce the number of black box calls required to converge to an optimum.

### 8.2.2 Implementing New Black Boxes

Once the signomial surrogate has been implemented, non-convex black boxes can be implemented. We would start with XFOIL [41], a low fidelity aero code which has been utilized in some previous work, and then progress up the fidelity tree. Other disciplines such as weights and propulsion must also be investigated and may prove more difficult than aerodynamic databases which tend to be nearly log-convex.

One more interesting future avenue for expanding black boxes is to utilize a black box to perform multi-level optimization. In many cases, a designer must make decisions that are simply too detailed to be captured in the GP or SGP, for example, the detailed airfoil shape on a wing or the number of turbine blades in a compressor. If desired, these detailed decisions can be left as free variables in the black box, resulting in an additional level of

optimization. If this freedom is utilized correctly, the output of a black box code will be a Pareto Front rather than a pure analysis output.

### **8.2.3 Developing a General SGP Algorithm**

Perhaps the ultimate vision of this work is to develop a general SGP algorithm. Such an algorithm would exhibit the same flexibility of a SQP algorithm, while retaining many of the advantages of sequential convex programs such as DOC. A great deal of work and study must be done to reach this vision, but given the role geometric programming is beginning to play in aircraft design, an SGP algorithm could have a great impact on the future of aircraft design.



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# Appendix A

## Full Report of Design Results

### A.1 Original Formulation From Burton

Cost

----

122 [lbf]

Free Variables

-----

```
Mission, Aircraft |
  W_{cent} : 31.27
  W_{total} : 122
  W_{wing} : 80.71

Mission, Aircraft, Battery |
  E : 2.949e+07
  W : 51.62
  \mathcal{V} : 0.06126

Mission, Aircraft, Empennage |
  W : 20.98

Mission, Aircraft, Empennage, HorizontalTail |
  AR_h : 14.34
  C_{L_{max}} : 1.5
  S : 9.112
  W : 1.663
  b : 11.43
  c_{r_h} : 0.8858
  c_{t_h} : 0.7086
  l_h : 11.11

Mission, Aircraft, Empennage, TailBoom |
  I_0 : 1.676e-06
  J : 1.676e-06
  S : 10.48
  W : 11.49
  d_0 : 3.602
  l : 11.11
  t_0 : 5.571

Mission, Aircraft, Empennage, VerticalTail |
  AR_v : 4.427
  S : 24.3
  W : 7.831
  b : 10.37
  c_{r_v} : 2.756

center weight [lbf]
aircraft weight [lbf]
wing weight [lbf]

total battery energy [J]
battery weight [lbf]
battery volume [m**3]

empennage weight [lbf]

horizontal tail aspect ratio
maximum CL of horizontal tail
horizontal tail area [ft**2]
horizontal tail weight [lbf]
horizontal tail span [ft]
horizontal tail root chord [ft]
horizontal tail tip chord [ft]
horizontal tail moment arm [ft]

tail boom moment of inertia [m**4]
tail boom polar moment of inertia [m**4]
tail boom surface area [ft**2]
tail boom weight [lbf]
tail boom diameter [in]
tail boom length [ft]
tail boom thickness [mm]

vertical tail aspect ratio
total vertical tail surface area [ft**2]
one vertical tail weight [lbf]
one vertical tail span [ft]
vertical tail root chord [ft]
```

```

c_ft_v} : 1.929
l_v : 11.11

Mission, Aircraft, Engine |
P_{max} : 550.5
W : 0.2932
m : 0.1329

Mission, Aircraft, SolarCells |
S : 115
W : 6.36

Mission, AircraftLoading, HorizontalBoomBending |
F : 1556
\theta : 0.07997

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
F : 2433
\theta : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
T : 7692

Mission, AircraftLoading, WingLoading, ChordSparL |
\vec{M}_r : [ 1.89e+03 918 377 92.6 ]

Mission, AircraftLoading, WingLoading, ChordSparL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 1.68 0.829 0.299 0.0469 ]
\vec{\bar{M}} : [ 0.607 0.295 0.121 0.0297 ... ]
\vec{\bar{S}} : [ 1.37 0.794 0.456 0.2 ... ]
\vec{\bar{\Delta}} : [ 8.69e-05 0.0151 0.0517 0.109 ... ]
\vec{\theta} : [ 0.000458 0.0752 0.151 0.237 ... ]

Mission, AircraftLoading, WingLoading, GustL |
\vec{M}_r : [ 2.56e+03 1.58e+03 761 202 ]
\vec{\alpha}_{gust} : [ 8.85e-11 0.0309 0.113 0.231 ... ]
\vec{\bar{q}} : [ 1.33 1.9 3.29 4.74 ... ]

Mission, AircraftLoading, WingLoading, GustL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 4.61 2.45 0.989 0.2 ]
\vec{\bar{M}} : [ 2.05 1.27 0.611 0.162 ... ]
\vec{\bar{S}} : [ 3.35 2.95 2.3 1.3 ... ]

```

[ft]

vertical tail tip chord  
horizontal tail moment arm

[W]  
[lbf]  
[kg]

max power  
engine weight  
engine mass

[ft\*\*2]  
[lbf]

solar cell area  
solar cell weight

[N]

horizontal tail force  
tail boom deflection angle

[N]

vertical tail force  
tail boom deflection angle

[N\*m]

vertical tail moment

[N\*m]

wing section root moment

normalized length of element  
normalized  $Y_M$  and moment of inertia  
normalized moment  
normalized shear  
normalized displacement  
deflection slope

[N\*m]

wing section root moment  
gust angle of attack  
normalized loading

normalized length of element  
normalized  $Y_M$  and moment of inertia  
normalized moment  
normalized shear

```

\vec{\bar{\delta}} : [ 2.07e-05 0.013 0.0498 0.111 ... ] normalized displacement
\vec{\theta} : [ 0.000173 0.092 0.19 0.291 ... ] deflection slope

Mission, FlightSegment, AircraftPerf |
  CDA : 0.004203
  C_D : 0.03848
  P_{oper} : 550.5
  P_{shaft} : 0.7383
  [W]
  [hp]

Mission, FlightSegment, AircraftPerf, TailAero |
  C_d : 0.01821
  C_d : 0.009711
  Re : 5.631e+04
  Re : 1.655e+05

Mission, FlightSegment, AircraftPerf, TailBoomAero |
  C_f : 0.007754
  Re : 7.851e+05

Mission, FlightSegment, AircraftPerf, WingAero |
  C_L : 1.21
  C_d : 0.03428
  Re : 1.383e+05
  c_{dp} : 0.01702

Mission, FlightSegment, FlightState |
  (E/S)_C : 193.2
  (E/S)_{day} : 2159
  (P/S)_{min} : 234.3
  V : 25.52
  V_{wind} : 25.52
  \rho : 0.129

Mission, FlightSegment, SteadyLevelFlight |
  T : 17.26

Wing |
  AR : 30
  S : 115
  W : 32.73
  \tau : 0.115
  b : 58.73
  c_{MAC} : 1.958
  c_{root} : 2.61

  aspect ratio
  surface area
  weight
  airfoil thickness ratio
  wing span
  mean aerodynamic chord
  root chord

```

```

\vecfc_{ave}} : [ 2.45      2.12      1.79      1.47      ] [ft] mid section chord

Wing, CapSpar |
W : 3.832
\vec{I} : [ 3.81e-07  2.04e-07  8.33e-08  1.81e-08 ] [lbft] spar weight
\vec{S}_y} : [ 4.49e-06  2.77e-06  1.34e-06  3.54e-07 ] [m**4] spar x moment of inertia
\vec{dm} : [ 0.388      0.275      0.156      0.0498 ] [kg] section modulus
\vec{h}_{in}} : [ 3.3      2.86      2.43      2.01 ] [in] segment spar mass
\vec{t} : [ 0.0381     0.0312     0.0209     0.00816 ] [in] inner spar height
\vec{w} : [ 4.4      3.82      3.23      2.64 ] [in] spar cap thickness
\vec{w} : [ 4.4      3.82      3.23      2.64 ] [in] spar width

Wing, WingSkin |
W : 23.45 [lbft] wing skin weight
t : 0.012 [in] wing skin thickness

Mission, Aircraft |
W_{pay} : 10 [lbft] payload

Mission, Aircraft, Battery |
(E\mathcal{V}) : 800 [W*hr/l] volume battery energy density
\eta_{charge} : 0.98 Battery charging efficiency
\eta_{discharge} : 0.98 Battery discharging efficiency
g : 9.81 [m/s**2] gravitational constant
h_{batt} : 350 [W*hr/kg] battery energy density

Mission, Aircraft, Empennage |
m_{fac} : 1 Tail weight margin factor

Mission, Aircraft, Empennage, HorizontalTail |
V_h : 0.45 horizontal tail volume coefficient
\bar{A}_{MACA0008} : 0.0548 cross sectional area of MACA 0008
\lambda : 0.8 horizontal tail taper ratio
\lambda_h(\lambda_{h+1}) : 0.4444 horizontal tail taper ratio factor
\rho_{foam} : 1.5 Density of formular 250
\rho_{skin} : 0.049 horizontal tail skin density
\tau : 0.08 horizontal tail thickness ratio
g : 9.81 [m/s**2] Gravitational acceleration
m_h : 5.514 horizontal tail span effectiveness
m_{fac} : 1.1 horizontal tail margin factor

Mission, Aircraft, Empennage, TailBoom |
(1-k/2) : 0.6 (1-k/2)

```

Constants  
-----

```

E : 1.5e+11
\rho_{CFRP} : 1.6
g : 9.81
k : 0.8
m_{fac} : 1
t_{min} : 0.25

Mission, Aircraft, Empennage, VerticalTail |
  C_{L_{fmax}} : 1.1
  V_v : 0.04
  \bar{N}_{MACA0008} : 0.0548
  \lambda : 0.7
  \lambda_v / (\lambda_{delta_v+1}) : 0.4118
  \rho_{foam} : 1.5
  \rho_{skin} : 0.049
  \tau : 0.08
  g : 9.81
  m_{fac} : 1.1

Mission, Aircraft, Engine |
  B_{PM} : 4141
  g : 9.81

Mission, Aircraft, SolarCells |
  \eta : 0.22
  \rho_{solar} : 0.27
  g : 9.81

Mission, AircraftLoading, HorizontalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
  V_{NE} : 40
  \rho_{sl} : 1.225

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
  \tau_{CFRP} : 210

Mission, AircraftLoading, WingLoading, ChordSparL |
  N_{fmax} : 5
  \kappa : 0.2

```

```

[N/m**2] young's modulus carbon fiber
[g/cm**3] density of CFRP
[m/s**2] Gravitational acceleration
tail boom inertia value
tail boom margin factor
[mm] minimum tail boom thickness

maximum CL of vertical tail
vertical tail volume coefficient
cross sectional area of MACA 0008
vertical tail taper ratio
vertical tail taper ratio factor
[lbf/ft**3] Density of formular 250
[g/cm**2] vertical tail skin density
vertical tail thickness ratio
[m/s**2] Gravitational acceleration
vertical tail margin factor

[M/kg] power mass ratio
[m/s**2] gravitational constant

Solar cell efficiency
[kg/m**2] solar cell area density
[m/s**2] gravitational constant

max tail boom deflection angle

[m/s] never exceed vehicle speed
[kg/m**3] air density at sea level

max tail boom deflection angle

[Mpa] torsional stress limit

max loading
max tip deflection ratio

```



$\backslash\sigma_{\text{CFRP}}$ : 4.7e+08	[Pa]	CFRP max stress			
$\backslash\text{vec}\{\bar{g}\}$ : [ 1.33	1.17	1	0.833	...	normalized loading
Mission, AircraftLoading, WingLoading, ChordSparL, Beam					
$\backslash\text{bar}\{M\}_{\text{tip}}$ : 1e-10		Tip moment			
$\backslash\text{bar}\{S\}_{\text{tip}}$ : 1e-10		Tip loading			
$\backslash\text{bar}\{\delta\}_{\text{root}}$ : 1e-10		Base deflection			
$\backslash\theta_{\text{root}}$ : 1e-10		Base angle			
Mission, AircraftLoading, WingLoading, GustL					
$N_{\text{max}}$ : 2		max loading			
$V_{\text{gust}}$ : 10	[m/s]	gust velocity			
$\kappa$ : 0.2		max tip deflection ratio			
$\backslash\sigma_{\text{CFRP}}$ : 5.7e+08	[Pa]	CFRP max stress			
$\backslash\text{vec}\{1-\cos\{\eta\}\}$ : [ 1e-10	0.0761	0.293	0.617	...	1 minus cosine factor
Mission, AircraftLoading, WingLoading, GustL, Beam					
$\backslash\text{bar}\{M\}_{\text{tip}}$ : 1e-10		Tip moment			
$\backslash\text{bar}\{S\}_{\text{tip}}$ : 1e-10		Tip loading			
$\backslash\text{bar}\{\delta\}_{\text{root}}$ : 1e-10		Base deflection			
$\backslash\theta_{\text{root}}$ : 1e-10		Base angle			
Mission, AircraftLoading, WingLoading, WingSkinL					
$C_{\text{fm}_w}$ : 0.121		negative wing moment coefficient			
$V_{\text{NE}}$ : 45	[m/s]	never exceed vehicle speed			
$\rho_{\text{sl}}$ : 1.225	[kg/m**3]	air density at sea level			
$\tau_{\text{CFRP}}$ : 570	[MPa]	torsional stress limit			
Mission, FlightSegment, AircraftPerf					
$P_{\text{acc}}$ : 0	[W]	Accessory power draw			
Mission, FlightSegment, AircraftPerf, WingAero					
$e$ : 0.9		Oswald efficiency			
Mission, FlightSegment, FlightState					
$(E/S)_{\text{irr}}$ : 5716	[W/hr/m**2]	total daytime solar energy			
$(E/S)_{\text{var}}$ : 1	[W/hr/m**2]	energy units variable			
$(P/S)_{\text{var}}$ : 1	[W/m**2]	power units variable			
$V_{\text{wind-ref}}$ : 100	[m/s]	reference wind speed			
$\mu$ : 1.42e-05	[N*s/m**2]	viscosity			
$\rho_{\text{ref}}$ : 1	[kg/m**3]	reference air density			
$m_{\text{fac}}$ : 1		wind speed margin factor			
$P_{\text{wind}}$ : 0.9		percentile wind speeds			
$t_{\text{flight}}$ : 13.78	[hr]	flight span			

```

Mission, FlightSegment, SteadyLevelFlight |
\eta_{prop} : 0.8

Wing |
\lambda : 0.5
m_{fac} : 1.2
\vec{\bar{c}_{ave}} : [ 1.25 1.08 0.917 0.75 ]
\vec{\bar{c}} : [ 1.33 1.17 1 0.833 ... ]

Wing, CapSpar |
E : 2e+07
\rho_{CFRP} : 1.6
g : 9.81
w_{lim} : 0.15

Wing, WingSkin |
\bar{J}/t : 0.0114
\rho_{CFRP} : 1.6
g : 9.81
t_{min} : 0.012

Wing, WingSkin |
g : 2.065
\rho_{CFRP} : 2.065
t_{min} : 2.065

Wing, CapSpar |
\rho_{CFRP} : 0.3375
g : 0.3375
w_{lim} : -0.0109

Wing |
m_{fac} : 2.403
\vec{\bar{c}_{ave}} : [ -0.167 -0.118 -0.0654 -0.0201 ]

Mission, FlightSegment, SteadyLevelFlight |
\eta_{prop} : -6.582

Mission, FlightSegment, FlightState |
t_{flight} : 5.075
P_{wind} : 3.251

```

propulsive efficiency

wing taper ratio  
wing weight margin factor  
normalized mid section chord  
normalized chord at mid element

[psi] Youngs modulus of CFRP  
[g/cm\*\*3] density of CFRP  
[m/s\*\*2] gravitational acceleration  
spar width to chord ratio

[1/mm] torsional moment of inertia  
[g/cm\*\*3] density of CFRP  
[m/s\*\*2] gravitational acceleration  
[in] minimum gauge wing skin thickness

gravitational acceleration  
density of CFRP  
minimum gauge wing skin thickness

density of CFRP  
gravitational acceleration  
spar width to chord ratio

wing weight margin factor  
normalized mid section chord

propulsive efficiency

Night span  
percentile wind speeds

Sensitivities  
-----

```

\mu : 2.133
V_{wind-ref} : 1.997
m_{fac} : 1.997
(E/S)_{var} : 1.259
(P/S)_{var} : -1.485
(E/S)_{irr} : -2.544
\rho_{ref} : -3.224

Mission, FlightSegment, AircraftPerf, WingAero |
e : -2.952

Mission, AircraftLoading, WingLoading, GustL |
N_{fmax} : 0.3484
V_{gust} : 0.2701
\vec{1-cos(\eta)} : [ 2.3e-12 0.00429 0.0364 0.125 ... ] 1 minus cosine factor
\sigma_{CFRP} : -0.3484

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
\tau_{CFRP} : -0.1841

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
\theta_{fmax} : -0.6838

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
V_{NE} : 1.736
\rho_{sl} : 0.868

Mission, Aircraft, SolarCells |
g : 0.4668
\rho_{solar} : 0.4668
\eta : -2.771

Mission, Aircraft, Engine |
g : 0.02216
B_{PM} : -0.02216

Mission, Aircraft, Empennage, VerticalTail |
V_v : 1.995
C_{L_{fmax}} : 0.868
m_{fac} : 0.5917
\rho_{foam} : 0.389
\bar{A}_{MACA0008} : 0.389
g : 0.2028
\rho_{fskin} : 0.2028

viscosity
reference wind speed
wind speed margin factor
energy units variable
power units variable
total daytime solar energy
reference air density

Oswald efficiency

max loading
gust velocity
CFRP max stress

torsional stress limit

max tail boom deflection angle

never exceed vehicle speed
air density at sea level

gravitational constant
solar cell area density
Solar cell efficiency

gravitational constant
power mass ratio

vertical tail volume coefficient
maximum CL of vertical tail
vertical tail margin factor
Density of formular 250
cross sectional area of MACA 0008
Gravitational acceleration
vertical tail skin density

```

```

Mission, Aircraft, Empennage, TailBoom |
\tau : 0.1416
m_{fac} : 0.868
g : 0.868
\rho_{CFRP} : 0.868
(1-k/2) : 0.868
k : 0.3039
E : -0.6838

Mission, Aircraft, Empennage, HorizontalTail |
V_h : 0.3254
m_{fac} : 0.1257
\tau : 0.09961
g : 0.07604
\rho_{skin} : 0.07604
\rho_{foam} : 0.04964
\bar{A}_{MACA0008} : 0.04964
m_h : 0.04723

Mission, Aircraft, Empennage |
m_{fac} : 1.585

Mission, Aircraft, Battery |
g : 3.789
\eta_{charge} : -1.583
h_{batt} : -3.789
\eta_{discharge} : -5.075

Mission, Aircraft |
W_{pay} : 0.7556

vertical tail thickness ratio

tail boom margin factor
Gravitational acceleration
density of CFRP
(1-k/2)
tail boom inertia value
young's modulus carbon fiber

horizontal tail volume coefficient
horizontal tail margin factor
horizontal tail thickness ratio
Gravitational acceleration
horizontal tail skin density
Density of formular 250
cross sectional area of MACA 0008
horizontal tail span effectiveness

Tail weight margin factor

gravitational constant
Battery charging efficiency
battery energy density
Battery discharging efficiency

payload

```

## A.2 Case 1: Hoburg Constraint Implemented as a Geometric Program

Cost

----

59.56 [lbf]

Free Variables

-----

```
Mission, Aircraft |
  W_{cent} : 15.88
  W_{total} : 59.56
  W_{wing} : 43.67

Mission, Aircraft, Battery |
  E : 1.421e+07
  W : 24.87
  \mathcal{V} : 0.03403

Mission, Aircraft, Empennage |
  W : 5.743

Mission, Aircraft, Empennage, HorizontalTail |
  AR_h : 14.34
  C_{L_{max}} : 1.5
  S : 2.506
  W : 0.3715
  b : 5.994
  c_{r_h} : 0.4645
  c_{t_h} : 0.3716
  l_h : 10.97

Mission, Aircraft, Empennage, TailBoom |
  I_0 : 6.813e-07
  J : 5.858e-07
  S : 13.76
  W : 2.607
  d_0 : 4.79
  l : 10.97
  t_0 : 0.9633

Mission, Aircraft, Empennage, VerticalTail |
  AR_v : 3.151
  S : 10.14
  W : 2.765
  b : 5.653
  c_{r_v} : 2.11

center weight [lbf]
aircraft weight [lbf]
wing weight [lbf]

total battery energy [J]
battery weight [lbf]
battery volume [m**3]

empennage weight [lbf]

horizontal tail aspect ratio
maximum CL of horizontal tail
horizontal tail area [ft**2]
horizontal tail weight [lbf]
horizontal tail span [ft]
horizontal tail root chord [ft]
horizontal tail tip chord [ft]
horizontal tail moment arm [ft]

tail boom moment of inertia [m**4]
tail boom polar moment of inertia [m**4]
tail boom surface area [ft**2]
tail boom weight [lbf]
tail boom diameter [in]
tail boom length [ft]
tail boom thickness [mm]

vertical tail aspect ratio
total vertical tail surface area [ft**2]
one vertical tail weight [lbf]
one vertical tail span [ft]
vertical tail root chord [ft]
```

```

c_ft_v} : 1.477
l_v : 10.97

Mission, Aircraft, Engine |
P_{max} : 265.2
W : 0.1413
m : 0.06405

Mission, Aircraft, SolarCells |
S : 55.39
W : 3.064

Mission, AircraftLoading, HorizontalBoomBending |
F : 491.8
\theta : 0.06959

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
F : 1016
\theta : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
T : 1881

Mission, AircraftLoading, WingLoading, ChordSparL |
\vec{M}_r : [ 915 438 179 44.1 ]

Mission, AircraftLoading, WingLoading, ChordSparL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 2.77 1.28 0.431 0.0599 ]
\vec{\bar{M}} : [ 0.677 0.324 0.133 0.0326 ... ]
\vec{\bar{S}} : [ 1.49 0.839 0.474 0.205 ... ]
\vec{\bar{\Delta}} : [ 0.000376 0.0138 0.047 0.101 ... ]
\vec{\theta} : [ 0.000456 0.0548 0.117 0.199 ... ]

Mission, AircraftLoading, WingLoading, GustL |
\vec{M}_r : [ 1.25e+03 777 376 99.9 ]
\vec{\alpha}_{gust} : [ 7.85e-11 0.0274 0.1 0.205 ... ]
\vec{\bar{q}} : [ 1.33 2.02 3.66 5.38 ... ]

Mission, AircraftLoading, WingLoading, GustL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 7.47 3.82 1.45 0.245 ]
\vec{\bar{M}} : [ 2.32 1.44 0.696 0.185 ... ]
\vec{\bar{S}} : [ 3.74 3.32 2.61 1.48 ... ]

```

```

\vec{\bar{\delta}} : [ 0.000209 0.0139 0.049 0.107 ... ] normalized displacement
\vec{\theta} : [ 0.000403 0.0704 0.152 0.249 ... ] deflection slope

Mission, FlightSegment, AircraftPerf |
  CDA : 0.004737
  C_D : 0.02456
  P_{oper} : 265.2
  P_{shaft} : 0.3557

Mission, FlightSegment, AircraftPerf, TailAero |
  C_d : 0.02361
  C_d : 0.01009
  Re : 3.61e+04
  Re : 1.549e+05

Mission, FlightSegment, AircraftPerf, TailBoomAero |
  C_f : 0.00733
  Re : 9.472e+05

Mission, FlightSegment, AircraftPerf, WingAero |
  C_L : 0.886
  C_d : 0.01982
  Re : 9.523e+04
  c_{dp} : 0.01372

Mission, FlightSegment, FlightState |
  (E/S)_C : 193.2
  (E/S)_{day} : 2159
  (P/S)_{min} : 234.3
  V : 28.89
  V_{wind} : 28.89
  \rho : 0.1392

Mission, FlightSegment, SteadyLevelFlight |
  T : 7.344

Wing |
  AR : 45.53
  S : 55.39
  W : 15.74
  \tau : 0.2714
  b : 50.21
  c_{f{MAC}} : 1.103
  c_{froot} : 1.471

non-wing drag coefficient
aircraft drag coefficient
operating power
shaft power

horizontal tail drag coefficient
vertical tail drag coefficient
horizontal tail reynolds number
vertical tail reynolds number

fuselage skin friction coefficient
fuselage reynolds number

lift coefficient
wing drag coefficient
Reynold's number
wing profile drag coeff

[M/hr/m**2] energy for batteries during sunrise/set
[M/hr/m**2] solar cells energy during daytime
[M/m**2] minimum necessary solar power
[m/s] true airspeed
[m/s] wind velocity
[kg/m**3] air density

[M] thrust

aspect ratio
surface area
weight
airfoil thickness ratio
wing span
mean aerodynamic chord
root chord

```



```

\vec{c_{ave}} : [ 1.38      1.19      1.01      0.827 ] [ft] mid section chord

Wing, CapSpar |
W : 1.193
\vec{I} : [ 2.5e-07      1.34e-07      5.5e-08      1.2e-08 ] [lbft] spar weight
\vec{S_y} : [ 2.2e-06      1.36e-06      6.6e-07      1.75e-07 ] [m**4] spar x moment of inertia
\vec{dm} : [ 0.12      0.0857      0.0489      0.0158 ] [kg] section modulus
\vec{h_{in}} : [ 4.44      3.85      3.27      2.68 ] [in] segment spar mass
\vec{t} : [ 0.0245      0.0202      0.0136      0.00537 ] [in] inner spar height
\vec{w} : [ 2.48      2.15      1.82      1.49 ] [in] spar cap thickness
\vec{w} : [ 2.48      2.15      1.82      1.49 ] [in] spar width

Wing, WingSkin |
W : 11.93 [lbft] wing skin weight
t : 0.012 [in] wing skin thickness

Mission, Aircraft |
W_{pay} : 10 [lbft] payload

Mission, Aircraft, Battery |
(E\mathcal{V}) : 800 [W*hr/l] volume battery energy density
\eta_{charge} : 0.98 Battery charging efficiency
\eta_{discharge} : 0.98 Battery discharging efficiency
g : 9.81 [m/s**2] gravitational constant
h_{batt} : 350 [W*hr/kg] battery energy density

Mission, Aircraft, Empennage |
m_{fac} : 1 Tail weight margin factor

Mission, Aircraft, Empennage, HorizontalTail |
V_h : 0.45 horizontal tail volume coefficient
\bar{A}_{MACA0008} : 0.0548 cross sectional area of MACA 0008
\lambda : 0.8 horizontal tail taper ratio
\lambda_h(\lambda_{h+1}) : 0.4444 horizontal tail taper ratio factor
\rho_{foam} : 1.5 Density of formular 250
\rho_{skin} : 0.049 horizontal tail skin density
\tau : 0.08 horizontal tail thickness ratio
g : 9.81 [m/s**2] Gravitational acceleration
m_h : 5.514 horizontal tail span effectiveness
m_{fac} : 1.1 horizontal tail margin factor

Mission, Aircraft, Empennage, TailBoom |
(1-k/2) : 0.6

```

Constants  
-----

```

E : 1.5e+11
\rho_{CFRP} : 1.6
g : 9.81
k : 0.8
m_{fac} : 1
t_{min} : 0.25

Mission, Aircraft, Empennage, VerticalTail |
  C_{L_{fmax}} : 1.1
  V_v : 0.04
  \bar{N}_{MACA0008} : 0.0548
  \lambda : 0.7
  \lambda_v / (\lambda v + 1) : 0.4118
  \rho_{foam} : 1.5
  \rho_{skin} : 0.049
  \tau : 0.08
  g : 9.81
  m_{fac} : 1.1

Mission, Aircraft, Engine |
  B_{PM} : 4141
  g : 9.81

Mission, Aircraft, SolarCells |
  \eta : 0.22
  \rho_{solar} : 0.27
  g : 9.81

Mission, AircraftLoading, HorizontalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
  V_{NE} : 40
  \rho_{sl} : 1.225

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
  \tau_{CFRP} : 210

Mission, AircraftLoading, WingLoading, ChordSparL |
  N_{fmax} : 5
  \kappa : 0.2

```

```

[N/m**2] young's modulus carbon fiber
[g/cm**3] density of CFRP
[m/s**2] Gravitational acceleration
tail boom inertia value
tail boom margin factor
[mm] minimum tail boom thickness

maximum CL of vertical tail
vertical tail volume coefficient
cross sectional area of MACA 0008
vertical tail taper ratio
vertical tail taper ratio factor
[lbf/ft**3] Density of formular 250
[g/cm**2] vertical tail skin density
vertical tail thickness ratio
[m/s**2] Gravitational acceleration
vertical tail margin factor

[M/kg] power mass ratio
[m/s**2] gravitational constant

Solar cell efficiency
[kg/m**2] solar cell area density
[m/s**2] gravitational constant

max tail boom deflection angle

[m/s] never exceed vehicle speed
[kg/m**3] air density at sea level

max tail boom deflection angle

[Mpa] torsional stress limit

max loading
max tip deflection ratio

```

```

\sigma_{CFRP} : 4.7e+08
\vec{\bar{g}} : [ 1.33      1.17      1      0.833      ... ]
[Pa]
CFRP max stress
normalized loading

Mission, AircraftLoading, WingLoading, ChordSparL, Beam |
\bar{M}_{tip} : 1e-10
\bar{S}_{tip} : 1e-10
\bar{\delta}_{root} : 1e-10
\theta_{root} : 1e-10
Tip moment
Tip loading
Base deflection
Base angle

Mission, AircraftLoading, WingLoading, GustL |
N_{max} : 2
V_{gust} : 10
\kappa : 0.2
\sigma_{CFRP} : 5.7e+08
\vec{1-\cos(\eta)} : [ 1e-10      0.0761      0.293      0.617      ... ]
[Pa]
max loading
gust velocity
max tip deflection ratio
CFRP max stress
1 minus cosine factor

Mission, AircraftLoading, WingLoading, GustL, Beam |
\bar{M}_{tip} : 1e-10
\bar{S}_{tip} : 1e-10
\bar{\delta}_{root} : 1e-10
\theta_{root} : 1e-10
Tip moment
Tip loading
Base deflection
Base angle

Mission, AircraftLoading, WingLoading, WingSkinL |
C_{fm_w} : 0.121
V_{NE} : 45
\rho_{sl} : 1.225
\tau_{CFRP} : 570
negative wing moment coefficient
never exceed vehicle speed
air density at sea level
torsional stress limit

Mission, FlightSegment, AircraftPerf |
P_{facc} : 0
[W]
Accessory power draw

Mission, FlightSegment, AircraftPerf, WingAero |
e : 0.9
Oswald efficiency

Mission, FlightSegment, FlightState |
(E/S)_{irr} : 5716
(E/S)_{var} : 1
(P/S)_{var} : 1
V_{wind-ref} : 100
\mu : 1.42e-05
\rho_{ref} : 1
m_{fac} : 1
P_{wind} : 0.9
t_{flight} : 13.78
[Whr/m**2] total daytime solar energy
[Whr/m**2] energy units variable
[W/m**2] power units variable
[m/s] reference wind speed
[N*s/m**2] viscosity
[kg/m**3] reference air density
wind speed margin factor
percentile wind speeds
[hr] Night span

```

```

Mission, FlightSegment, SteadyLevelFlight |
  \eta_{prop} : 0.8

  Wing |
    \lambda : 0.5
    m_{fac} : 1.2
    \vec{\bar{c}}_{ave} : [ 1.25 0.917 0.75 ]
    \vec{\bar{c}} : [ 1.33 1.17 1 0.833 ... ]

  Wing, CapSpar |
    E : 2e+07
    \rho_{CFRP} : 1.6
    g : 9.81
    w_{lim} : 0.15

  Wing, WingSkin |
    \bar{j}/t : 0.0114
    \rho_{CFRP} : 1.6
    g : 9.81
    t_{min} : 0.012

  Wing, WingSkin |
    g : 1.23
    \rho_{CFRP} : 1.23
    t_{min} : 1.23

  Wing, CapSpar |
    \rho_{CFRP} : 0.123
    g : 0.123

  Wing |
    m_{fac} : 1.353
    \vec{\bar{c}}_{ave} : [ -0.0574 -0.0409 -0.0231 -0.00731 ]

Mission, FlightSegment, SteadyLevelFlight |
  \eta_{prop} : -3.27

Mission, FlightSegment, FlightState |
  t_{flight} : 2.604
  P_{wind} : 1.407
  V_{wind-ref} : 0.9244

```

Sensitivities  
-----

```

m_{fac} : 0.9244
\nu : 0.7567
(E/S)_{var} : 0.5285
(P/S)_{var} : -0.6542
(E/S)_{irr} : -0.9949
\rho_{ref} : -1.501

Mission, FlightSegment, AircraftPerf, WingArea |
e : -0.8121

Mission, AircraftLoading, WingLoading, GustL |
N_{max} : 0.1249
V_{gust} : 0.09957
\vec{1-\cos(\eta)} : [ 9.95e-13 0.00158 0.0134 0.0462 ... ] 1 minus cosine factor
\sigma_{CFRP} : -0.1249

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
\theta_{max} : -0.2275

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
V_{NE} : 0.455
\rho_{sl} : 0.2275

Mission, Aircraft, SolarCells |
g : 0.2633
\rho_{solar} : 0.2633
\eta : -1.121

Mission, Aircraft, Engine |
g : 0.01233
B_{PM} : -0.01233

Mission, Aircraft, Empennage, VerticalTail |
V_v : 0.7149
m_{fac} : 0.2413
C_{L_{max}} : 0.2275
\rho_{foam} : 0.1436
\bar{A}_{MAC0008} : 0.1436
\tau : 0.09925
g : 0.09775
\rho_{skin} : 0.09775

Mission, Aircraft, Empennage, TailBoom |
m_{fac} : 0.2275

wind speed margin factor
viscosity
energy units variable
power units variable
total daytime solar energy
reference air density

Oswald efficiency

max loading
gust velocity
CFRP max stress

max tail boom deflection angle

never exceed vehicle speed
air density at sea level

gravitational constant
solar cell area density
Solar cell efficiency

gravitational constant
power mass ratio

vertical tail volume coefficient
vertical tail margin factor
maximum CL of vertical tail
Density of formular 250
cross sectional area of MACA 0008
vertical tail thickness ratio
Gravitational acceleration
vertical tail skin density

tail boom margin factor

```

```

g : 0.2275
\rho_{CFRP} : 0.2275
(1-k/2) : 0.2275
k : 0.1011
E : -0.2275

Mission, Aircraft, Empennage, HorizontalTail |
  V_h : 0.1373
  \tau : 0.05737
  m_h : 0.03736
  m_{fac} : 0.03242
  g : 0.02416
  \rho_{skin} : 0.02416

Mission, Aircraft, Empennage |
  m_{fac} : 0.5013

Mission, Aircraft, Battery |
  g : 2.137
  \eta_{charge} : -0.6192
  h_{batt} : -2.137
  \eta_{discharge} : -2.604

Mission, Aircraft |
  W_{pay} : 0.8729

Gravitational acceleration
density of CFRP
(1-k/2)
tail boom inertia value
young's modulus carbon fiber

horizontal tail volume coefficient
horizontal tail thickness ratio
horizontal tail span effectiveness
horizontal tail margin factor
Gravitational acceleration
horizontal tail skin density

Tail weight margin factor

gravitational constant
Battery charging efficiency
battery energy density
Battery discharging efficiency

payload

```

### A.3 Case 2: Hoburg Constraint Implemented as a Sequential Geometric Program

Cost

----

59.56 [lbf]

Free Variables

-----

```
Mission, Aircraft |
  W_{cent} : 15.85
  W_{total} : 59.56
  W_{wing}  : 43.71

Mission, Aircraft, Battery |
  E : 1.423e+07
  W : 24.9
  \mathcal{V} : 0.03411

Mission, Aircraft, Empennage |
  W : 5.711

Mission, Aircraft, Empennage, HorizontalTail |
  AR_h : 14.34
  C_{L_{max}} : 1.5
  S : 2.525
  W : 0.3747
  b : 6.017
  c_{r_h} : 0.4663
  c_{t_h} : 0.373
  l_h : 10.98

Mission, Aircraft, Empennage, TailBoom |
  I_0 : 6.791e-07
  J : 5.857e-07
  S : 13.79
  W : 2.591
  d_0 : 4.799
  l : 10.98
  t_0 : 0.9549

Mission, Aircraft, Empennage, VerticalTail |
  AR_v : 3.157
  S : 10.09
  W : 2.746
  b : 5.645
  c_{r_v} : 2.103

center weight [lbf]
aircraft weight [lbf]
wing weight [lbf]

total battery energy [J]
battery weight [lbf]
battery volume [m**3]

empennage weight [lbf]

horizontal tail aspect ratio
maximum CL of horizontal tail
horizontal tail area [ft**2]
horizontal tail weight [lbf]
horizontal tail span [ft]
horizontal tail root chord [ft]
horizontal tail tip chord [ft]
horizontal tail moment arm [ft]

tail boom moment of inertia [m**4]
tail boom polar moment of inertia [m**4]
tail boom surface area [ft**2]
tail boom weight [lbf]
tail boom diameter [in]
tail boom length [ft]
tail boom thickness [mm]

vertical tail aspect ratio
total vertical tail surface area [ft**2]
one vertical tail weight [lbf]
one vertical tail span [ft]
vertical tail root chord [ft]
```



```

c_ft_v} : 1.472
l_v : 10.98

Mission, Aircraft, Engine |
P_{max} : 265.6
W : 0.1415
m : 0.06414

Mission, Aircraft, SolarCells |
S : 55.47
W : 3.068

Mission, AircraftLoading, HorizontalBoomBending |
F : 493.5
\theta : 0.06988

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
F : 1011
\theta : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
T : 1873

Mission, AircraftLoading, WingLoading, ChordSparL |
\vec{M_r} : [ 903 429 175 43 ]

Mission, AircraftLoading, WingLoading, ChordSparL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 2.79 1.28 0.416 0.0552 ]
\vec{\bar{M}} : [ 0.673 0.32 0.131 0.0321 ... ]
\vec{\bar{S}} : [ 1.52 0.835 0.471 0.204 ... ]
\vec{\bar{\Delta}} : [ 0.000233 0.014 0.0468 0.1 ... ]
\vec{\theta} : [ 0.000458 0.054 0.115 0.197 ... ]

Mission, AircraftLoading, WingLoading, GustL |
\vec{M_r} : [ 1.24e+03 771 374 99.2 ]
\vec{\alpha_{gust}} : [ 7.87e-11 0.0274 0.1 0.206 ... ]
\vec{\bar{q}} : [ 1.33 2.02 3.66 5.38 ... ]

Mission, AircraftLoading, WingLoading, GustL, Beam |
dx : 0.25
\vec{\bar{EI}} : [ 7.59 3.89 1.46 0.235 ]
\vec{\bar{M}} : [ 2.32 1.44 0.696 0.185 ... ]
\vec{\bar{S}} : [ 3.74 3.32 2.61 1.48 ... ]

```

```

\vec{\bar{\delta}} : [ 0.000228 0.014 0.0479 0.104 ... ] normalized displacement
\vec{\theta} : [ 0.000359 0.0687 0.148 0.242 ... ] deflection slope

Mission, FlightSegment, AircraftPerf |
  CDA : 0.004741 non-wing drag coefficient
  C_D : 0.02472 aircraft drag coefficient
  P_{oper} : 265.6 [W] operating power
  P_{shaft} : 0.3562 [hp] shaft power

Mission, FlightSegment, AircraftPerf, TailAero |
  C_d : 0.0236 horizontal tail drag coefficient
  C_d : 0.01013 vertical tail drag coefficient
  Re : 3.613e+04 horizontal tail reynolds number
  Re : 1.539e+05 vertical tail reynolds number

Mission, FlightSegment, AircraftPerf, TailBoomAero |
  C_f : 0.007334 fuselage skin friction coefficient
  Re : 9.452e+05 fuselage reynolds number

Mission, FlightSegment, AircraftPerf, WingAero |
  C_L : 0.8889 lift coefficient
  C_d : 0.01988 wing drag coefficient
  Re : 9.562e+04 Reynold's number
  c_{dp} : 0.01376 wing profile drag coeff

Mission, FlightSegment, FlightState |
  (E/S)_C : 193.2 [W/hr/m**2] energy for batteries during sunrise/set
  (E/S)_{day} : 2159 [W/hr/m**2] solar cells energy during daytime
  (P/S)_{min} : 234.3 [W/m**2] minimum necessary solar power
  V : 28.84 [m/s] true airspeed
  V_{wind} : 28.84 [m/s] wind velocity
  \rho : 0.1391 [kg/m**3] air density

Mission, FlightSegment, SteadyLevelFlight |
  T : 7.367 [N] thrust

Wing |
  AR : 44.96 aspect ratio
  S : 55.47 [ft**2] surface area
  W : 15.73 [lbf] weight
  \tau : 0.27 airfoil thickness ratio
  b : 49.94 [ft] wing span
  c_{MAC} : 1.111 [ft] mean aerodynamic chord
  c_{root} : 1.481 [ft] root chord

```

```

\vec{c_{ave}} : [ 1.39      1.2      1.02      0.833      ] [ft] mid section chord

Wing, CapSpar |
W : 1.176
\vec{I} : [ 2.48e-07  1.33e-07  5.47e-08  1.19e-08 ] [lbft] spar weight
\vec{S_y} : [ 2.18e-06  1.35e-06  6.55e-07  1.74e-07 ] [m**4] spar x moment of inertia
\vec{dm} : [ 0.118      0.0845     0.0482     0.0156 ] [kg] section modulus
\vec{h_{in}} : [ 4.45      3.86      3.27      2.69 ] [in] segment spar mass
\vec{t} : [ 0.0241     0.0199     0.0134     0.00528 ] [in] inner spar height
\vec{w} : [ 2.5      2.17      1.83      1.5 ] [in] spar cap thickness
\vec{w} : [ 2.5      2.17      1.83      1.5 ] [in] spar width

Wing, WingSkin |
W : 11.94
t : 0.012

Mission, Aircraft |
W_{pay} : 10 [lbft] payload

Mission, Aircraft, Battery |
(E\mathcal{V}) : 800 [W*hr/l] volume battery energy density
\eta_{charge} : 0.98 Battery charging efficiency
\eta_{discharge} : 0.98 Battery discharging efficiency
g : 9.81 [m/s**2] gravitational constant
h_{batt} : 350 [W*hr/kg] battery energy density

Mission, Aircraft, Empennage |
m_{fac} : 1 Tail weight margin factor

Mission, Aircraft, Empennage, HorizontalTail |
V_h : 0.45 horizontal tail volume coefficient
\bar{A}_{MACA0008} : 0.0548 cross sectional area of MACA 0008
\lambda : 0.8 horizontal tail taper ratio
\lambda_h(\lambda_{h+1}) : 0.4444 horizontal tail taper ratio factor
\rho_{foam} : 1.5 Density of formular 250
\rho_{skin} : 0.049 horizontal tail skin density
\tau : 0.08 horizontal tail thickness ratio
g : 9.81 [m/s**2] Gravitational acceleration
m_h : 5.514 horizontal tail span effectiveness
m_{fac} : 1.1 horizontal tail margin factor

Mission, Aircraft, Empennage, TailBoom |
(1-k/2) : 0.6

```

Constants  
-----

```

E : 1.5e+11
\rho_{CFRP} : 1.6
g : 9.81
k : 0.8
m_{fac} : 1
t_{min} : 0.25

Mission, Aircraft, Empennage, VerticalTail |
  C_{L_{fmax}} : 1.1
  V_v : 0.04
  \bar{N}_{MACA0008} : 0.0548
  \lambda : 0.7
  \lambda_v / (\lambda_{delta_v+1}) : 0.4118
  \rho_{foam} : 1.5
  \rho_{skin} : 0.049
  \tau : 0.08
  g : 9.81
  m_{fac} : 1.1

Mission, Aircraft, Engine |
  B_{PM} : 4141
  g : 9.81

Mission, Aircraft, SolarCells |
  \eta : 0.22
  \rho_{solar} : 0.27
  g : 9.81

Mission, AircraftLoading, HorizontalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
  V_{NE} : 40
  \rho_{sl} : 1.225

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
  \theta_{max} : 0.1

Mission, AircraftLoading, EmpennageLoading, VerticalBoomTorsion |
  \tau_{CFRP} : 210

Mission, AircraftLoading, WingLoading, ChordSparL |
  N_{fmax} : 5
  \kappa : 0.2

```

```

[N/m**2] young's modulus carbon fiber
[g/cm**3] density of CFRP
[m/s**2] Gravitational acceleration
tail boom inertia value
tail boom margin factor
[mm] minimum tail boom thickness

maximum CL of vertical tail
vertical tail volume coefficient
cross sectional area of MACA 0008
vertical tail taper ratio
vertical tail taper ratio factor
[lbf/ft**3] Density of formular 250
[g/cm**2] vertical tail skin density
vertical tail thickness ratio
[m/s**2] Gravitational acceleration
vertical tail margin factor

[M/kg] power mass ratio
[m/s**2] gravitational constant

Solar cell efficiency
[kg/m**2] solar cell area density
[m/s**2] gravitational constant

max tail boom deflection angle

[m/s] never exceed vehicle speed
[kg/m**3] air density at sea level

max tail boom deflection angle

[Mpa] torsional stress limit

max loading
max tip deflection ratio

```

```

\sigma_{CFRP} : 4.7e+08
\vec{\bar{g}} : [ 1.33      1.17      1      0.833      ... ]
[Pa]
CFRP max stress
normalized loading

Mission, AircraftLoading, WingLoading, ChordSparL, Beam |
\bar{M}_{tip} : 1e-10
\bar{S}_{tip} : 1e-10
\bar{\delta}_{root} : 1e-10
\theta_{root} : 1e-10
Tip moment
Tip loading
Base deflection
Base angle

Mission, AircraftLoading, WingLoading, GustL |
N_{max} : 2
V_{gust} : 10
\kappa : 0.2
\sigma_{CFRP} : 5.7e+08
\vec{1-\cos(\eta)} : [ 1e-10      0.0761      0.293      0.617      ... ]
[Pa]
max loading
gust velocity
max tip deflection ratio
CFRP max stress
1 minus cosine factor

Mission, AircraftLoading, WingLoading, GustL, Beam |
\bar{M}_{tip} : 1e-10
\bar{S}_{tip} : 1e-10
\bar{\delta}_{root} : 1e-10
\theta_{root} : 1e-10
Tip moment
Tip loading
Base deflection
Base angle

Mission, AircraftLoading, WingLoading, WingSkinL |
C_{fm_w} : 0.121
V_{NE} : 45
\rho_{sl} : 1.225
\tau_{CFRP} : 570
negative wing moment coefficient
never exceed vehicle speed
air density at sea level
torsional stress limit

Mission, FlightSegment, AircraftPerf |
P_{acc} : 0
[W]
Accessory power draw

Mission, FlightSegment, AircraftPerf, WingAero |
e : 0.9
Oswald efficiency

Mission, FlightSegment, FlightState |
(E/S)_{irr} : 5716
(E/S)_{var} : 1
(P/S)_{var} : 1
V_{wind-ref} : 100
\mu : 1.42e-05
\rho_{ref} : 1
m_{fac} : 1
P_{wind} : 0.9
t_{flight} : 13.78
[Whr/m**2] total daytime solar energy
[Mhr/m**2] energy units variable
[W/m**2] power units variable
[m/s] reference wind speed
[Ns/m**2] viscosity
[kg/m**3] reference air density
wind speed margin factor
percentile wind speeds
[hr] Night span

```

```

Mission, FlightSegment, SteadyLevelFlight |
  \eta_{prop} : 0.8

  Wing |
    \lambda : 0.5
    m_{fac} : 1.2
    \vec{\bar{c}}_{ave} : [ 1.25 0.917 0.75 ]
    \vec{\bar{c}} : [ 1.33 1.17 1 0.833 ... ]

  Wing, CapSpar |
    E : 2e+07
    \rho_{CFRP} : 1.6
    g : 9.81
    w_{lim} : 0.15

  Wing, WingSkin |
    \bar{J}/t : 0.0114
    \rho_{CFRP} : 1.6
    g : 9.81
    t_{min} : 0.012

  Wing, WingSkin |
    g : 1.209
    \rho_{CFRP} : 1.209
    t_{min} : 1.209

  Wing, CapSpar |
    \rho_{CFRP} : 0.119
    g : 0.119

  Wing |
    m_{fac} : 1.328
    \vec{\bar{c}}_{ave} : [ -0.0654 -0.0395 -0.0223 -0.00707 ]

Mission, FlightSegment, SteadyLevelFlight |
  \eta_{prop} : -3.213

Mission, FlightSegment, FlightState |
  t_{night} : 2.558
  P_{wind} : 1.396
  V_{wind-ref} : 0.9161

```

propulsive efficiency

wing taper ratio  
wing weight margin factor  
normalized mid section chord  
normalized chord at mid element

[psi] Youngs modulus of CFRP  
[g/cm\*\*3] density of CFRP  
[m/s\*\*2] gravitational acceleration  
spar width to chord ratio

[1/mm] torsional moment of inertia  
[g/cm\*\*3] density of CFRP  
[m/s\*\*2] gravitational acceleration  
[in] minimum gauge wing skin thickness

Gravitational acceleration  
density of CFRP  
minimum gauge wing skin thickness

density of CFRP  
Gravitational acceleration

wing weight margin factor  
normalized mid section chord

propulsive efficiency

Night span  
percentile wind speeds  
reference wind speed

Sensitivities  
-----

```

m_{fac} : 0.9161
\nu : 0.7754
(E/S)_{var} : 0.5186
(P/S)_{var} : -0.6422
(E/S)_{irr} : -0.9757
\rho_{ref} : -1.488

Mission, FlightSegment, AircraftPerf, WingArea |
e : -0.8079

Mission, AircraftLoading, WingLoading, CustL |
N_{max} : 0.1208
V_{gust} : 0.09631
\vec{1-cos(\eta)} : [-5.33e-12 0.00152 0.0129 0.0447 ...] 1 minus cosine factor
\sigma_{CFRP} : -0.1208

Mission, AircraftLoading, EmpennageLoading, VerticalBoomBending |
\theta_{max} : -0.222

Mission, AircraftLoading, EmpennageLoading, TailBoomState |
V_{NE} : 0.444
\rho_{sl} : 0.222

Mission, Aircraft, SolarCells |
g : 0.2589
\rho_{solar} : 0.2589
\eta : -1.099

Mission, Aircraft, Engine |
g : 0.01212
B_{PM} : -0.01212

Mission, Aircraft, Empennage, VerticalTail |
V_v : 0.8968
m_{fac} : 0.2353
C_{L_{max}} : 0.222
\rho_{foam} : 0.1398
\bar{A}_{MAC0008} : 0.1398
\tau : 0.09662
g : 0.09549
\rho_{skin} : 0.09549

Mission, Aircraft, Empennage, TailBoom |
m_{fac} : 0.222

wind speed margin factor
viscosity
energy units variable
power units variable
total daytime solar energy
reference air density

Oswald efficiency

max loading
gust velocity
CFRP max stress

max tail boom deflection angle

never exceed vehicle speed
air density at sea level

gravitational constant
solar cell area density
Solar cell efficiency

gravitational constant
power mass ratio

vertical tail volume coefficient
vertical tail margin factor
maximum CL of vertical tail
Density of formular 250
cross sectional area of MACA 0008
vertical tail thickness ratio
Gravitational acceleration
vertical tail skin density

tail boom margin factor

```

```

g : 0.222
\rho_{CFRP} : 0.222
(1-k/2) : 0.222
k : 0.09866
E : -0.222

Mission, Aircraft, Empennage, HorizontalTail |
  V_h : 0.1351
  \tau : 0.05632
  m_h : 0.03663
  m_{fac} : 0.0321
  g : 0.02389
  \rho_{skin} : 0.02389

Mission, Aircraft, Empennage |
  m_{fac} : 0.4893

Mission, Aircraft, Battery |
  g : 2.101
  \eta_{charge} : -0.6072
  h_{batt} : -2.101
  \eta_{discharge} : -2.568

Mission, Aircraft |
  W_{pay} : 0.8568

Gravitational acceleration
density of CFRP
(1-k/2)
tail boom inertia value
young's modulus carbon fiber

horizontal tail volume coefficient
horizontal tail thickness ratio
horizontal tail span effectiveness
horizontal tail margin factor
Gravitational acceleration
horizontal tail skin density

Tail weight margin factor

Gravitational constant
Battery charging efficiency
battery energy density
Battery discharging efficiency

payload

```