DISSERTATION

A MULTIDISCIPLINARY APPROACH FOR DEPLOYING A WILDFIRE UAV FLEET FOR DETECTION AND COMMUNICATION

Submitted by

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ABSTRACT

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Wildfire constitutes a global crisis, with both frequency and severity increasing over the past several decades. In the United States, wildfires have emerged as a significant concern in the western regions, especially in California, Colorado, Hawaii, and along the West Coast of North America. Wildfires in Canada have produced smoke that has affected air quality as distant as New York in the United States. Australian wildfires have had severe impacts, affecting billions of animals, including koalas, kangaroos, and wallabies, in recent years. Wildfires inflict severe local damage on land and communities and present global challenges to interconnected natural ecosystems. These effects spread to natural resources and wildlife worldwide. As these threats progressively increase, early detection and communication become key in minimizing the adverse impact on wildlife, humans, and the environment.

Numerous strategies are being evaluated for detecting and communicating about wildfires, but one of the most effective emerging tools is turning out to be unmanned aerial vehicles (UAVs). Not all UAVs are suited for the purpose of wildfire detection and communication, as most UAVs are designed for universal activities like security, agriculture, power line monitoring. Traditional general-purpose UAVs are not able to detect wildfire early because their deployment strategies, wildfire susceptibility assessment strategies, and UAV aerodynamics are not optimized for that specific purpose. During the evaluation of UAVs for the purpose of wildfire detection and communication, surveillance capability is the most significant factor if the goal is to develop an effective and cost-efficient solution. To consider an entire fleet of UAVs for wildfire detection and communication, we can determine surveillance capability only by understanding the overall system in a holistic way. We accomplish this understanding by deploying a comprehensive systemic approach with

model-based systems thinking (MBST) to address this real-world complex problem. We also use both systemic and numerical techniques to come up with novel systems methods of addressing the specific challenges of wildfire.

The research results show that the most efficient possible detection of wildfires compared to any state-of-the-art available strategies occurs using UAVs designed specifically for wildfire detection, with integrated UAV flight paths and a comprehensive deployment method. Outcomes for this research study demonstrate that existing generic UAV design elements, such as flight controls, airfoil aerodynamics, sensor packages, and communication schemes, are not optimized for wildfire.

The systemic methods documented in this dissertation to address the problems of detecting and managing wildfires enabled by the optimal deployment strategies (ODS) and wildfire point-optimization strategies (WPO). This mission-oriented fleet deployment is also coupled with the most effective airfoil design, specifically developed to detect wildfires.

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DEDICATION

To my parents, Golam Ahmed and Ayesha Ahmed, for instilling the value of lifelong education. To Summer and Ariana, for their love, inspiration, and constant belief in me. To Bhiya, Marya, and all my family and friends, for their unwavering encouragement.

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Chapter 1

Introduction and Background

Addressing wildfire detection and communication requires understanding all elements of wildfire as well as their interconnections, structural framework, and emergent behaviors, including feedback mechanisms and delays [6], [26]. Additionally, our investigation must acknowledge the importance of mental models, diverse perspectives, mission goal, and the inherent difficulty of a complex issue of wildfire detection. We utilize systems thinking principles and relevant model-based systems thinking (MBST) tools to address the real-world challenges presented by wildfires [5], [9], [19], [42].

1.1 Motivation

Wildfire detection involves unique challenges such as changing wind patterns, dense smoke, dangerous heat, and potentially vast affected areas, all of which require specialized equipment and systems. These challenges also require task-specific deployment and predictive wildfire-prone locations, as well as specialized surveillance capabilities.

Currently available general-purpose UAV designs, while versatile in some ways, are not effectively suited for the challenges of wildfires [1]. They do not address the unpredictable nature of wildfires or the specialized needs of wildfire detection. Low-range, low-altitude small UAVs do not have the necessary range and are unable to navigate challenging terrain such as mountains, forests, vast farms, and vineyards. Similarly, extended-range large UAVs, designed for high-reliability commercial or military applications, are overly expensive and are not designed specifically for a wildfire application.

1.2 Wildfire Detection and Communication: UAV-Based Operational Concept

The core of the wildfire UAV fleet is a central base station (CBS) that dispatches a series of mobile base stations (MBS) and facilitates communication among them. CBS is managed by a fleet coordinator who is part of the human-centric strategy. The fleet coordinator manages the entire fleet, including all UAVs and MBS vehicles, and has access to multiple methods to dispatch MBS vehicles and deploy UAVs. Each MBS carries up to three UAVs, folded into large pieces, and ready for rapid assembly and launch. The MBS is manned by an MBS operator (the launch crew) who is available whenever human intervention is required. The MBS operators can deploy various methods as needed for UAV launch and wildfire points (WP) planning.

Given that most wildfires do not occur in areas near standard runways, our UAVs are equipped for vertical lifts utilizing the fan-in-wings (FIW) surface-less flight control (SFC) concept for launching, once the MBS delivers them as close as possible to the fire area [4], [3]. Each UAV maintains communication with its respective MBS. Figure 1.1 shows the fundamental concept of the use of specialized wildfire UAVs for wildfire detection and communication.

Individual UAVs can communicate directly with CBS as necessary for overall operations. The UAVs can also form their own mesh communications network while operating in the sky. In the event of satellite communication disturbances, the UAVs can intercommunicate using their mesh network. This provides redundancy and strengthens the overall system.

The response time to the fire departments is also a factor to be considered in this operational concept for the Wildfire UAVs enterprise system. Depending on circumstances, including the availability and location of firefighting resources, sirens may be necessary to alert nearby residents to the rapid spread of wildfires from uninhabited areas to populated areas.

In general, the core concept we utilize throughout this research study is systems thinking, specifically model-based systems thinking (MBST), for wildfire detection applications by promoting a holistic understanding of both the challenges and potential solutions. The systems thinking for the

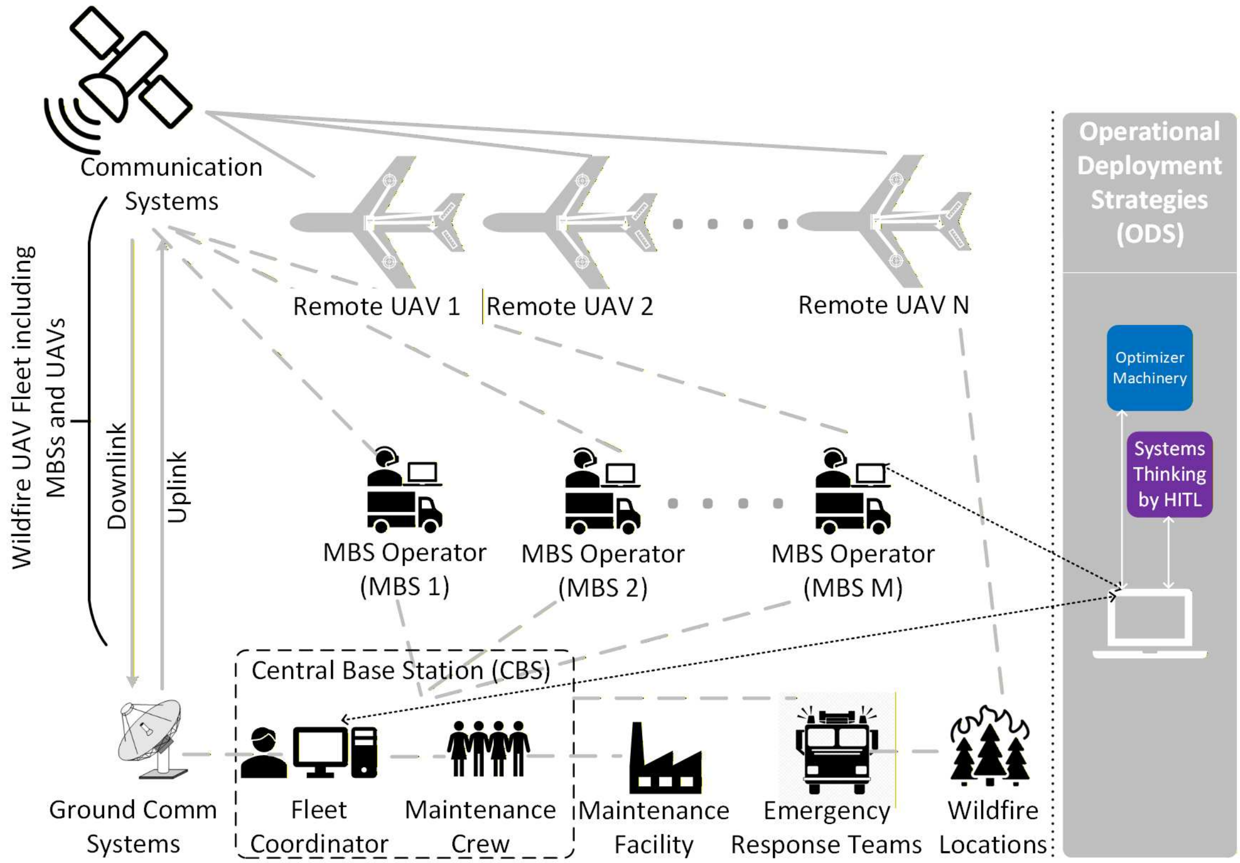


Figure 1.1: Concept of Operations (ConOps) for wildfire UAV fleet deployment

Note:

[1] Overall enterprise level architecture includes a fleet of UAVs that are designed for wildfire communication and detection, , ground communication systems or CBS, MBS vehicles, Satellite communication (SATCOM) systems.

[2] Enabling systems can be emergency response teams, wildfire locations, etc.

wildfire detection application is depicted in Figure 1.2. The integration of systems thinking and the concept of operation of the wildfire UAV fleet deployment structure, including wildfire-specific UAV design, will be more detailed in Chapter 4, and Chapter 5, while deployment aspects are addressed in Chapter 6, Chapter 7, and Chapter 8.

We utilize the model-based system architecture process (MBSAP) method in Chapter 3 to develop architectures from different perspectives for surface-less flight controls (SFC), and thus we

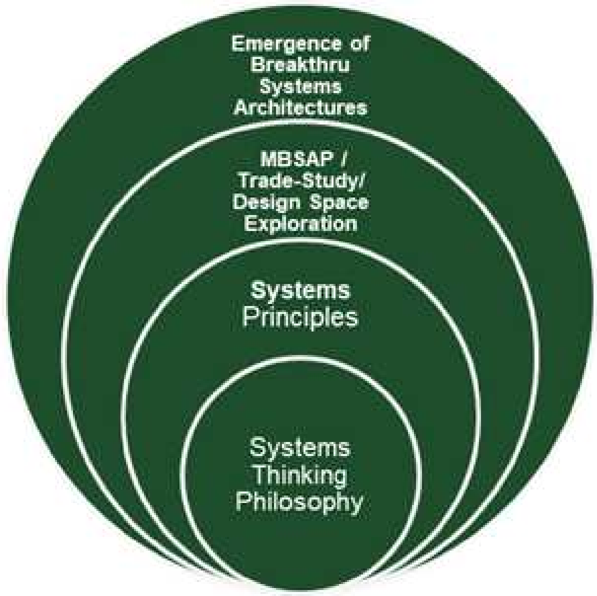


Figure 1.2: Systems Thinking for Wildfire Application

find an effective UAV design of the flight controls architecture that essentially enables effective fleet deployment [2].

1.3 Identification of Research Gaps

Several research gaps have been identified that must be addressed before developing the UAV-based solution, which is the research goal of this project.

1.3.1 Research Gap 1

Lack of Aerodynamics and Operating Parameters for Wildfire UAV Fleet deployment

Existing UAV fleet deployment strategies commonly neglect critical aerodynamic requirements for wildfire applications, especially those related to range and altitude. The majority of approaches in the literature utilize general-purpose, ultra-low-cost small UAVs. These are insufficient for the operational demands of wildfire terrain. Although several studies have introduced UAV concepts for wildfire applications, these designs are predominantly theoretical and do not effectively address the specific aerodynamic and operational barriers of wildfire environments [10], [20], [21], [22], [46], [47], [48]. Some research suggests deploying UAVs at altitudes between 50 and 200 meters, with optimal cases reaching 1000 meters. However, these altitudes are insufficient for wildfire detection in zones where mountains exceed 3000 meters. In contrast, the UAVs proposed in this project are generally 2 to 10 times larger and can fly efficiently at altitudes up to 10,000 feet (3048 meters). The maximum ceiling is approximately 15,000 feet (4572 meters). This capability supports effective operation in high mountain or high elevation environments.

The majority of current unmanned aerial vehicle (UAV) fleets are composed of short-range, low-altitude platforms that are not optimized for wildfire response. Effective wildfire detection requires UAV fleets capable of reaching altitudes up to 10,000 feet, operating at higher speeds, and accessing geographically challenging areas. However, research on high-altitude, long-range UAV fleets specifically designed for wildfire applications is limited. Additionally, deployment strategies for small, non-wildfire-specific UAVs differ significantly from those for mid-sized and large-sized UAVs due to logistical, operational, and aerodynamic-related factors. The Federal Aviation Administration (FAA) categorizes UAVs by weight and operating altitude [66]. Most existing studies have concentrated on Group 1 UAVs, which typically weigh less than 20 lb (9 kg) and operate below 1,200 feet above ground level. In contrast, Group 2 UAVs generally weigh between 21 and 55 lb (9.5 to 25 kg) and operate at altitudes below 3,500 feet [66].

Group 3 unmanned aerial vehicles (UAVs) have a maximum takeoff weight of less than 1,320 lb (approximately 600 kg). They can operate at altitudes up to 18,000 ft. Groups 4 and 5 comprise UAVs weighing more than 1,320 lb and operational at altitudes exceeding 18,000 ft. According to Crawford [6], specialized Group 3 UAVs provide an optimal mix of endurance, payload capacity, and operational altitude for wildfire detection and communication missions. Platforms operating at 10,000 to 15,000 feet can achieve substantially greater coverage, even with some performance degradation at higher altitudes. They also maintain sufficient sensor and communication features. The UAV examined in this study has a maximum takeoff mass of about 46 kg and a cruise speed of about 100 mph [173]. Its working range is approximately 100 miles. While its weight places it at the lower end of the Group 3 category, its relatively considerable operational ceiling for its weight improves its suitability for wildfire detection and emergency communication. This combination of moderate weight, extended range, high speed, and high-altitude capability makes it an efficient platform for rapid wildfire deployment, persistent surveillance, and communications support across large incident areas.

In the context of human-in-the-loop (HITL)[1] and decision support system (DSS), current optimization approaches show considerable limitations. While some studies show the feasibility of fully automated algorithmic optimization with minimal human participation, several important works, notably those by Shahroudi [7], [8], clearly incorporate HITL interaction. This distinction points to a gap between algorithm-based optimization and practical decision-making. Shahroudi develops a semi-automatic optimization system in which a human designer collaborates continuously with a numerical optimizer [7]. A subsequent study extends this system to aircraft design, arguing that the true value of design cannot be fully represented by fixed, machine-centric objective and constraint functions alone [8]. Thus, human involvement is essential to achieve the desired optimization outcomes.

Current state-of-the-art research primarily addresses generic coverage, agriculture, infrastructure, and communication networks rather than wildfire detection and suppression. When wildfire is considered, the focus is typically limited to detection or asset placement, rather than adopting a holistic perspective of the system suitable for integration into a decision support system (DSS) [10], [16], [50], [191].

Building on this perspective, Langen argues that humans and machines should be regarded as a unified socio-technical system [211]. Thus, optimization processes cannot fully exclude human participation, and the optimization engine must incorporate it into the system's loop.

The UAV design parameters are often treated as static and lack integration. Hildemann investigates data and environmental uncertainty, while Pandey addresses design uncertainty [204], [205]. The present research changes this scope by incorporating data, environmental, operational, and

[1] Human-in-the-loop (HITL), in the context of a decision support system (DSS), refers to the involvement of a human decision maker in the optimization process by modifying objective functions, constraints, and parameters within the numerical optimizer's iteration loop while the optimizer is running, thereby continuously contributing to improvements in the solution.

HITL uncertainties. Pandey utilizes Monte Carlo simulation to evaluate the expected utility under preference ambiguity. In contrast, this study applies Monte Carlo simulation to model interacting environments, operational autonomy, and human uncertainties.

1.3.2 Research Gap 2

Lack of multiple UAVs per launcher and multiple launchers per fleet

While numerous tools exist for optimizing UAV trajectories within the research community, few studies focus on fleet deployment optimization [43], [55], [59], [81], [145]. In particular, there is limited research on optimization strategies involving multiple UAVs per launcher (MBS vehicle) and multiple launchers per fleet, especially in the context of wildfire-specific UAV operations.

Achieving effective area coverage during wildfires commonly requires deploying a large number of UAVs. The deployment of multiple UAVs from a single launcher constitutes an efficient strategic method. The simultaneous use of multiple launchers facilitates a systematic approach to wildfire detection and fleet-wide coordination, encompassing both launchers (MBS vehicles) and UAVs.

Currently, no integrated system design comprehensively addresses the deployment of multiple UAVs per launcher and multiple launchers per fleet for wildfire detection. Most existing studies treat UAV design, detection, and UAV fleet deployment as separate challenges. Many consider platforms to be fixed or focus solely on deployment optimization, without co-designing UAV capabilities, payloads, and fleet architecture specifically for wildfire missions [16], [45], [46], [47], [48], [60], [62].

1.3.3 Research Gap 3

Lack of joint optimization of fleet deployment and fleet flight paths/ Wildfire Points [2].

No research has been done on the areas of joint optimization of wildfire "fleet deployment" and "fleet flight paths/Wildfire Points" optimization when it comes to wildfire application. Very limited research on joint optimization is available for applications other than wildfires. Many of

[2]The wildfire point (WP) refers to a geographic location characterized by a measurable risk of wildfire. These points may be specified using latitude and longitude coordinates, specific landmarks, or geo-location identifiers.

the standard wildfire point planning methods do not consider environmental parameters critical to the efficiency of wildfire UAVs, such as elevation, temperature, and wind gust [51], [52], [53] and [145].

In currently existing UAVs that are geared towards disaster response, flight controls are not optimized for the challenges of wildfires. Our research indicates that UAVs are generally designed for post-event responses rather than predictive deployment, detection, or communication [10], [45], [48]. Only one of the studies specifically considers the wildfire case [45]. This study addresses a research gap in wildfire detection by jointly optimizing fleet deployment and flight paths and considers the following inquiries.

1. Is it optimal to launch and retrieve a wildfire UAV from the same launch location for UAVs, or would a different retrieval location be more efficient?

2. How does fleet deployment impact Wildfire UAV wildfire points plan and WPO?

3. How can we use environmental conditions to improve optimization while minimizing the impact of unforeseen negative environmental conditions?

In order to explore the above items, in Chapter 6, we explore the implications of assigning the same launch and retrieval location for UAVs to the same MBS vehicle, as well as scenarios where the launch and retrieval locations differ. Multiple operational scenarios are developed and evaluated to investigate these configurations. Chapter 7 analyzes the effects of pre-flight wildfire points (PFWP) planning and runtime wildfire points (RTWP) planning on operational decision-making during mission execution. The influence of varying environmental conditions on UAV performance and the potential for performance-related issues are also examined. Additionally, the system dynamics model introduced in Chapter 5 demonstrates the impact of environmental parameters on overall UAV system behavior, offering further insight into these operational challenges.

Joint optimization of fleet deployment and flight paths based on pre-identified wildfire points provides a significant advantage in developing a comprehensive tool for detection and communication in UAV-based wildfire monitoring.

There is also a lack of optimization of launchers and UAV Wildfire Points (pre-identified flight paths for wildfire objectives, including risk). Several works consider an undesigned UAVs fleet (some cases a single-UAV system) or lack comprehensive fleet-level coordination, multi-objective trade-offs, and scalable task allocation across multiple UAVs in dynamic wildfire environments [45], [47], [48], [49], [61], [62].

1.3.4 Research Gap 4

Lack of joint optimization of fleet deployment and UAV design

Additional efficencies can be achieved if flight controls are specialized for wildfire applications, as we have explored [3]. The research done by Crawford offers some help by clearly identifying advantageous fuel usages that would further the objective of the UAV fleet but research is still needed to determine all the options for leveraging flight controls specifically for wildfire applications [6].

More research is needed to address these flight control issues:

1. How do we identify the Flight Control Architecture that is operationally suitable for wildfire mitigation?

2. Is it possible to modify the design of Flight Controls to reduce Lift-over-Drag (L/D) with wildfire application in mind?

There is inadequate scholarly research available for joint optimization of "fleet deployment" and "UAV design". Joint optimization of UAV fleet deployment and UAV design help support the Concepts of Operations (ConOps) for the UAV-based solution for wildfire detection and communication.

Joint design and deployment, together with human-in-the-loop (HITL) integration, are essential components of any decision support system (DSS). However, most existing approaches lack genuine joint design and deployment, and even when both are mentioned in research, they are often excluded from a comprehensive feedback loop that incorporates HITL. Many state-of-the-art methods rely on offline optimization or planning frameworks without real-time execution, HITL, or decision-support capabilities. These approaches do not address operational deployment in dynamic and uncertain wildfire scenarios [10], [16], [46], [48], [50], [60], [61], [62], [191].

1.4 Research Questions and Tasks

The research questions listed in this section define and clarify the purpose, scope, and focus of this research project. The research is supplemented by existing literature on wildfire detection and communication efforts, as well as available wildfire data. We develop a research summary chart that describes the research questions and the evidence in Figure 1.1.

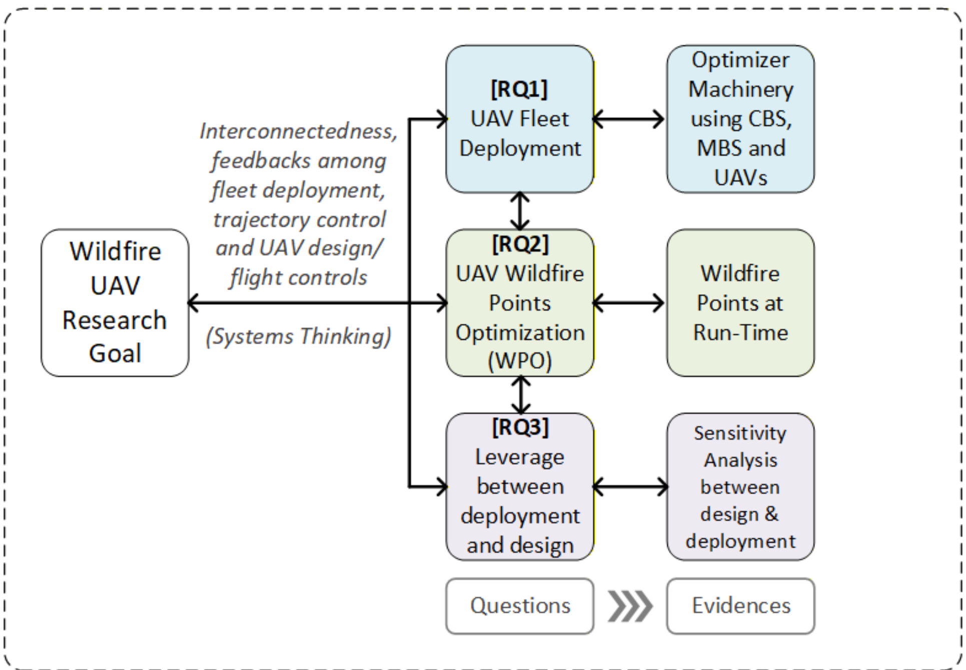


Figure 1.3: Research Summary – Research Questions and Evidence

Note:

[1] The research goal is achieved analyzing interconnectedness, feedback among fleet deployment, trajectory control and UAV design/flight controls.

1.4.1 Research Question 1: Wildfire UAV Fleet Operational Deployment Strategies (ODS)

Can a specification of the deployment problem of a UAV fleet be mathematically specified to enable deployment decision support?

An operational strategy for the deployment of a fleet of UAVs specifically designed for wildfires is critical to maximize the limited resources for detection and communication. Each mobile base station (MBS) consists of a vehicle that can carry up to three UAVs folded into three parts. Each UAV can be assembled rapidly with these three parts right before the launch from the MBS from a desired location.

Several different types of constraints come into play for this purpose, such as topological constraints, which can include mountains, forests, and access roads to the surface area. In addition, geographical constraints such as the location of MBS vehicle deployment, distance, and wildfire risks are also critical to the success of the fleet deployment. In addition, a specific set of operational constraints should be considered, including logistical and environmental constraints and constraints on UAV design.

RQ1.T1 – Assessment of deployment Strategies of UAV launches utilizing Multi-Objective Optimization (MOO) problem formulation / mathematical specification

The initial step of the deployment strategy is to understand the holistic problem of the deployment of a fleet of UAVs that are designed specifically for wildfire detection. Therefore, gathering information and identifying constraints and parameters is a critical step.

The deployment of a fleet of UAVs for wildfire detection and monitoring is a complex problem due to interdependencies, feedback loops, and other interconnected behaviors. This complexity is particularly evident in two major areas directly impacting deployment scenarios: first, managing aerodynamic/environmental parameters (i.e.,, climb time or Rate of Climb (ROC)); and second, managing the size and availability of the UAV fleet. Develop a dynamic model with variable parameters that affect the number of available UAVs, using the MBST framework.

RQ1.T2 – Development of Optimized Deployment Strategy (ODS) based on operating conditions scenario-based optimization

Operational Deployment Strategy (ODS) is a comprehensive and systematic method for deploying multiple Base Station vehicles (MBS), based on a map that includes topology, geographic conditions, operational scenarios, and communication or other constraints. The results of these tasks inform the selection of the merit functions, parameters, and operational constraints necessary to develop or integrate appropriate solutions for UAV deployment.

- The deployment strategy includes assessing fire risk, analyzing the map, and identifying access roads for vehicles (MBS) from the central base station (CBS).
- The deployment strategy also accounts for MBS operational constraints, such as MBS operator availability, shift duration, and technical expertise. In addition, MBS's fuel consumption needs to be considered. In the event of an MBS vehicle failure, an alternative measure should be taken. MBS needs to identify a location where SATCOM links can be established with CBS, as well as UAVs pre-planned flight paths.
- The deployment strategy also accounts for communication and other operational constraints, including validation and pre-check of decision support prior to launching the UAVs. This strategy also includes when and where to launch each UAVs and when and where to retrieve the UAVs. Retrieval locations are not necessarily the same as launch locations.

Operational Deployment Strategy (ODS) is a comprehensive, systemic approach, and a robust way to deploy a set of mobile base station (MBS) vehicles, given a map with topology, geographic conditions, operational scenarios, environmental constraints, and other constraints.

1.4.2 Research Question 2: UAV Wildfire Points Optimization (WPO)

Can the operational configuration and design decisions *adapt* to situational variations, field events, mission changes at run-time?

Methods for planning Wildfire Points can guide unmanned aerial vehicles (UAVs) in mapping and characterizing the likelihood of wildfire hazard. This study examines the integration of deployment strategies with Wildfire Points planning strategies. Unexpected events, including severe weather, road blockages, updated statuses of known fires, and variations in fire travel speeds, may impact the overall fleet deployment strategy.

Two wildfire points planning stages are considered based on run-time situations for the deployment of wildfire UAVs:

1. The preflight wildfire points (PFWP) plan

2. The run-time wildfire points (RTWP) plan

RQ2.T1 – Initial Wildfire Point Identification for Individual UAVs in Deployment Scenarios

This wildfire point-planning strategy enables each unmanned aerial vehicle (UAV) to identify, locate, and communicate about wildfire events. Identifying several critical deployment scenarios should include initial constraints, a merit figure, and a probability map. These elements enable simultaneous optimization of the control and operational parameters for each UAV. UAVs use satellite communication (SATCOM) for command, control, and communications (C3). For future work, it is proposed that, in the event of communication failure, unmanned aerial vehicles (UAVs) should rely on a mesh network. If the mesh network is not available, the UAV must maintain satellite coverage. Several trajectory variations are evaluated to determine their effectiveness under varying operational conditions [215].

RQ2.T2 – Changes/Compare Pre-Flight Wildfire Points (PFWP) plan vs Run-Time Wildfire Points (RTWP) plan

There is a set of pre-flight wildfire points (PFWP) plan strategies in place, but some decisions can be made based on real-time data. RFWP considers the following adaptivity based on MBS deployment and pre-flight.

- Pre-flight route plan based on wind direction, headwind/tailwind
- Pre-flight route based on return location of the MBS vehicle (same launch location or another location)
- Pre-flight flight route based on altitude, temperature, and other environmental conditions.

RTWP considers if there is confirmation of a wildfire or a very highly susceptible or probable wildfire observation, UAV can gather data without compromising UAV safety and a safe return plan (fuel usage).

- Adaptability to confirmation of wildfire, very highly susceptible or likely detection of wildfires.
- Adaptability to maintain UAV safety and safe return plan (fuel usage).
- Adaptability to minimize resources in the case of an area already covered recently.

1.4.3 Research Question 3: Robust Deployment and UAV Architecture/Design

Can we identify the best point of leverage on deployment strategy outcomes at run-time?

We consider optimization strategies and incorporate them into the flight control architecture (surfaceless flight controls) and the UAV's design parameters. Finding the highest leverage on wildfire detection from a holistic systemic perspective helps with practical implementation and sets the direction for future research.

Table 1.1: Organization of the chapters in this dissertation

Research Questions and Major Claims	Chapters	Chapter Type	Comments/Notes
RQ 1: Wildfire UAV Fleet Operational Deployment Strategies (ODS)	Chapter 6	**RQ Response Chapter:** Optimization Model	
RQ 2: Wildfire UAV Run-Time Wildfire Points Optimization (WPO)	Chapter 7	**RQ Response Chapter:** Optimization Model	
RQ 3: Sensitivities of UAV design and UAV fleet Deployment integrating (HITL)	Chapter 8	**RQ Response Chapter:** Optimization Model	
Supporting theories and work for wildfire UAV design and UAV fleet deployment	Chapter 1	Introduction & Background	
	Chapter 2	**Supporting Chapter:** Systems Thinking applied to Wildfire UAV fleet deployment and UAV design	Co-authored book on Systems Thinking and MBST
	Chapter 3	**Supporting Chapter:** MBSE	Published paper at INCOSE
	Chapter 4	**Supporting Chapter:** CFD	Published paper at AIAA
	Chapter 5	**Supporting Chapter:** Systems Dynamics	
	Chapter 9	**Future Work and Reflection Chapter:** Future work, Nature Inspired Algorithms and Design	
	Chapter 10	Conclusions and Research Contributions	

RQ3.T1 – Architect UAV Flight Controls and Aerodynamic concepts

We are looking for a flight control strategy that leverages the most efficient flight control mechanism to increase range. Surface-less flight controls (SFC) can potentially save energy sources and optimize flight dynamics. We utilize MBSE to architect flight controls and perform CFD analysis to study aerodynamic needs using fan-in-wing (FIW) concepts, and then document all these aerodynamic UAV parameters included in the decision support system (DSS).

RQ3.T2 – Identify critical parameters for fleet deployment and UAV design based on flight controls and aerodynamic concepts

UAV design decisions must optimize energy use in line with UAV operational concepts. The goal of this task would be to identify critical parameters for fleet deployment and UAV design based on the concept of flight controls using fan-in wings (FIW).

RQ3.T3 – Determine leverage points between deployment and design for the fleet of UAVs

Deployment and wildfire point planning strategies are incorporated as design decisions for the wildfire UAV to maximize operational efficiency in wildfire detection and communication. The primary objective of this research is to identify leverage points between UAV design and UAV fleet deployment. In addition, this study evaluates the potential benefits of developing deployment and design strategies simultaneously. The results of the described research tasks provide a novel and comprehensive understanding of a systemic approach to deploying a fleet of UAVs in wildfire scenarios.

1.5 Organization of Chapters

The research presented in this dissertation is organized into the first eight chapters. Chapter 6 addresses research gaps 1 and 2, encompassing research tasks RQ1.T1 and RQ1.T2. Chapter 7 focuses on research gap 3 and includes research tasks RQ2.T1 and RQ2.T2. Chapter 8 addresses research gap 4 and comprises research tasks RQ3.T1, RQ3.T2, and RQ3.T3. A summary conclusion is provided in Chapter 10.

Table 1.1 provides an overview of the dissertation structure. Chapters 6 through 8 address the primary research questions, while Chapters 2 to 5 present supporting material relevant to these core chapters. Chapter 9 offers a reflection on related research in adjacent fields and discusses the application of nature-inspired algorithms to the solution of complex problems.

Chapter 2

Model-Based Systems Thinking (MBST) integrated with Specifications for Wildfire UAV Fleet Deployment and UAV Design

2.1 Preface

This chapter provides a theoretical formulation of the wildfire detection problem using a fleet of unmanned aerial vehicles (UAVs) and the model-based systems thinking (MBST) approach [42]. The MBST offers a comprehensive framework for applying systems thinking principles, as outlined in the book "Practical Systems Thinking: Finding Leverage on Complex Problems," co-authored by the author of this dissertation. This chapter derives concepts from the book and develops a set of mathematical specifications that constitute the optimization machinery discussed in Chapter 6, thus addressing research question 1 (RQ1). RQ1 investigates the deployment problem for a wildfire UAV fleet by applying the MBST framework and principles of system thinking.

2.2 Overview

This research study uses systems thinking to investigate its role in supporting the deployment of the UAV fleet and in the design of UAVs for wildfire detection. An optimizing machinery is adopted for multi-objective optimization (MOO) problem formulation, with an operating conditions scenario-based optimization approach. The goal is to vary operating conditions that may affect wildfire detection missions in a structured two-level manner. The first level of the multi-objective problem (MOP) addresses optimal deployment strategies (ODS), while the second level problem concerns wildfire point optimization (WPO). In addition, integration of a human-in-the-loop (HITL) within the optimization machinery is explored to enhance the optimization process. Thus, the mathematical specification constitutes a central component of this study.

A system structure is established for the wildfire UAV fleet deployment problem that aligns with the overall systems architecture, encompassing CBS, MBS vehicles (launchers), UAVs, and scenario-based (operating conditions) deployment for wildfire detection. This overall system structure facilitates the development of a decision support system (DSS) for deploying a wildfire UAV fleet.

2.3 Introduction

Systems thinking is a critical component in the design of an effective wildfire UAV fleet deployment and UAV design for this research. Therefore, a definition of systems thinking is established prior to introducing MBST. Systems thinking is defined as an inter-relational, trans-disciplinary philosophy and method for understanding complex real-world problems and enhancing the likelihood of success of systems that influence them [42]. It employs a set of reliable, practical, system-oriented, and universally applicable principles that guide analysis, actions, and methods to facilitate the understanding and resolution of real-world problems.

These principles of the system and their application constitute the foundation of model-based system thinking (MBST). This is a framework that integrates languages and models to combine rigorous systems thinking methods and improve the ability to view, understand, and address real-world problems as interconnected systems [42]. Thus, an MBST framework is adopted specifically for wildfire UAV deployment and UAV design.

A set of mathematical specifications or problem formulations can be developed that incorporate multi-objective optimization within a human-in-the-loop framework. This optimization mechanism is structured around the overall deployment system. The first stage of optimization addresses the deployment of MBS vehicles and CBS with ODS, while the second stage focuses on optimizing the UAV flight-path with WPO. It is essential to develop a set of specifications that is both effective and comprehensive. Achieving this requires a thorough understanding of the deployment and UAV design problem.

2.4 Systems Thinking Methodology

We have developed five distinct and detailed architecture models: the DSM architecture model, the model-based systems engineering (MBSE) architecture model, the computational fluid dynamics (CFD) architecture model, the system dynamics architecture model, and the Optimization architecture model (mathematical specification). Each model provides a different perspective; however, the DSM architecture model is uniquely effective in integrating and managing the complexity of the other models. It enables organized exploration of inter-connectivity, aerodynamic characteristics, deployment dynamics of the system, and design aspects, and supports optimal decision-making.

2.4.1 Translating Systems Principles into Systems

To achieve the goal of the wildfire deployment mission, we integrate an MBST framework into the system architecture, leveraging *the principles* of the system to guide the overall design of the system and the architectural construction.

Utilization of 3-Systems Principle

One of the main systems principles is the "3-Systems Principal" [5]. It states, "*Systems come in (at least) three - context systems, systems of interest (SoI) and enabling systems*" [42].

- **The SOI**: The System of Interest (SOI) is the fleet of wildfire UAVs for wildfire detection and communication.
- **Context System**: Environmental parameters including wildfires, temperature, air density, etc are context systems.
- **Enabling System**: Here are some enabling systems to consider.
  - *Road and path infrastructures*: Road and path infrastructures for mobile base station (MBS) to travel with a UAV.
  - *Satellite Communication System*: Satellite Communication to be used for deployment and communication with the UAVs.

Utilization of Learning Principle

Another key principle of systems thinking is the "Learning Principle": "*(Common) Mental Models influencing human decisions about architectures and learnable and adaptable*" [42].

We utilize this core principle to approach the deployment architecture. The research study demonstrates that mental models dictate human decisions and heavily impact systems architecture, and in this example, MBSE and DSM are ways to incorporate mental models within the systems architecture under consideration.

The DSM and MBSE have been used as the key architectural tool, as shown in Figure 2.3, to develop a robust architecture for the Wildfire UAV deployment strategies. Figure 2.3 shows how the Wildfire UAV fleet development and design process has used the MBST framework [42].

Utilization of Architecture Principle - Designing Architecture Models with Systems Thinking

The "Architecture Principle" mentions, "*The purpose, structure, and behavior of systems influence each other*" [42].

Architecture models are one of the most effective systems thinking tools, as they help define the structure and interrelationships of systems with their environment and within their own internal subsystems and components.

We have developed five distinct and detailed models: the DSM architecture model, the model-based systems engineering (MBSE) architecture model [3], the computational fluid dynamics (CFD) model [173], the system dynamics model, and the Optimization model (mathematical model). The first two (DSM and MBSE) are system architecture models that capture systems thinking through the system of interest (SOI), enabling systems, and context system, and help develop the rest of the models with clear intent and vision of wildfire deployment objectives and mission in mind. Each model provides a different perspective; however, the DSM architecture model serves as an integrating framework that situates and connects the other models. It is uniquely effective in managing complexity, enabling an organized exploration of dependencies among aerodynamic characteristics, the dynamics of the deployment system, and design aspects, while supporting informed and optimal decision-making.

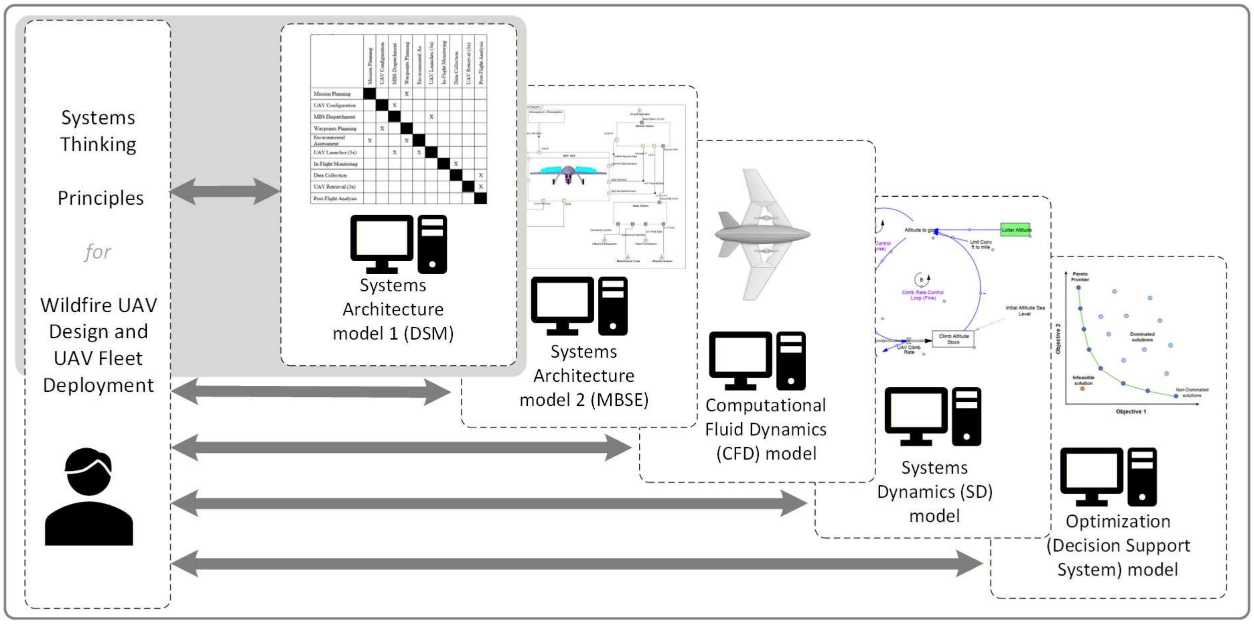


Figure 2.1: Architecture Models and Systems Thinking Principles

Note:

[1] We adopt systems thinking to visualize different types of system architecture models to capture Wildfire UAV fleet deployment and UAV design [9], [19], [5].

[2] Two systems architecture models (MBSE and DSM) capture the desired systems architecture. CDF, SD and Optimization (Decision Support System) models capture structure and behavior of the wildfire UAV fleet deployment system.

Figure 2.1 shows how different types of architecture models fit together and are enhanced by systems thinking principles. The architecture models that we develop using MBSE, DSM, or any other modeling mechanism need to adhere to the architecture principle and other systems principles. Effective architectural models built in MBSE or DSM consider the purpose of the system, evaluate the structure of the system, and characterize the behavior of the system in general.

2.4.2 Case Study of the Southwestern Region of Colorado (San Juan River Region Jurisdictions)

The deployment of wildfire UAV fleets is examined by analyzing wildfire and logistical parameters in four counties in the southwestern region of Colorado, specifically within the San Juan

River Region. The counties under analysis are Montezuma, La Plata, San Juan, and Archuleta, as illustrated in Figure 2.2.

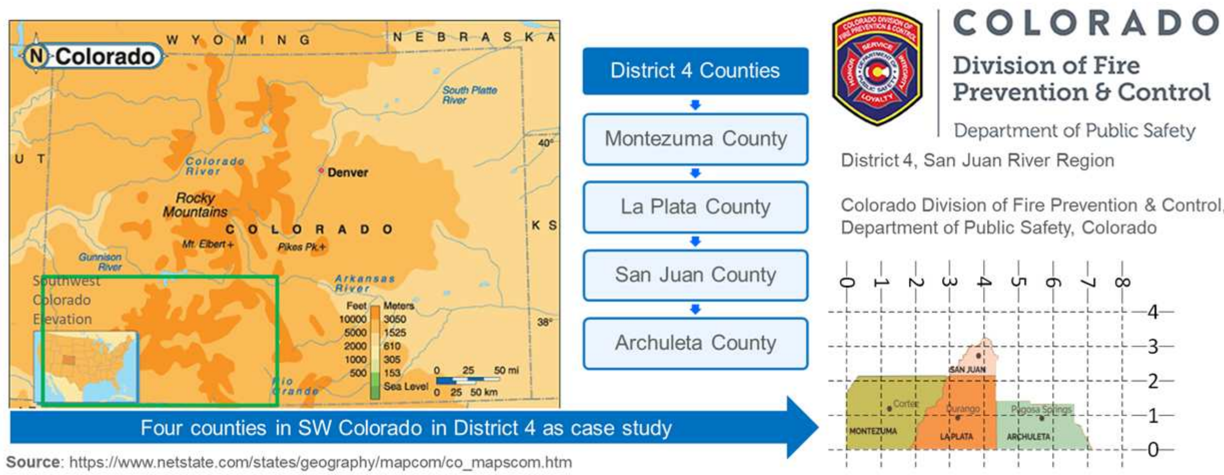


Figure 2.2: The southwestern region of Colorado has been used as a case study

Historical wildfire data from the southwestern region of Colorado are collected for this case study, while Figure 2.11 presents historical wildfire data for the entire state of Colorado. These data sets are utilized to generate a risk map that characterizes wildfire risk and facilitates integration with terrain data for the case study.

Spatial locations, identified by unique geographic coordinates and their associated risk levels, are incorporated to support the deployment objectives. Additional logistical factors, such as travel cost and travel time to each location, as well as coverage areas, are also considered and represented using data that closely reflect real-world conditions.

2.5 Multidisciplinary Modeling Approach Integrated with MBST

Optimizing the deployment of a fleet of unmanned aerial vehicles (UAVs) for the detection and monitoring of wildfires presents a complex challenge due to interconnected behaviors, feedback loops, and dependencies. This complexity can be systematically analyzed using the steps described in Figure 2.3. The implemented models are presented in Figure 2.4.

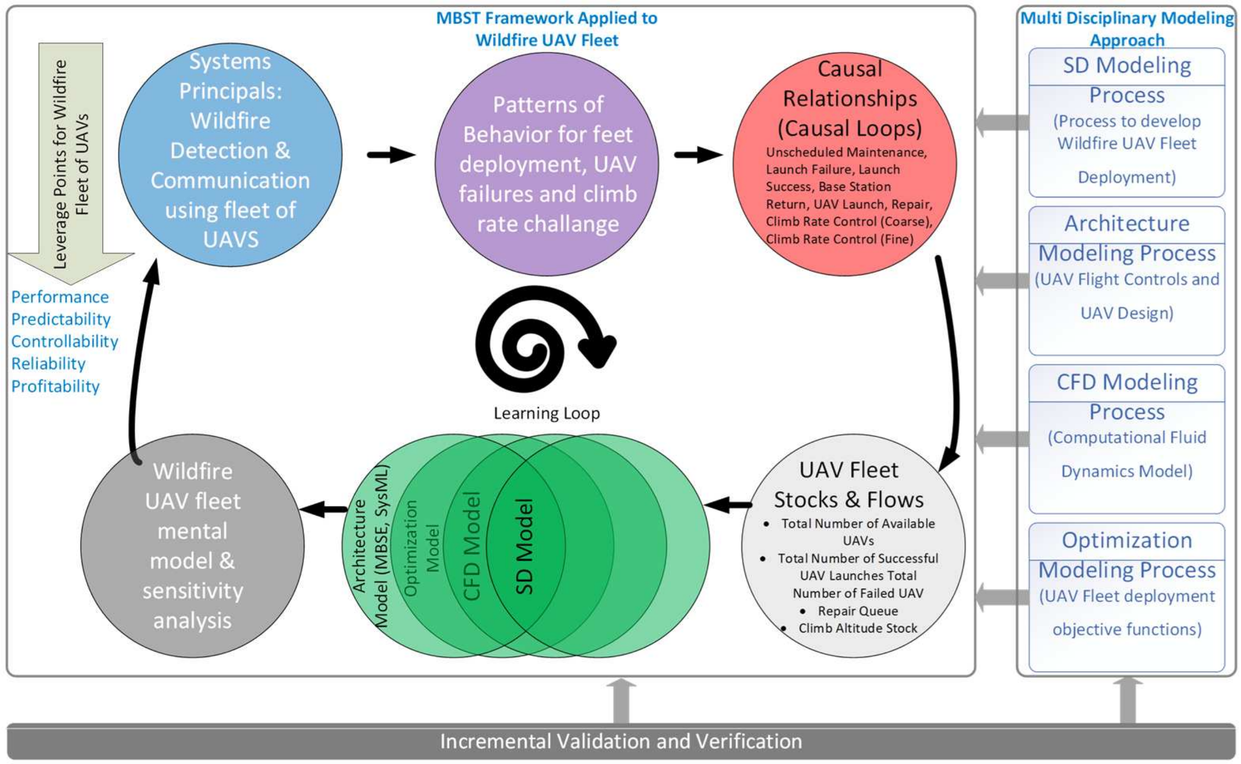


Figure 2.3: MBST Framework Applied to Develop Wildfire UAV and Fleet Deployment Strategies

The MBST model functions as a rapid prototyping tool during the Concept of Operations (ConOps) phase. The output of this model assists in identifying key parameters for optimization in subsequent optimizer models. This approach is effective before engaging in extensive modeling, analysis, and the development of detailed UAV fleet deployment strategies.

Although the primary focus of this dissertation is optimization modeling, the proposed framework also incorporates multidisciplinary systems engineering principles for wildfire unmanned aerial vehicle (UAV) deployment and UAV design as depicted in 2.4. This optimizer operates iteratively, receiving input from the mobile base station (MBS) and the central base station (CBS), and applies appropriate optimization methods as required.

2.5.1 Architecture Modeling

The relationship between wildfire UAV fleet deployment and UAV design, including their dependencies, is examined [42]. Several domains are considered, such as the system-product

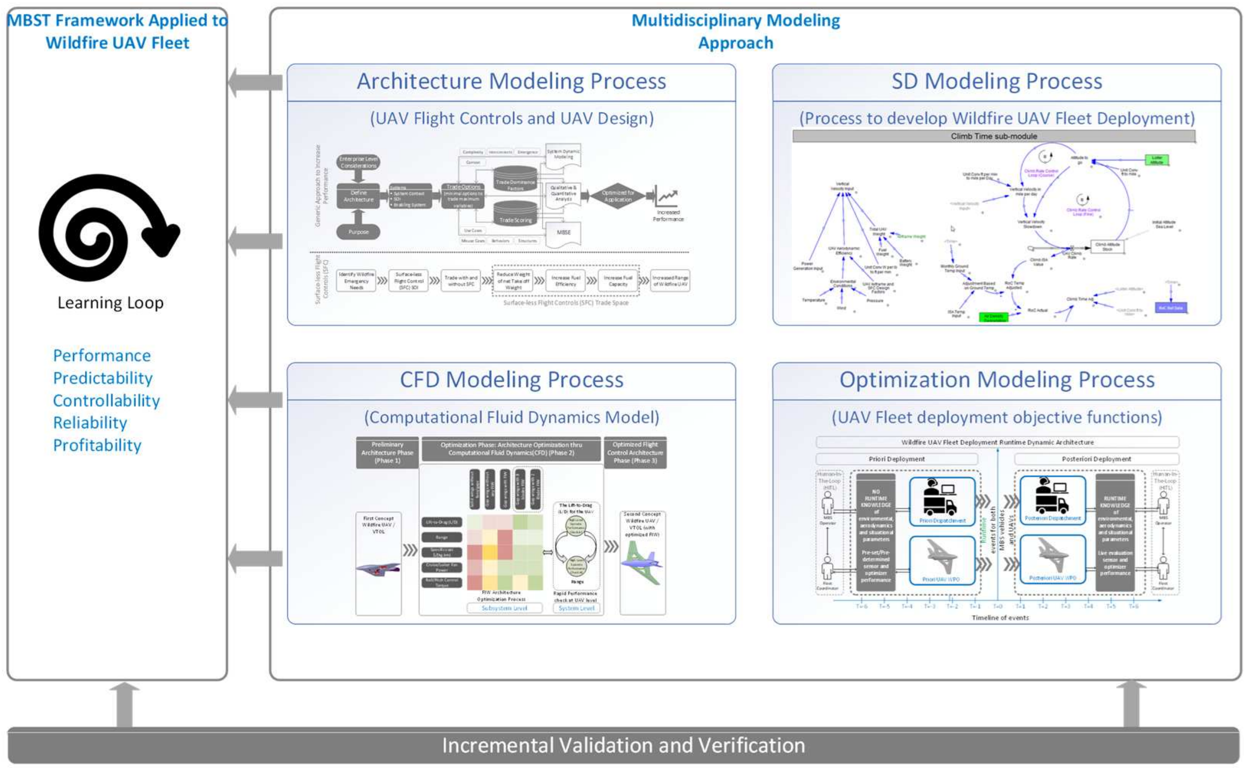


Figure 2.4: Implementation of multidisciplinary models Wildfire UAV Deployment and Design using MBST

Note:

[1] Development of SFC architecture is detailed in Chapter 3, utilizing MBSE, shown top left here.

[2] Process is bottom left, CFD modeling process is captured in Chapter 4.

[3] Systems dynamics model is discussed in Chapter 5, from the top right figure here.

[4] The details of the optimization modeling process are in Chapter 6, Chapter 7, and Chapter 7.

domain and the information item (specifying) domain. The analysis includes UAV sizing for specific applications to identify leverage points, such as predictability, profitability, and performance. For instance, a UAV with a length of 10 meters, a wingspan of 7 meters, and an approximate weight of 46 kg is considered optimal. The design structure matrix (DSM) for the deployment problem is presented in Figure 2.5.

For example, Weather Assessment serves as an input to Mission Planning, which subsequently produces Waypoints Planning as an output. UAV launches and retrievals are limited to a maximum of three UAVs per MBS, with a minimum of one UAV per operation.

	Mission Planning	UAV Configuration	MBS Dispatchment	Waypoints Planning	Environmental As.	UAV Launches (3x)	Runtime Monitoring	Data Collection	UAV Retrieval (3x)	Post-Flight Analysis
Mission Planning			X	X						
UAV Configuration			X	X						
MBS Dispatchment						X				
Waypoints Planning		X					X			
Environmental Assessment	X			X						
UAV Launches (3x)			X		X					
Runtime Monitoring								X		
Data Collection										X
UAV Retrieval (3x)										X
Post-Flight Analysis										

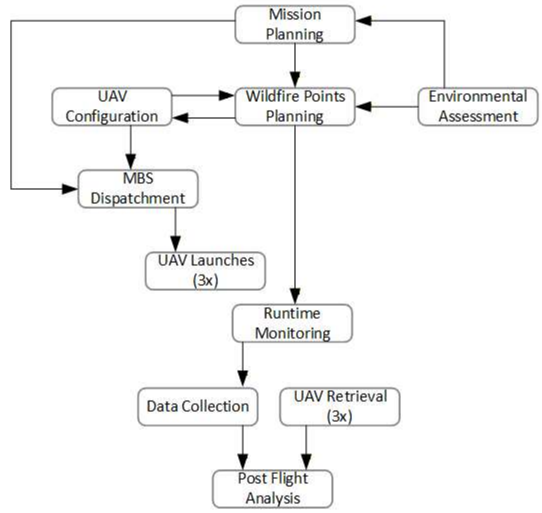


Figure 2.5: Architectural interconnectedness using DSM for wildfire fleet deployment

Architecture models, including Model-Based Systems Engineering (MBSE) and Design Structure Matrix (DSM), provide the rigor of systems engineering by defining the overall system architecture that supports the optimization framework (discussed in this chapter and in Chapter 3).

2.5.2 Aerodynamics Modeling

Computational fluid dynamics (CFD) modeling identifies flight-control and UAV-design considerations that complement the optimization process by incorporating CFD into the design analysis (discussed in Chapter 4).

2.5.3 Systems Dynamics / Prototyping Modeling

The system dynamics (SD) model further validates environmental behavior and aerodynamic interactions between wildfire UAVs, thereby strengthening the system-level evaluation of the proposed framework (discussed in Chapter 5). This SD model also can serve as rapid Prototypes - Initially by taking advantage of MBST thought process [5], [42]. Additionally, system dynamics model also provides additional means of validation of the optimization model capabilities discussed in Chapter 10.

To achieve the deployment objective, this study develops an adaptable systemic optimizer that supports wildfire UAV fleet deployment under varying operational conditions based on the scenarios (details in Chapter 6, Chapter 7 and Chapter 8).

2.5.4 Optimization Machinery Modeling

We integrate an optimizer to achieve the deployment objective. This optimizer runs in a loop, receiving input from MBS and CBS, and uses various methods as required, as shown in Figure 2.6.

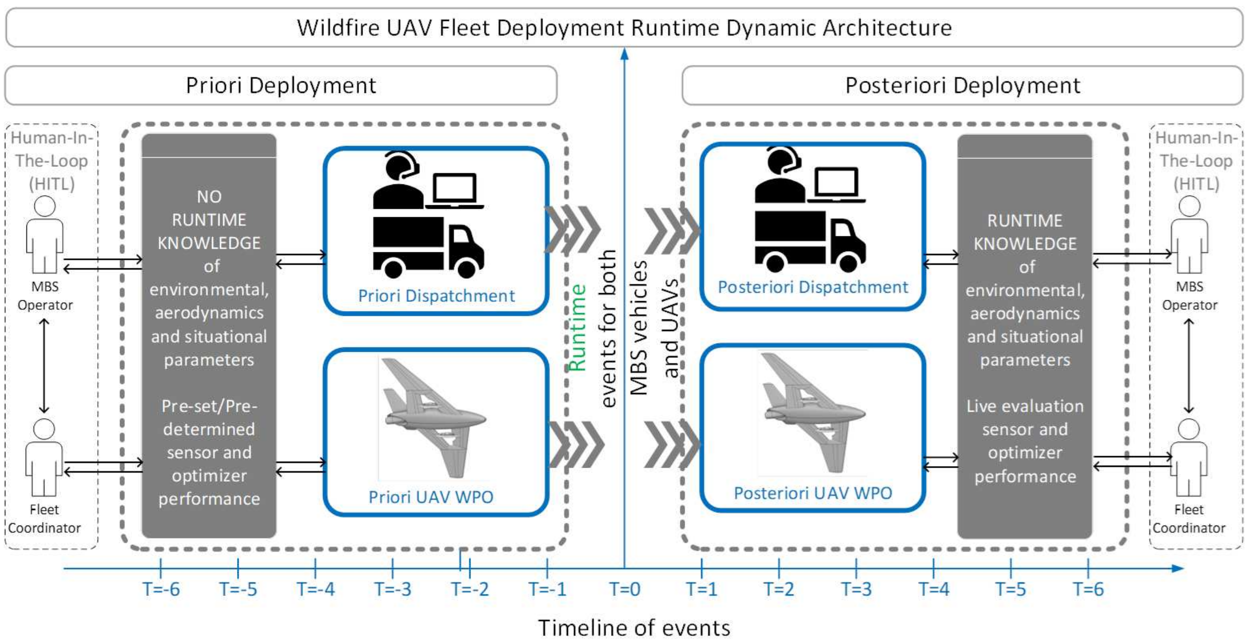


Figure 2.6: Human-in-the-loop (HITL) Optimizer for Wildfire Detection and Communication

A solution that is optimal across all four objectives of a Multi-Objective Optimization (MOO) problem of an optimization machinery may appear suboptimal in pair-wise (2D) visualizations. Each 2D slice conceals interactions and trade-offs present in the remaining dimensions as show in Figure 2.7.

Thus, the true four-dimensional minimum may not be evident in any individual two-dimensional projection. A possible set of solutions of the MBS can be depicted as a Pareto hypersurface solution in Figure 2.8 for four different objectives of cost, time, risk and area.

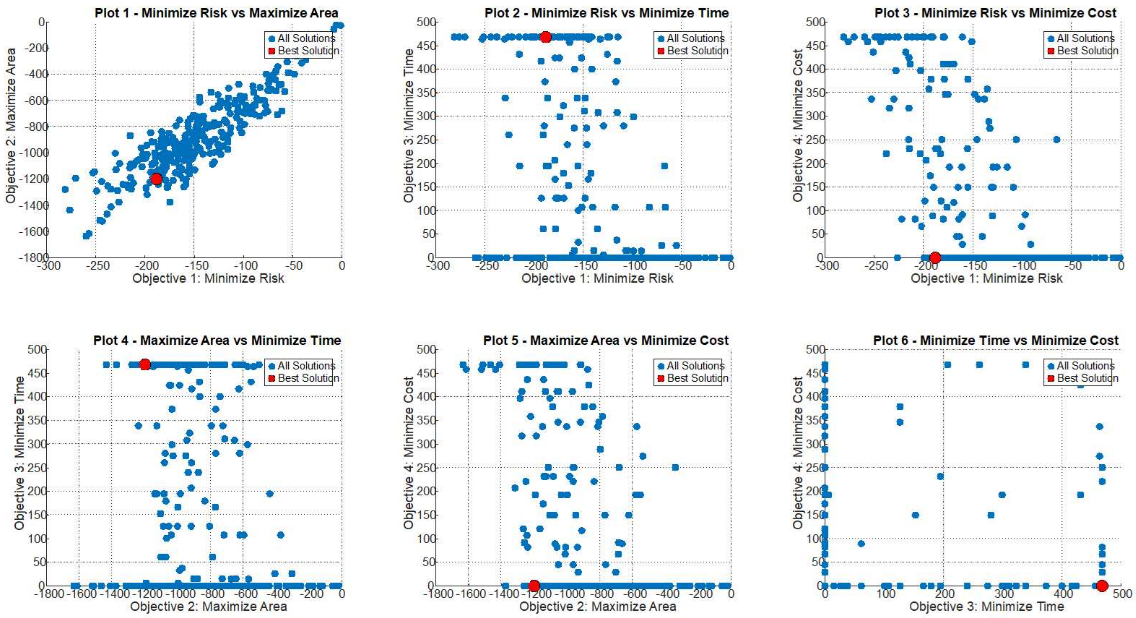


Figure 2.7: 2D representation of 4D MOO

Note:

[1] Breaking a 4D optimization landscape into 2D slices can distort where the “best” solution appears to be.

[2] The global optimum depends on all four objectives simultaneously, while each 2D plot only captures a subset of the trade-offs.

We also employ human-in-the-loop (HITL) concepts, utilizing various methods to be deployed in the optimizer [7], [8]. The optimizer loop consists of four states: assessing the current state, evaluating constraints, evaluating objective functions, and finally identifying a better state, which can provide input back into assessing the current state, thus completing the loop.

Systems Optimization Model

A hierarchical decomposition of an optimization can help with a complex optimization problem. We consider a preliminary concept for optimizer machinery that integrates hierarchical decomposition and allows systemic level of adaptability features (adaptability slider) in order to gear focuses on the systemic need of a broader complex problem as shown in Figure 2.9. We consider two scenarios in figure 2.9 where there is a pre-determined location for CBS and second case where it is

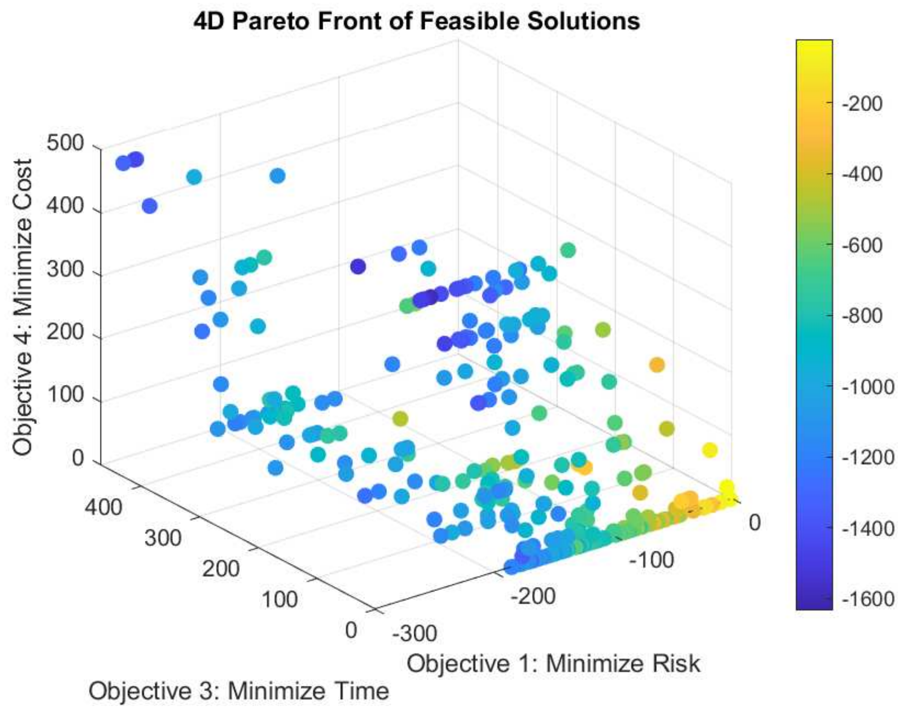


Figure 2.8: Pareto Hypersurface of the MOO

possible to determine an optimized location for CBS given a specific region/area that need to be serviced by this CBS.

2.6 Optimization Problem Formulation for Wildfire UAV Fleet Deployment and Design

The following section outlines problem formulation for the optimizer. Mathematical expressions of the optimizer machinery are depicted in this section.

2.6.1 System Adaptability via Mission Objective for Optimization machinery

The optimization approach for deployment of a fleet of UAVs (Unmanned Aerial Vehicles) for wildfire detection and monitoring is a complex problem because of interconnected behaviors, feedback loops, and dependencies. This complexity can be explored and deconstructed with two steps process:

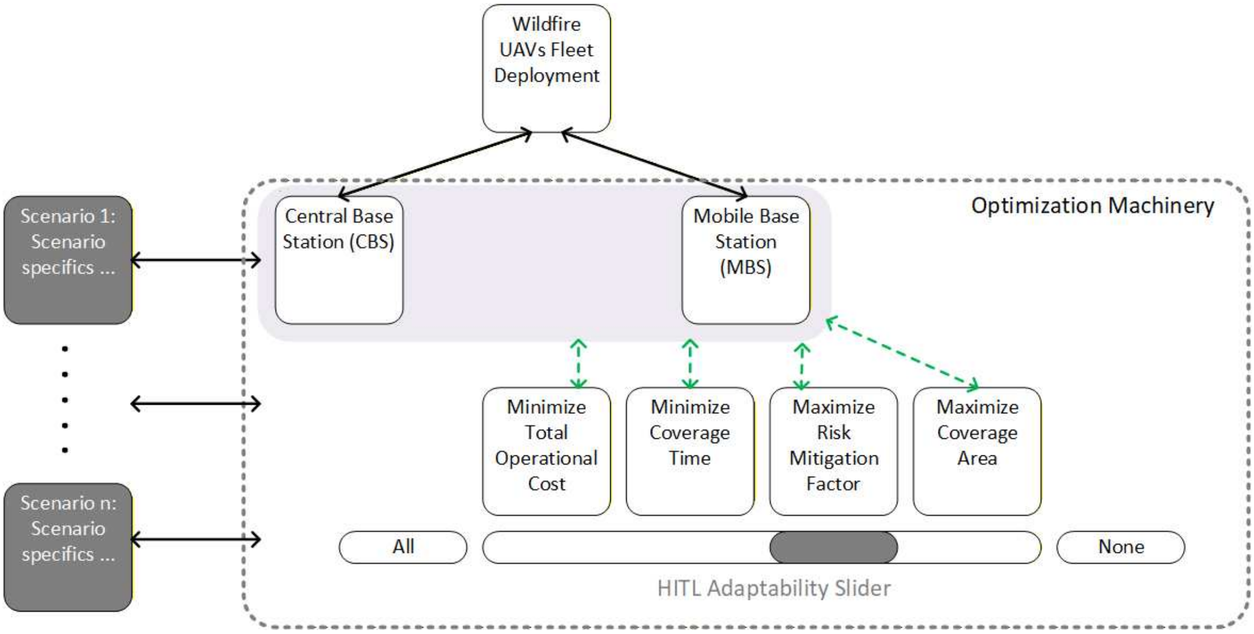


Figure 2.9: Adaptability Slider for Optimization Machinery

2.6.2 Launching and Retrieval of UAVs

The selection of launch and retrieval locations for unmanned aerial vehicles (UAVs) is a strategic component of the overall deployment plan. The launch and retrieval strategy at the same location (LRSL) allows the MBS vehicle to deploy and recover the UAV at the same site, as shown in Figure 2.10. In contrast, the different location launch and retrieval strategy (LRDL) enables the MBS vehicle to deploy and recover the UAV at separate sites.

Several strategic operating conditions scenarios are established in Chapter 6 to utilize the launch and retrieval strategies. These strategies are also incorporated into the mathematical models detailed later in this chapter, Section 2.7, for optimization purposes.

2.6.3 Identification of Objective Functions for Optimizing Engine

In developing the optimizer, we formulate several components of objective functions that can be optimized independently if required.

Minimization of the risk: of wildfires. An objective function is formulated to minimize wildfire risk.

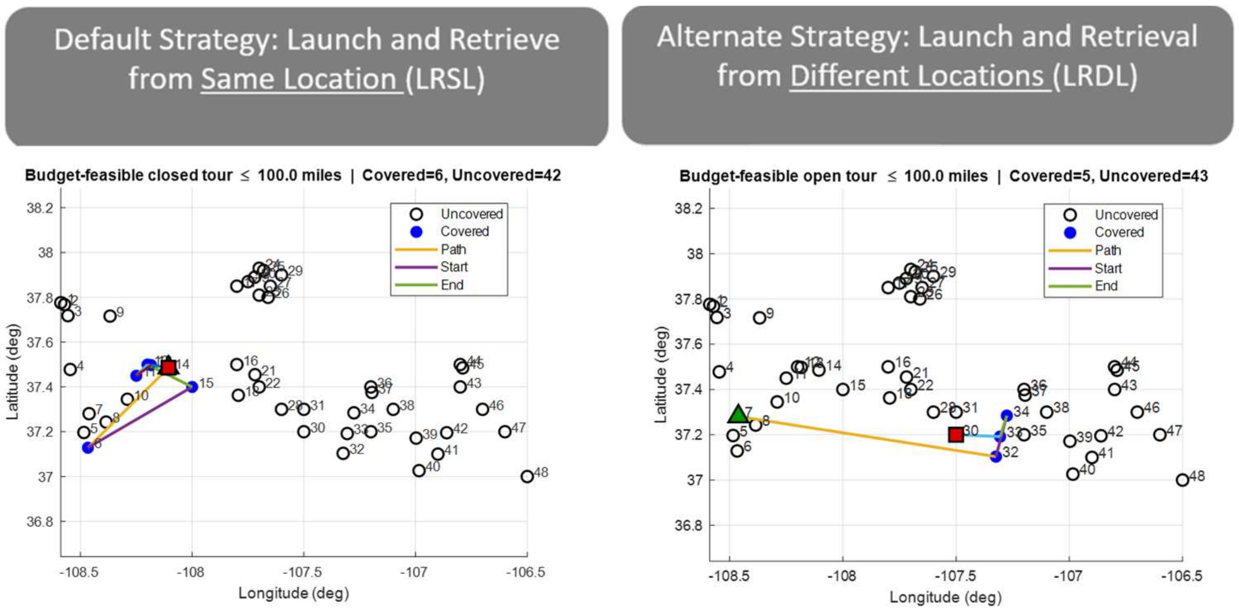


Figure 2.10: Deployment Strategies – Launching and Retrievals

Maximization of coverage area: The objective function for maximizing coverage area can be expressed as follows.

Minimization of coverage time: A similar detailed objective function can be formulated to minimize coverage time.

Minimization of cost: The operating times of the MBS and UAVs are consolidated into a comprehensive objective function that minimizes the total costs associated with the CBS, MBS, and UAVs.

These four objectives motivate a multi-objective optimization (MOO) framework for the deployment of a fleet of wildfire UAVs. The detailed equations for these objective functions, along with constraints, are in Section 2.7 of this Chapter.

2.6.4 Historical Risk Data and Natural Ignition Map

Figure 2.11 presents the historical risk of wildfires in Colorado. To address the complex challenge of the deployment of the wildfire UAV fleet, the southwestern region of Colorado was selected as a representative case study, incorporating both wildfire and logistical parameters. This methodology provides a comprehensive overview of the geographic distribution and scale of wildfire risk within the state. Historical wildfire data for the southwestern region were obtained from the Colorado wildfire database [161].

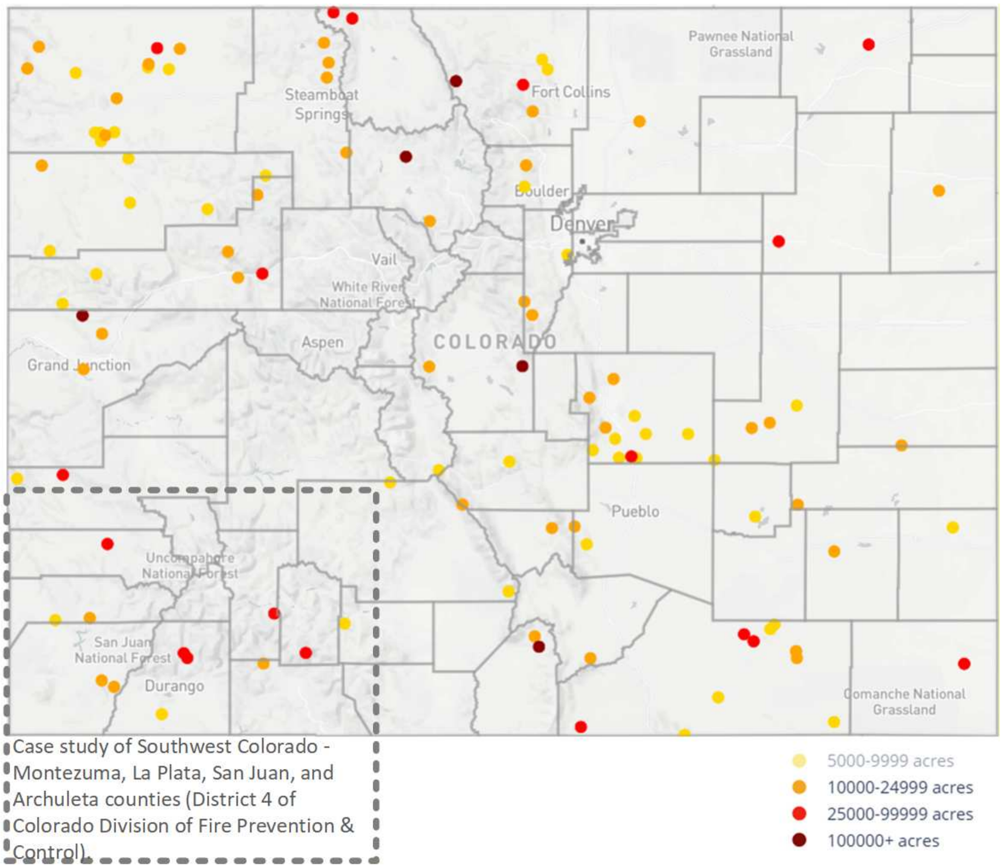


Figure 2.11: Wildfire Historical risk in Colorado

Note:

[1] Historical wildfire risk map for Colorado, adapted and modified from the Colorado Climate Center at Colorado State University. [161].

Figure 2.11 presents the historical wildfire distribution for Colorado. These data inform the generation of a wildfire risk map, in which wildfire risk is spatially characterized and integrated with terrain data for the case study. Clusters of wildfire incidents and darker shaded regions denote areas of elevated wildfire risk, such as Haile, Reese Wall, and Faris Road. In contrast, lighter shaded regions or areas with few recorded incidents represent lower wildfire risk.

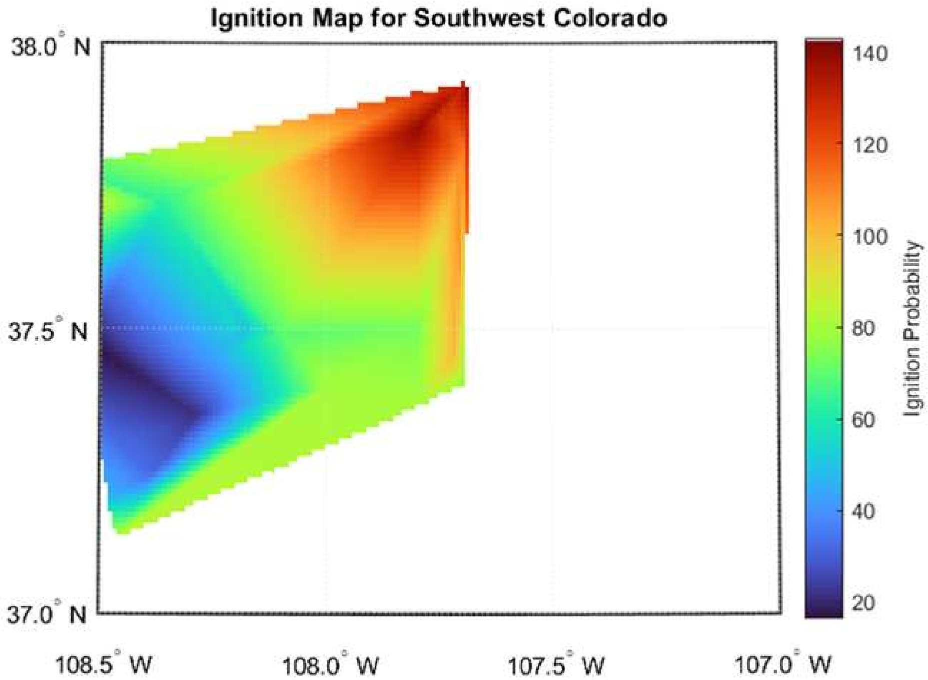


Figure 2.12: Composite Ignition Map of Southwest Colorado

Lightning represents one of the primary natural causes of wildfire ignition. To enhance understanding of natural ignition patterns, this study compares historical wildfire data with the statewide lightning distribution. Figure 2.12 demonstrates that the lightning distribution exhibits a strong spatial correlation with historical wildfire occurrences across Colorado, supporting its inclusion as a key environmental factor in wildfire risk assessment.

Assumptions - sufficient off-road routes for Wildfire UAV deployment

The MBS vehicles are dispatched from the CBS carrying UAVs according to the map, but additional off-road access may be needed to achieve precise positioning of the MBS vehicle for more efficient launching and retrieval of the UAVs. Off-road access may not need to be long, but it is assumed that in most cases such access is available for the most efficient launching and retrieval.

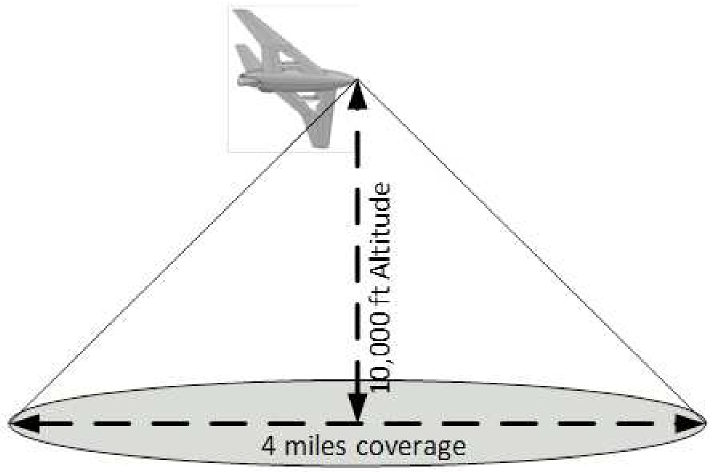


Figure 2.13: UAV sensor coverage

Assumptions - UAV sensor coverage

The primary assumption, as outlined by Crawford, is that the coverage width of the UAV sensor is approximately 4 miles. Therefore, a UAV with a range of 100-miles can cover approximately 400 square miles under this exemption [6]. The capability of the UAV sensor, the accuracy of the sensor, and the coverage at an altitude of approximately 10,000 feet determine the achievable coverage area for a given assignment. Figure 2.14 shows that the UAV can cover a width of 4-miles. The expansion of the sensor capability may be included in future UAV designs. It will also be considered for commercialization or as a focus for future research.

2.6.5 Urban corridors using population contours

A population density map can demonstrate wildfire correlations. Urban corridors are highly prone to wildfires, whereas densely populated areas are less risky due to the availability of closer monitoring. Colorado's population density is shown in Figure 2.14.

2.6.6 Observation from Deployment Modeling and Scenarios

In this section we discuss the observations of the scenarios from the deployment model and how a mental model can be developed.

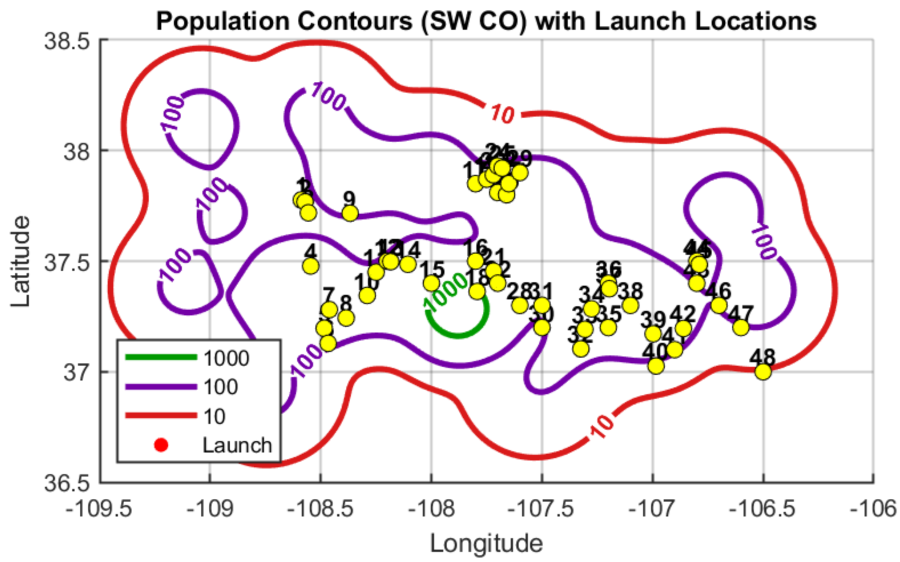


Figure 2.14: Population contours of Southwest Colorado

2.6.7 MBST to Wildfire Deployment Conclusion

The multiobjective optimization model, ODS, has been developed effectively using the MBST methodology, and parameters with leverage points are identified to maximize the impacts of the resources that are available. Previously, we developed a new CFD model specifically proposed for wildfire detection and communication, and now, with this research, we are able to identify the optimization approaches for deployment. Essentially, we are exploring both UAV design and fleet deployment spaces to maximize opportunities. The MBST model demonstrated opportunities to minimize coverage time due to environmental, aerodynamics, and operational constraints (failure rate, maintenance, fleet size, etc.). In the wildfire case study for Colorado, utilizing 10 UAVs, the ODS can optimize for time to cover the entire state for wildfire monitoring and detection. This model clearly identified additional elements such as fuel efficiency, high-risk scenarios, no-fly zones, and access road availability. Similar conclusions can be drawn to minimize risk factors and operating costs. The output of the multiobjective model is a decision support system that is a robust way to deploy a number of MBS vehicles and UAVs, given a map with topology, geographic conditions, operational scenarios, communication, and other constraints. Future work will involve developing and using a wildfire detection and communication optimizer model with artificial intelligence (AI) to find further efficiencies for this deployment problem.

2.7 Mathematical Formulation for Wildfire UAV Fleet Deployment and Design

In this section, we discuss the mathematical specification for deploying a wildfire UAV fleet. This specification can be developed in stages. The first stage is the Optimal Deployment Strategies (ODS) optimization and the second stage is the (WPO) for UAV that are part of a wildfire UAV fleet. These strategies for wildfire detection and communication are part of the combined ODS and WPO.

We address two main segments of the optimization machinery: (1) optimal dispatch of MBS which are movable launchers or trucks that provide communication support for UAVs. (2) Planning and optimization of UAV flight paths, including predefined wildfire points. Wildfire points are locations identified as important for detection or monitoring.

A set of algorithms has been developed under the ODS framework to address the fleet deployment problem. These include topological mapping, geographic positioning, operational constraints, and communication requirements. They also account for restricted airspace and minimization of time, cost, and energy use. All efforts must adhere to problem-specific constraints.

Each UAV is initialized with an optimal flight path, based on a PFWP plan. The plan is modified during run-time and RTWP fills in any unforeseen issues from PFWP which is detailed in Chapter 7. The default route is considered optimal under anticipated conditions; however, it may need to be adjusted if unforeseen real-time constraints arise. The primary mechanism for addressing such deviations is human-in-the-loop (HITL) intervention in optimization objective functions, constraint functions, or variables. More details on HITL mechanisms and implementations for optimization of operational condition-based scenarios will be provided, which considers both anthropogenic (man-made) and environmental factors influencing fire causation and fleet deployment.

2.7.1 Optimization Problem Formulation

The development of a mathematical specification required extensive research in both fleet deployment and UAV design objectives and constraints. Several critical elements of the specifications are summarized in this section. Further details are provided in Chapter 6 for the first stage optimization and in Chapter 7 for the second stage optimization.

Real-world Complexity in Wildfire UAV deployment problem formulation

Nonlinear equations are essential for representing the details of real-world wildfire UAV fleet deployment and for modeling the UAV design problem itself. A logical initial step in tackling such a complex optimization task is to select an appropriate formulation, either nonlinear or linear, for the objective functions (Cost, Time, Risk reduction, and Area coverage) and the associated constraints for those objectives.

In practice, specifying mathematical equations that reflect real-world conditions often requires starting with nonlinear models, which are more accurate. Although practitioners in the industry often start with linear approximations or convert a nonlinear problem into a linear one to simplify its structure, these linear equations are then incorporated into the overall optimization process. An example of inherent nonlinearity arises in UAV design: the rate of climb depends on elevation, seasonal variations, air density, and temperature, leading to differences between locations. None of these are linear problems and require non-linear mathematical expressions to express them accurately. The maximum attainable climb rate and the lift-to-drag ratio (L/D) are design variables, and UAV operators base their decisions on the interaction between these choices and the UAV's performance capabilities. In the second phase of the optimization problem in this research, some nonlinearities are reflected.

Nonlinearities are observed in deployment decisions when spatial relationships among wildfire points (potential launch sites) are specified. This can be observed in attempts to influence minimum-risk requirements, cost calculations, repair considerations, and lightning susceptibility. Special distribution matters because it shows how wildfire-causing events are geographically interconnected. Proximity can increase or reduce impacts on objectives.

Lightning, especially positive lightning thunderstorms, often has a radius of 5 to 10 miles, and lightning can impact miles away [126]. If a site is selected within the proximity of the positive lightning, nearby sites will have an elevated risk of wildfire due to lightning as well. Positive lightning starts at the top of the cloud and can travel much farther from its origin. Therefore, it is reasonable to establish this relationship that if site x_i has baseline risk r_i, and $x(i-1)$ is within a 5-mile radius and $x(i+1)$ is within a 10-mile radius, then the risk for $x(i-1)$ may be 50% more, and $x(i+1)$ may be 10% more. Thus, considering both individual and neighborhood-influenced risk creates non-linear relationships.

First Stage and Second Stage Interconnections

The interconnections between the ODS optimization problem and the WPO problem are essential for evaluating the overall system. When constructing the ODS model, we initialize data generated by the WPO model; this shared information includes the locations of fire points, the severity of each incident, and the temporal constraints on UAV deployment. The ODS formulation incorporates parameters such as the number of MBS vehicles, the CBS metrics, and the UAV utilization rates derived from the WPO solution. These variables appear both in the objective functions, as they influence the cost-benefit trade-offs of a deployment plan, and in certain constraints that enforce feasibility with respect to fire risk mitigation and resource availability.

Data sharing between the two models is bidirectional, with ODS as the first-stage, higher-level MOP and WPO as the second-stage, lower-level MOP. After the ODS optimization determines an optimal deployment configuration, it outputs additional data, including selected environmental parameters, site choices, time of day and seasonal considerations, and the resulting UAV performance metrics. These outputs feed back into the WPO model, affecting the navigation and mitigation strategies employed during runtime. In turn, the WPO model supplies runtime information such as MBS related conditions and dynamic fire spread predictions, which are incorporated into the ODS's subsequent refinement cycles. This two way data exchange ensures that both models remain synchronized, enabling the overall system to continuously adapt to evolving wildfire scenarios while maintaining the integrity of the two stage optimization framework.

2.7.2 Optimization Model Constructions

The optimization approach for the deployment of a fleet of unmanned aerial vehicles (UAVs) for wildfire detection and monitoring is a complex problem due to interconnected behaviors, feedback loops, and dependencies. The mathematical expression for the deployment of the Wildfire UAVs fleet of the design problem can be shown below.

The wildfire point optimization (WPO) mathematical model focuses primarily on the flight paths of the UAVs. This essentially determines the launch points and the retrieval points of the UAVs. This information also feeds into the overall optimization problem. The final utilization of optimization approach involves a bi-level problem setup, which consists of two optimization problems.

- First, the leader problem, which solves the issues of CBS locations, deploying MBS vehicles based on the logistic input from the DSS input.
- The second is the follower problem, which effectively solves the selection of launching and retrieval locations for the UAV.

2.7.3 First Stage ODS Mathematical Model

First, the leader problem, which solves the issues of CBS locations, deploying MBS vehicles based on the logistic input from the DSS input. The mathematical first stage optimal deployment strategy (ODS) can be expressed as the following in Equation 2.2.

changing:

$$x \tag{2.1}$$

minimize:

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \\ f_4(x) \end{bmatrix} \tag{2.2}$$

$$f(x) = \begin{bmatrix} min(\textit{total UAV feet dep cost}) \\ min(\textit{total UAV feet dep time}) \\ max(\textit{total wildfire risk reduction}) \\ max(\textit{total coverage area}) \end{bmatrix} \tag{2.3}$$

We maximize risk reduction, which is equivalent to minimizing risk. In optimization, a maximization problem can be converted into an equivalent minimization problem by negating the objective function, that is, $max(f(x))$ = $min(-f(x))$.

$$f(x) = \begin{bmatrix} min(\textit{total UAV feet dep cost}) \\ min(\textit{total UAV feet dep time}) \\ min(\textit{-total wildfire risk reduction}) \\ min(\textit{-total coverage area}) \end{bmatrix} \tag{2.4}$$

The above expression is equivalent to the following expression as a minimization problem.

minimize:

$$f(x) = \begin{bmatrix} \textit{total UAV feet dep cost} \\ \textit{total UAV feet dep time} \\ \textit{-total wildfire risk reduction} \\ \textit{-total coverage area} \end{bmatrix} \tag{2.5}$$

minimize:

$$f(x) = \begin{bmatrix} \sum_{i=1}^{n} c_i \, x_i \\ \sum_{i=1}^{n} t_i \, x_i \\ -\sum_{i=1}^{n} r_i \, x_i \\ -\sum_{i=1}^{n} a_i \, x_i \end{bmatrix} \tag{2.6}$$

where c is total UAV feet deployment cost, t = total UAV feet deployment time, r = total wildfire risk reduction and a = total coverage area.

subject to:

$$g(x) \tag{2.7}$$

where $g(x)$ represents the set of inequality constraints defined below.

[1] **[Min Risk Reduction]** Minimum risk reductions to be take by the deployment effort

$$0 < R_{\min} < \sum_{i=1}^{n} r_i x_i \tag{2.8}$$

[2] **[Max Risk Reduction]** Maximum risk reductions to be take by the deployment effort

$$\sum_{i=1}^{n} r_i x_i \leq R_{\max} \tag{2.9}$$

[3] **[Min Area]** Minimum number of areas to be covered by the deployment effort

$$\sum_{i=1}^{n} a_i x_i \geq A_{\min} \tag{2.10}$$

[4] **[Min Time]** Minimum time to be taken by the deployment effort

$$T_{\min} < \sum_{i=1}^{n} t_i x_i \tag{2.11}$$

[5] **[Max Time]** Maximum time to be taken by the deployment effort

$$\sum_{i=1}^{n} t_i x_i \leq T_{\max} \tag{2.12}$$

[6] **[Total Cost]** Total available budget for the deployment effort

$$\sum_{i=1}^{n} \left(c_{UAV,i} + c_{MBS,i} + c_{WFBurn,i}\right) x_i \leq C_{\max} \tag{2.13}$$

[7] **[Max Number of Wildfire Points]** Maximum number of areas to be monitored which is also the max available UAV

$$\sum_{i=1}^{n} x_i \leq N_{\max} \tag{2.14}$$

Note: N max is all the wildfire points (WP) which also the is the max number sites that are designated for UAVs to be launched and retrieved from.

where $h(x)$ represents the set of equality constraints defined below.

[1] **[Number of UAVs to be deployed]** Exact number of areas to be monitored which is also the max available UAV

$$\sum_{i=1}^{n} x_i = k \tag{2.15}$$

[2] **[Number of sites to be picked]** Exact number of sites to be selected for the MBS vehicle to be sent.

$$\sum_{j=1}^{m} x_j = n \tag{2.16}$$

2.7.4 Second Stage WPO Mathematical Model

The second-stage optimization problem is the follower problem (first-stage is the leader problem), which addresses the effective selection, launch, and retrieval of locations for the UAV. The run-time wildfire points (RTWP) using the ant colony optimization (ACO) for a multiobjective optimization problem.

The second-stage WPO mathematical expression can be expressed as follows from Equations 2.17 to 2.23.

changing:

$$x \tag{2.17}$$

minimize:

$$f_u(x) = \begin{bmatrix} f_{u1}(x) \\ f_{u2}(x) \\ f_{u3}(x) \\ f_{u4}(x) \end{bmatrix} \tag{2.18}$$

The risk reduction for each wildfire point (WP) per UAV needs to be maximized for a single launch and retrieval while maximizing area coverage.

$$f_u(x) = \begin{bmatrix} min(\textit{UAV cost}) \\ min(\textit{UAV time}) \\ max(\textit{wildfire risk reduction}) \\ max(\textit{coverage area}) \end{bmatrix} \tag{2.19}$$

We maximize risk reduction, which is equivalent to minimizing risk. In optimization, a maximization problem can be converted into an equivalent minimization problem by negating the objective function, that is, $max(f_u(x))$ = $min(-f_u(x))$.

$$f_u(x) = \begin{bmatrix} min(\textit{UAV cost}) \\ min(\textit{UAV time}) \\ min(\textit{-wildfire risk reduction}) \\ min(\textit{-coverage area}) \end{bmatrix} \tag{2.20}$$

The above expression is equivalent to the following expression as a minimization problem.

minimize:

$$f_u(x) = \begin{bmatrix} \textit{UAV cost} \\ \textit{UAV time} \\ \textit{-wildfire risk reduction} \\ \textit{-coverage area} \end{bmatrix} \tag{2.21}$$

minimize:

$$f_u(x) = \begin{bmatrix} \sum_{i=1}^{n} c_{\mathit{UAV},i}\, x_i \\ \sum_{i=1}^{n} t_{\mathit{UAV},i}\, x_i \\ -\sum_{i=1}^{n} r_{\mathit{UAV},i}\, x_i \\ -\sum_{i=1}^{n} a_{\mathit{UAV},i}\, x_i \end{bmatrix} \tag{2.22}$$

where c_{UAV} is UAV cost, t_{UAV} = UAV time, r_{UAV} = wildfire risk reduction and a_{UAV} = coverage area.

subject to:

$$g_u(x) \tag{2.23}$$

where: $g_u(x)$ represents the set of constraints defined

[1] [UAV Design Constraint] UAV L/D (Lift-to-drag ratio) – L/D within optimization problem takes consideration of the flight profile for the UAV that it is specifically designed for. Expected L/D range is 2 to 20 as we discuss that later in Chapter 4.

$$\frac{L}{D} \geq k_{UAV1} \tag{2.24}$$

[2] [UAV Design Constraint] UAV Range – UAV range for the current design is maximum of 100 miles. Therefore, we ensure that the total length of the flight path covering wildfire points must not exceed 100 miles.

$$D_{\text{total}} = D_{\text{loitering}} + D_{\text{RTH}} \leq 100 \text{ miles} \tag{2.25}$$

[3] [UAV Design Constraint] UAV Max altitude – The maximum operating altitude for the UAV cannot exceed 10,000 ft.

$$h_{\text{UAV}} \leq 10{,}000 \text{ ft} \tag{2.26}$$

[4] [Wildfire Constraint] Wildfire Points - Leader problem is wildfire points optimization (WPO) for wildfire.

$$\forall p_i \in \chi, \quad \text{RiskReducion}(p_i) \geq k_2 \tag{2.27}$$

[5] [Wildfire Constraint] Recent Wildfire exclusion – Wildfire points recently had wildfire can be excluded from revisit if those WFP had activity in the last 6 hours.

$$p_i \notin \text{RecentWildFireData}(t_j), \quad \text{for } t_j < 6 \text{ hours} \tag{2.28}$$

[6] [Wildfire Constraint] No-Fly Zones – The UAV's path must exclude previously determined local authority (i.e., FAA) no-fly zones.

$$\text{location}(lat, lon)_i \notin \text{NoFlyZone}(lat, lon)_i \tag{2.29}$$

[7] [Wildfire Constraint] Recent Visitation Exclusion (same UAV) – Wildfire Points recently were visited in the last 6 hours can be excluded.

$$p_i \notin \text{VisitedWFP}(t_j), \quad \text{for } t_j < 6 \text{ hours} \tag{2.30}$$

[8] [Wildfire Constraint] Recent Visitation Exclusion (Different UAV) – Wildfire Points recently were visited in the last 8 hours by another UAV can be excluded to order to ensure operational safety.

$$p_i \notin \text{OtherUAVsVisitedWFP}(t_j), \quad \text{for } t_j < 8 \text{ hours} \tag{2.31}$$

2.7.5 Observations regarding mathematical specifications and using systems thinking

In this section, we discuss observations regarding mathematical specification with respect real-world complex behavior for wildfire UAV fleet deployment problem.

Risk Capture: Lightning Risk as Nonlinear Behavior

Lightning risk often exhibits nonlinear behavior because different types of lightning positive and negative produce different wildfire ignition rates under varying weather conditions [126], [193], [194]. Positive lightning accumulates a large amount of positive charge at the top of the cloud, extending toward the stratosphere. This excess electric energy can travel horizontally over considerable distances before striking the ground, thereby releasing substantially more energy. Thus, heavily positively charged lightning may strike dry areas or those that receive little rainfall, increasing the probability of wildfire ignition. Although negative lightning events occur roughly nine to ten times more frequently than positive ones, the latter can ignite fires within a five-kilometer radius at rates two to five times greater for the present analysis, a factor of three is adopted.

The nonlinear nature of lightning can be incorporated into risk calculations for a deployment area by integrating automatically retrieved lightning data into risk calculation. In our testing, simulated datasets of positive and negative lightning were fed into a risk calibration model, enabling it to capture the nonlinear influence of lightning on the risk of wildfire.

This approach embeds the nonlinear behavior of lightning within the overall optimization framework, where the objective functions themselves exhibit nonlinear characteristics.

Refining Objective Functions and Constraints from Concept to Commercialization

Non linear formulations capture the realistic complexities of wildfire related UAV fleet deployment, yet it is often impossible to express both the objective functions and the constraints entirely as non linear equations. Thus, a systematic transition proceeds from coarse tuning of the constraints to fine tuning of the objective functions. In a complex system such as the deployment of wildfire UAV, criticality must be considered in both objectives and constraints. For the objectives, linear functions are typically used during the development of the mathematical specification and model, whereas the constraints incorporate both linear and nonlinear elements.

Including non linearity in the constraints is especially important because constraints limit feasible deployment solutions and ensure that at least some solutions are viable in practice. Introducing non linearity too early into the objective functions can render the objectives infeasible, so the development strategy emphasizes coarse tuning through the constraints while reserving fine tuning for the objectives.

The formulation of constraints (coarse tuning) addresses risk calculation, lightning complexity, non linear cost estimation, and aerodynamic considerations such as the maximum rate of climb of the UAV (ROC) and the lift to drag (L/D) ratio. These aerodynamic parameters are closely related to environmental factors associated with wildfires, and their integration within the constraint set provides a realistic foundation for the subsequent fine tuning of the target functions.

2.8 Chapter Conclusions

This mathematical specification tries to capture the deployment of a complex real-world wildfire UAV fleet. Our research study develops this problem construct that includes Multi-Objective Optimization (MOO) with human-in-the-loop (HITL) and includes two stages of optimization. The first stage is focused on more MBS/CBS based. The second stage is designed towards run-time issues and wildfire points/flight paths. The construct of this mathematical model thus serves as a step towards real world implementation and commercialization. We have demonstrated that, by applying principles of system thinking such as *Learning Principle* and *Architecture Principle*, mental models can be transformed from the MBST framework to mathematical specifications.

Thus, we can conclude that a novel mathematical specification for an optimizer machinery that includes CBS fleet coordinator(s), MBS operator(s) and wildfire systems analysts enables human-in-the-loop (HITL) interface by taking input and comparing with optimizer solution. Previously, there was no other mathematical specification in which HITL could provide input to a UAV-based solution for wildfire detection and communication.

2.9 Chapter Summary

Model-based systems thinking (MBST) is exercised throughout this research work where we have taken systems thinking philosophies into our multi-objective optimization problem (MOP). We have collected data from preliminary MBSE, SD, and CFD models and feed those into the final Decision support system (DSS).

Chapter 3

Integrated Systems Architectural Modeling with Architectural Trade Study of a UAV Surface-less Flight Control Systems for Wildfire Detection and Communication utilizing MBSAP

3.1 Preface

This chapter is adapted from a model-based systems engineering paper [3], which was authored by the author of this dissertation. The author's contributions have also appeared in systems-thinking chapters in [42] and are incorporated here. In this chapter, we present our investigation into the integration of a model-based systems engineering methodology with a system architectural trade study, specifically applied to the flight control systems of a locally owned and operated, cost-effective unmanned aerial vehicle (UAV) design. This chapter also addresses the systems design aspects of the UAV prior to the development of the computational fluid dynamics (CFD) model in Chapter 4. Subsequently, the flight control design introduced here is further examined in Chapter 7, where the impact of these novel flight controls on wildfire points (WP) and overall deployment is analyzed, with additional discussion provided in Chapter 8.

3.2 Overview

In this chapter, we report our progress on integrating a model-based system engineering methodology with a system architectural trade study applied to flight control systems of a locally owned and operated, cost effective unmanned aerial vehicles (UAV) design utilizing the concepts of model-based systems architecture processes (MBSAP). The primary objective of the UAV is to monitor wildfires and to gather information and to provide surveillance data for predicting and

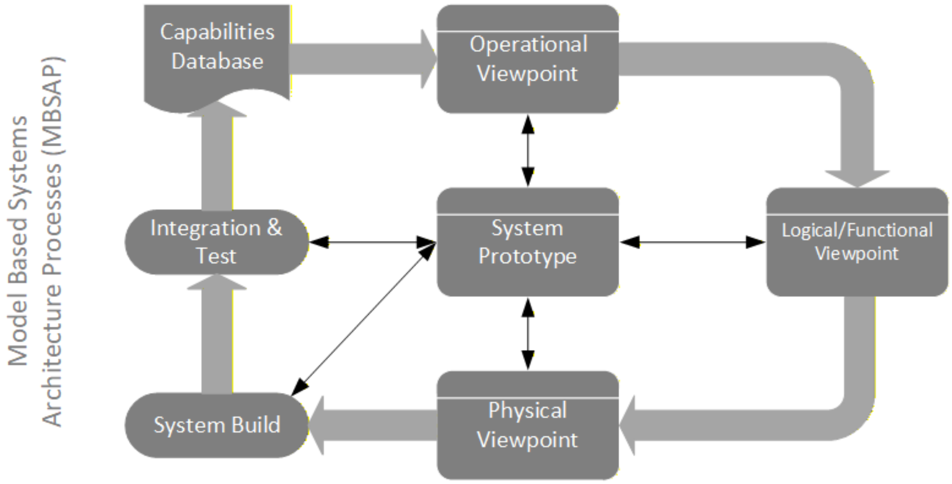


Figure 3.1: Integrating MBSAP Methodology into flight controls Trade Study

Note:

[1] This figure is adapted from Borky's "Effective Model-Based Systems Engineering" [2].

preventing wildfires [1]. We describe our experience with a holistic approach to architect flight controls (the system-of-interest), in a way that is tightly coupled with high-level stakeholder needs and concerns, operational scenarios, (normal, inadvertent, and mis-) use cases, Context System, and enabling systems. Several architectural variants of surface-less flight controls (SFC) were traded. Our systemic approach showed that classical flight controls are feasible for the baseline UAV. It also helped us identify a novel architecture with a potential to drastically improve UAV performance (range, survey time), UAV weight, and specific cost. Our approach has resulted in an architecture that has the potential to significantly reduce the costs of manufacturing as well as operating UAVs, at the same time it drastically improves their performance. This development could mean a wide increase in the availability and improved effectiveness of UAVs in fire detection and prevention.

3.3 Introduction

Our research integrates a flight control systems trade study with model-based systems architecture processes (MBSAP), as exhibited in Figure 3.1 [2]. We have designed an architecture for novel surface-less flight controls (SFC) that replaces traditional flight control systems, which consist of ailerons, rudder, and elevators. We considered three different variations of SFC and compared them against traditional flight control systems to optimize their operation.

The MBSAP process is a specific implementation of the MBSE philosophies, and we have used it to develop a new systemic approach that increases overall performance, as shown in Figure 3.2. With this approach, we identified a SFC architecture that saves a significant amount of weight relative to the classical flight controls enhance the range of the wildfire UAV.

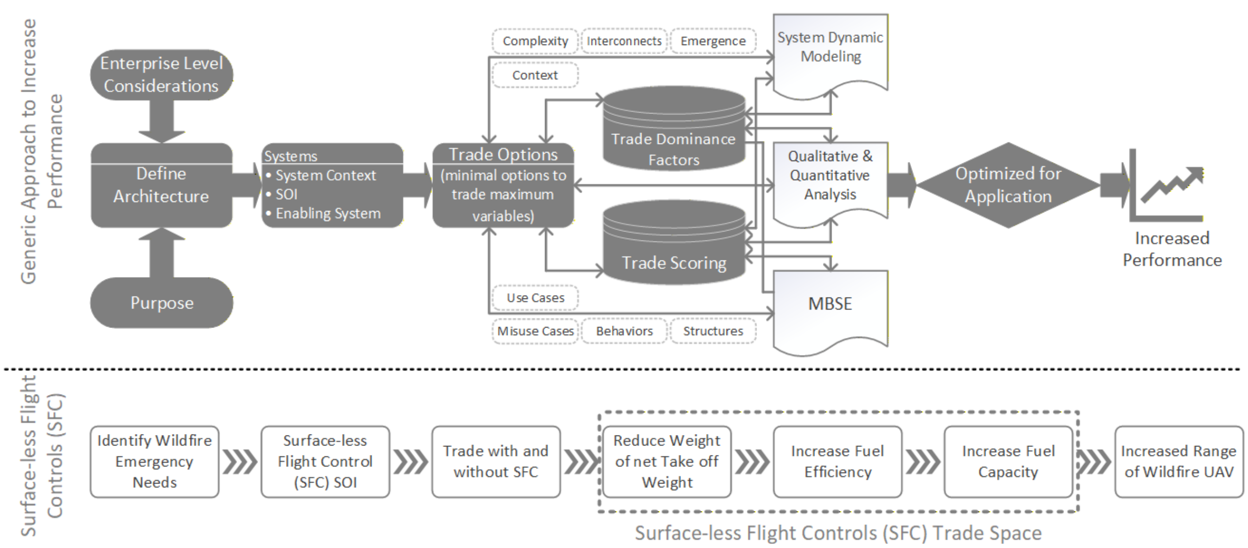


Figure 3.2: Development Method Utilizing the concepts of MBSAP to Increase Performance

The method starts with defining an architecture based on enterprise-level considerations (the UAV and the wildfire mission objectives). Once the architecture has been defined, the System-of-Interest (SOI) must be narrowed down and clarified, and then the trade options must be identified. The goal number of trade options should be limited. In this trade study, the number of options is less than four compared to the number of variables (6) that are traded, as shown in Table 3.1.

Two major criteria for the trade study are “Dominance Factor” and “Scoring.” The dominance factor is critical to increasing the performance of the trade study, so both qualitative and quantitative steps have been taken to determine the dominance factor. Specific tools from MBSE, such as Use cases/Misuse cases, behaviors, and structural diagrams, were also analyzed to examine the dominance factors and scoring system. Also, systems dynamic models (Vensim, for example)

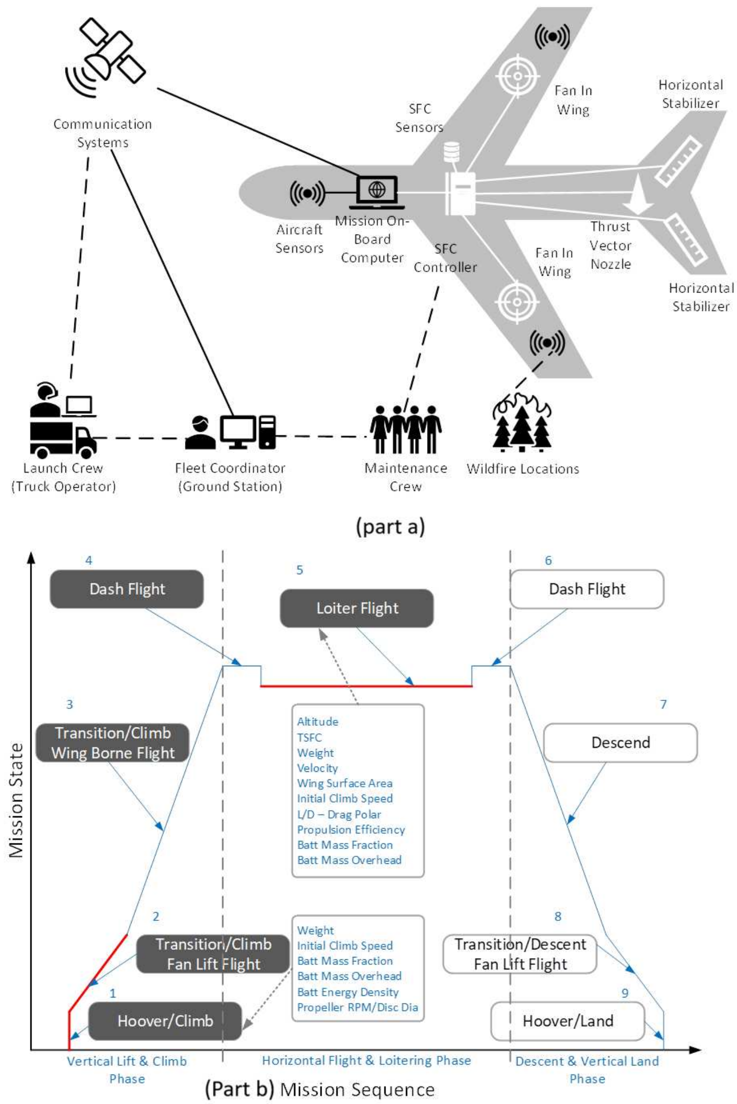


Figure 3.3: Wildfire UAV Flight Mission of the Context System

Note:

[1] The top figure (Part a) demonstrates the SOI to be the SFC system. Elements under trade are part of the SFC system, marked in white icons.

[2] The bottom figure (Part b) shows the profile of the typical flight path for wildfire UAV [1].

were used to further substantiate the performance elements in the system. Essentially, these tools optimize the system for final application in the enterprise level system.

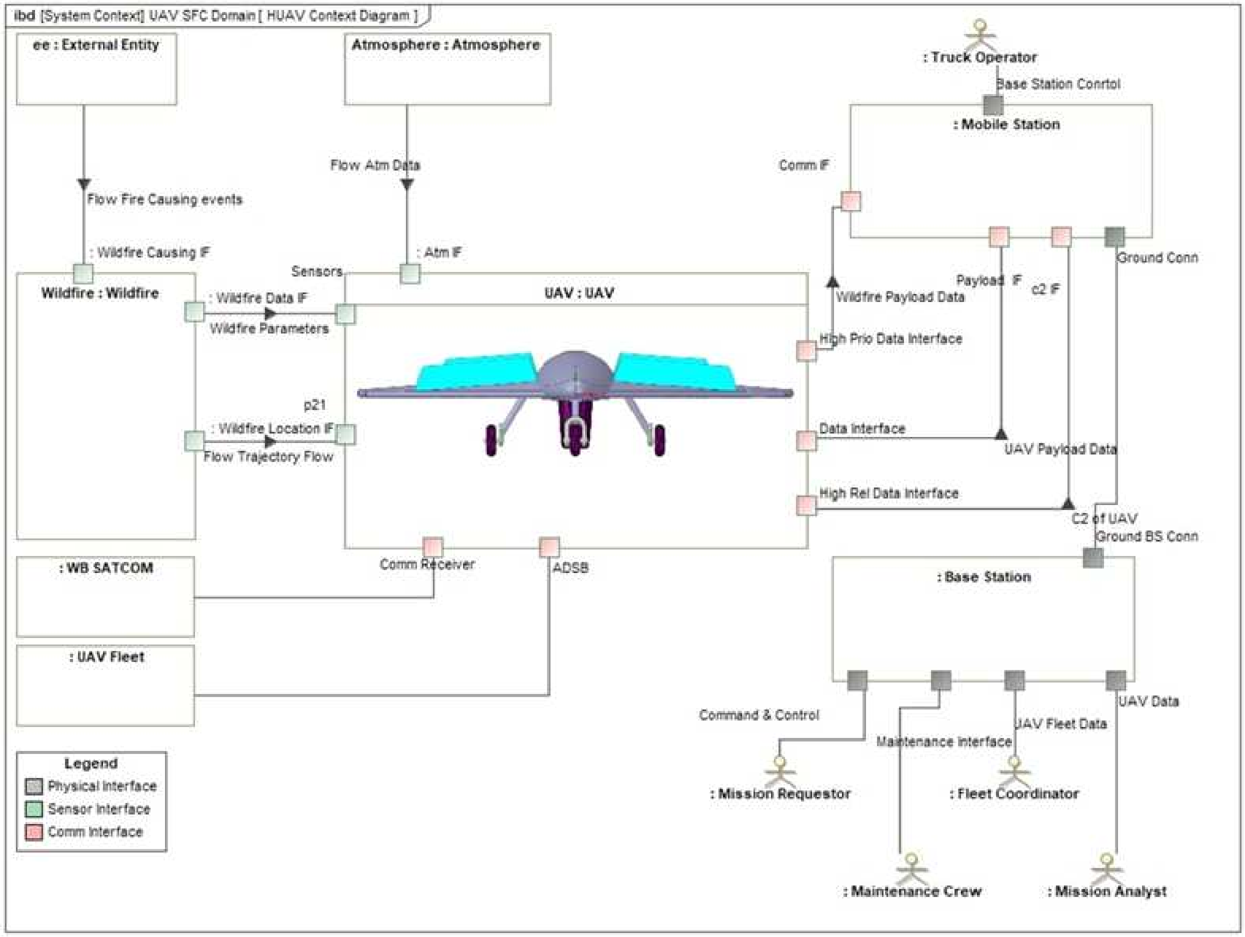


Figure 3.4: System Context Diagram (Cameo)

3.4 Boundaries of the Context, SOI, and Enabling Systems

In general, complex systems come in at least 3 systems: system-of-interest (SOI), system context, and enabling systems [5]. Our research investigates proposed flight control systems from the perspective of the principle of 3-Systems. Figure 3.3 (Part a and Part b) shows the primary elements of the enterprise systems or system of systems (SoS), including participating systems and their domains or subsystems.

3.4.1 SFC System of Interest (SOI)

The system of interest (SOI) includes a) SFC controller (controls logic), b) flight controls actuation systems and c) flight controls relevant sensors (feedback utilized by SFC).

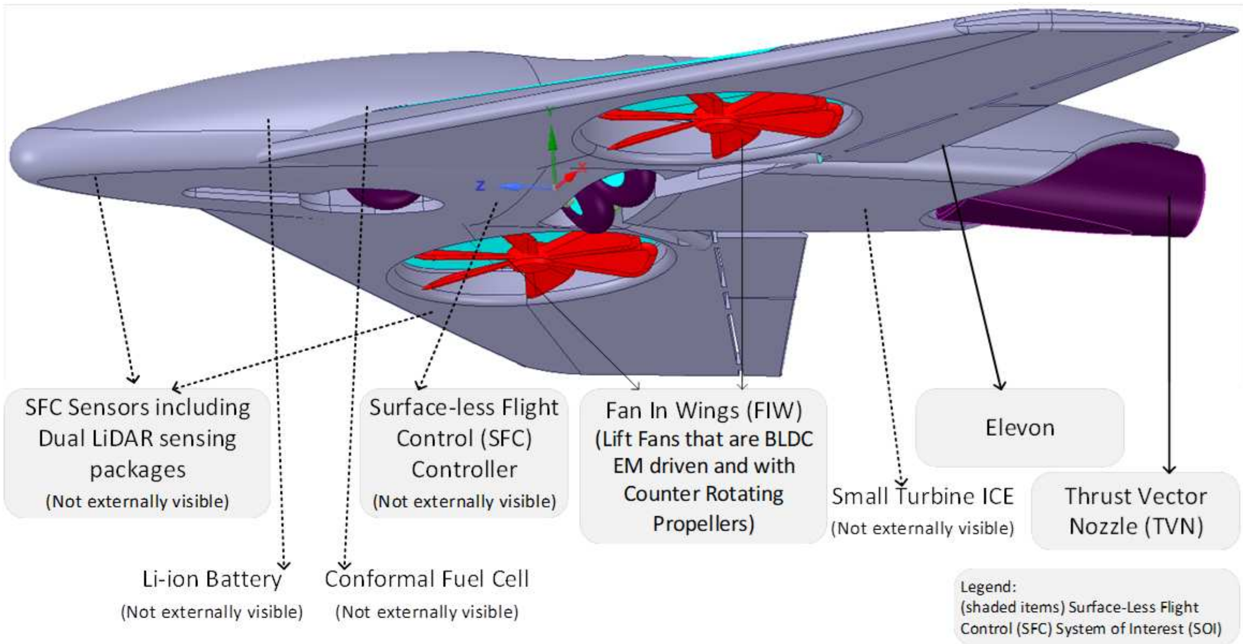


Figure 3.5: External View of SFC SOI at Loiter Configuration of the UAV (3D rendering)

3.4.2 SFC Context System

The context of SOI is the UAV airframe, including mission on-board computer (UAV more electric aircraft (MEA) components interfacing other than SFC) and remaining aircraft sensors that can be used for other sensor fusion activities. Additional system context items are the harsh environmental (gusty), low visibility condition it may fly in, and wildfire environmental conditions. A systems context diagram is depicted in the Figure 3.4 below.

The context diagram demonstrates how the UAV interfaces with interfacing systems such as atmosphere, mobile base station (MBS), UAV fleet, wideband satellite communication (SATCOM) and Wildfire (external entity). The SOI for this paper is the SFC within the wildfire UAV in the Figure 3.5, from known information from Crawford [6].

In the above figure, the surface-less flight controls (SFC) system is the System of Interest (SOI) and is highlighted in shaded text.

3.4.3 SFC Enabling Systems

Several enabling systems support the system-of-interest (SOI), specifically the surface-less flight controls (SFC) of the UAV. These enabling systems facilitate the UAV SFC in achieving its mission objectives. A primary enabling system is the UAV launch system (MBS vehicle logistics), which is operated by the launch crew. The launch crew and truck operator assemble the UAV from three components prior to launch, fuel the UAV, conduct a pre-launch SFC check, establish retrieval coordinates, and subsequently retrieve and reload the UAV following vertical landing. In addition to the launch system, other critical enabling systems include the maintenance system operated by the maintenance crew, the ground station fleet coordination performed by the fleet coordinator, and communication systems. Communication systems enable the fleet coordinator to access the SFC and the UAV, if needed. The navigation Systems (i.e. GPS), satellite imagery [215], and other auxiliary systems that can be useful for the end purpose of the UAV are also considered to be enabling systems.

3.5 Stakeholder Identification, Needs, and Viewpoints

The development process for this surface-less flight controls (SFC) points to the needs of the stakeholder via the architecture refinement and functional/non-functional requirements definition phases. As an example, the fleet coordinator need is to have the capability for stable flight controls of all three axes. Also, the flight should be able to handle gust wind, force fighting, and environmental parameters such as temperature and pressure.

Another key stakeholder is the UAV fleet management system or fleet coordinator, whose requirements include minimal impacts and intervention. No intervention and/or minimal intervention reduce the essential cost of the operation, and thus more resources can be allocated for wildfire monitoring. From an aircraft perspective, fuel efficiency and increased availability of SFC support the specific application of UAV's wildfire detection and mitigation capability.

#	Name	Need/Concerns	SFC Viewpoints
1	Fleet Coordinator	Ground Station Fleet Coordination performed by the Fleet Coordinator. Communication systems is an enabling system that allows Fleet Coordinator to access SFC if needed. Fleet coordination include calculation of fleet waypoint, integration/fusion with satellite and other detecting and firefighting assets.	Operational Viewpoint
2	Launch Crew	Launch crew, the truck operator assembles the 3 major pieces of the UAV pre-launch, fuels the UAV and does a pre-launch check, sets up retrieval coordinate, retrieves and reload the UAV after vertical landing.	Operational Viewpoint
3	Maintenance Crew	Maintenance System operated by the maintenance crew	Operational Viewpoint
4	Mission Crew	"Mission Crew" consists of "Launch Crew" and "Fleet Coordinator".	Operational Viewpoint
5	UAV AI	UAV AI is the logic for the entire flight management system that potentially resides in On Board Computer that interfaces with SFC Controller.	Logical/Functional Viewpoint
6	SFC Controller	Both UAV AI and Launch Crew (Truck Operator) are considered to be able to control SFC as "SFC Controller".	Logical/Functional Viewpoint and Physical Viewpoint
7	Training Personnel	Training Personnel are knowledgeable on the System of Systems and performs training on the SOI.	Operational Viewpoint
8	Fleet Owner	The Fleet owner of the fleet operator are the Neighborhood/Local Community or Local Fire Department)	Operational Viewpoint
9	General Public	General Public or Social Media is a vital but indirect stakeholder. It is important to generate awareness to general public and social media as devasted community and local fire department may be overloaded	Operational Viewpoint

Figure 3.6: System Context Diagram (Cameo)

3.6 Normal, Inadvertent, and Misuse Operational Scenarios

Presented below are MBSAP operational viewpoint scenarios for flight controls analyzed by primary behaviors (use cases, activity diagrams, domain or system context diagrams). The use case diagram and the accidental use or misuse case diagram of the wildfire UAV SFC are captured in Figure 3.7. The SFC detects and prevents incorrect calibration of the flight control actuators.

Both the "UAV AI" and the "Launch Crew" (MBS vehicle operator) can control SFC as “SFC Controller”. “Mission Crew” consists of “Launch Crew” and “Fleet Coordinator”. In the figure above, the green use cases illustrate the novel SFC approach, which adds value by improving performance and, thus, the UAV’s range. The blue use cases are for including or extending the previous cases.

Misuse case diagrams (such as a cybersecurity breach by an intruder) can be analogous to an inadvertent use case (e.g., incorrect calibration during SFC maintenance by SFC Support personnel). Cybersecurity will be discussed later in this chapter.

The bottom-left example in Figure 3.7 illustrates an attack scenario involving fault injection via malicious software. In our research, we validate the security dominance factor using the MBSE approach to the attack scenario and how SFC handles an adverse situation.

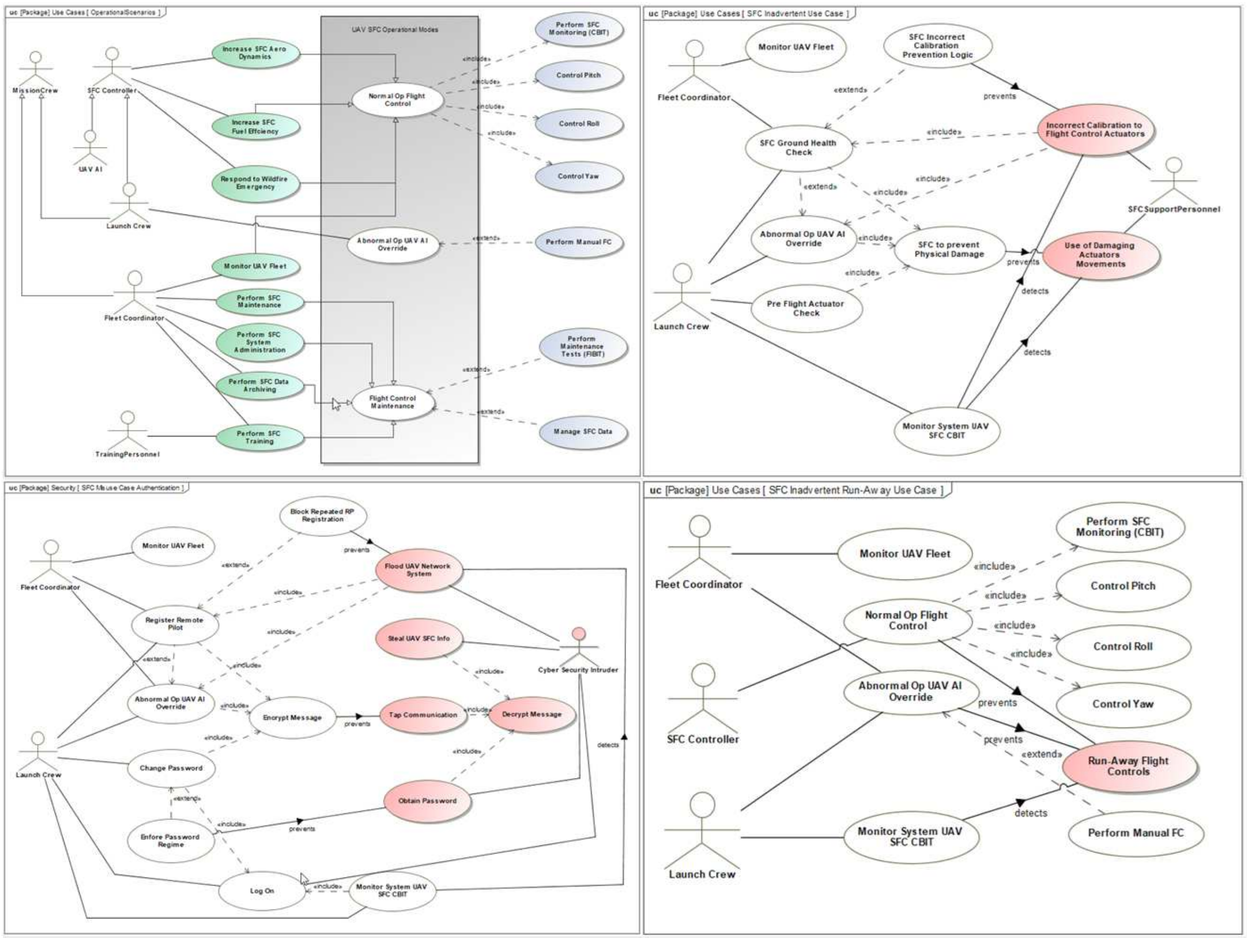


Figure 3.7: SFC Use Case vs. SFC Inadvertent/Misuse Case

3.6.1 Mission Thread Modeled as an Activity Diagram

The enterprise mission thread is modeled as an activity diagram, as shown in Figure 3.8. The aircraft's flight control systems interface with the mission on-board computer.

Domains, subdomains, and actors have been used for this activity diagram, which demonstrates the capability of the SFC for fire confirmation and efficient control loops for flight control systems.

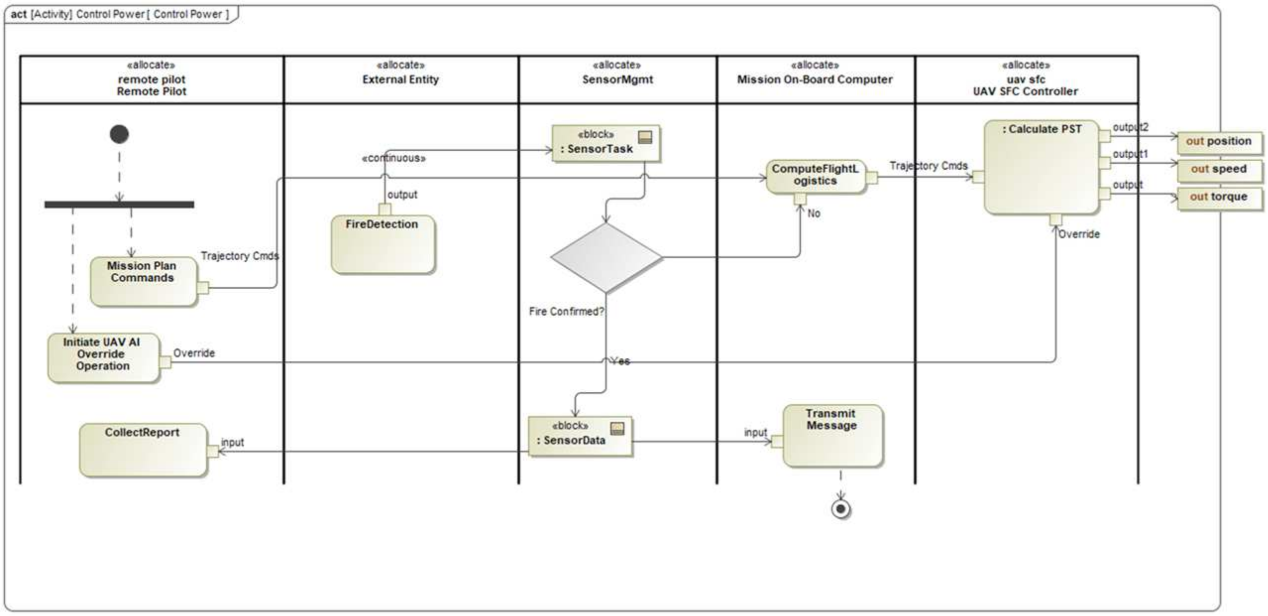


Figure 3.8: Activity Diagram for Fire Confirmation and SFC Power Control

3.7 System of Interest (SoI) Context Diagram for SFC

The controller commands the UAV actuators for each TVN, fan-in-wings (left and right), elevons (left and right). It addresses any use case scenarios as well as inadvertent/misuse case scenarios that are discussed later in this chapter. A comprehensive package of sensors is available for this UAV. Three sensors out of the set are within the scope of SFC development, and those are Flight Controls surface encoder, LiDAR, and camera. SFC will have access to FC surface encoder (which receives feedback from the surfaces), Camera, and LiDAR to validate the commands and FC encoder feedback.

In Figure 3.9, the Actuation Systems block includes actuation systems. Not-shown items include fan-in-wings (FIW), fan doors, thrust vector nozzle (TVN), elevons.

3.8 Logical Viewpoint (LV) Architecture of the SFC

The SFC logical architecture is independent of any physical implementation viewpoint perspective. As per MBSAP, this SFC Logical Viewpoint architecture captures the operational scenarios and stakeholder needs and functional requirements. The SFC accepts an initial mission plan/command

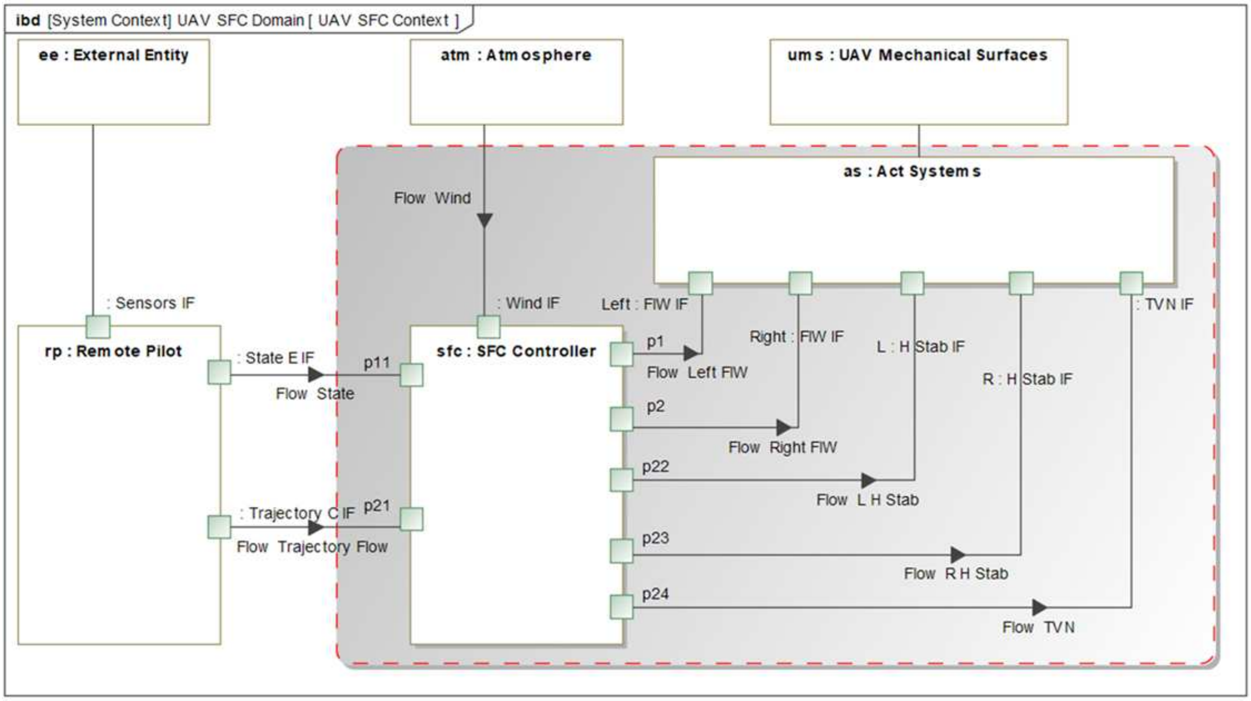


Figure 3.9: Wildfire UAV SFC System Context in MBSAP

and state estimation/trajectory commands as input to the system, as shown in Figure 3.10. The control logics are implemented in a logically separated computer or partitioned computer and perform surface control algorithms that include Position Speed Torque (PST) calculations and command/status generation.

The UAV actuation systems for the flight controls receive the PST, respond to control loops (Torque, Speed and Position loops), and optimize any mechanical movement. The kinematic states and observations are captured through a set of sensors and are used for state estimation. SFC utilizes Flight Controls Surface Encoder, Camera, and dual (LiDAR) inputs for sensor fusion (to be reflected in future research work) and advanced logic controls of the three axes. As per MBSAP, our research also developed a Logical Data Model (LDM)to analyze the maturity and validity of the data.

Utilization of 3-Systems Principle - Thinking in 3-Systems

The mental model is to design an UAV for wildfires to maximize coverage area and risk-reduction while minimizing production and manufacturing costs and time, making it accessible to local wildfire fighting organizations. The 3-Systems Principle, "*Systems come in (at least)*

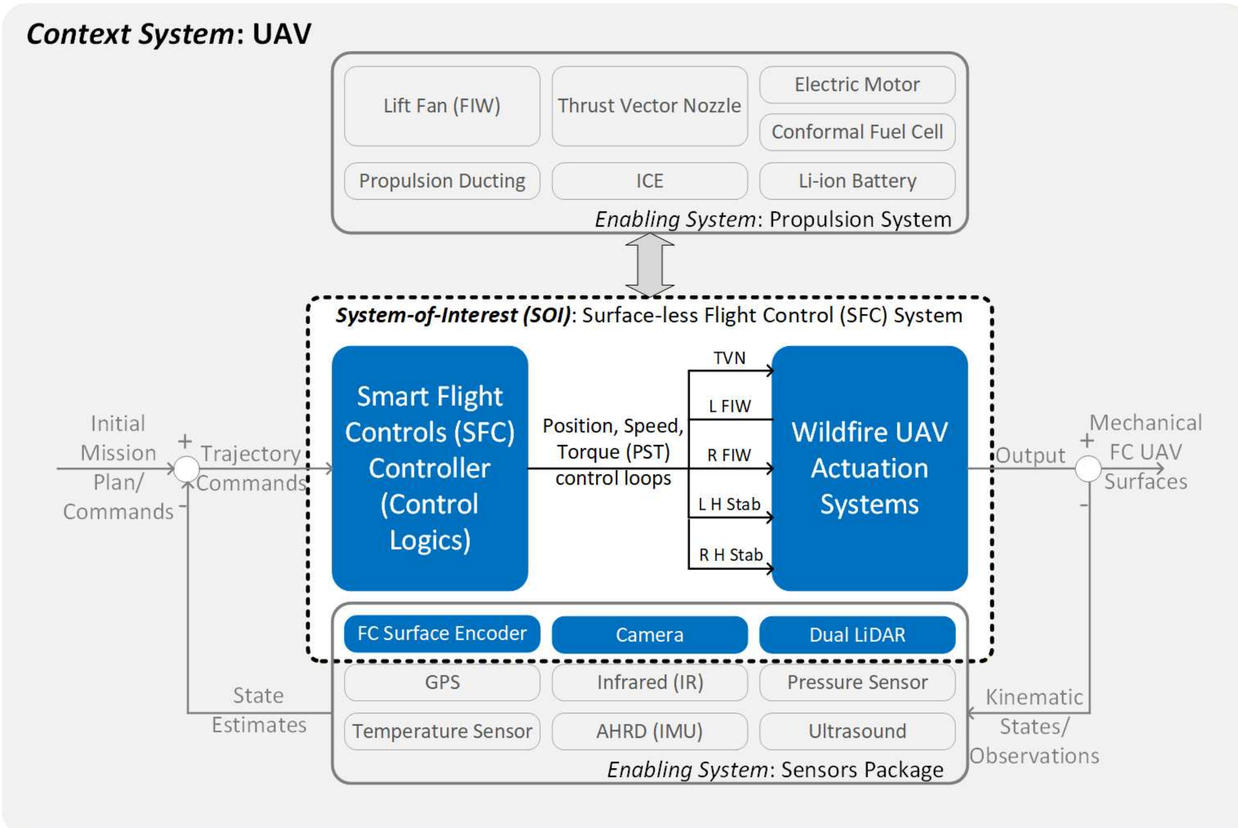


Figure 3.10: Wildfire UAV SFC System Context in MBSAP

3s: context systems, systems of interest (SOI), and enabling systems" [42]. Through a series of systemic steps of the MBST framework, we have discovered a novel and efficient architecture, customizing the UAV airfoil design and flight controls with FIW to address the specific needs of wildfire detection and communication shown in Figure 3.10 identifying three types of systems: SFC system-of-interest (SOI), enabling systems (such as propulsion system, sensor package), and entire context system (the UAV in this case). This architecture can significantly reduce the costs of manufacturing and operating UAVs while drastically improving the performance of wildfire detection and monitoring. Our UAV design includes a game-changing surface-less flight control (SFC) system, which radically changes the architecture of the existing UAV and redefines the overall UAV operation to focus on wildfire detection [6]. By omitting traditional and general-purpose flight control aspects, we enhance the aerodynamic capability of the UAV and reduce its weight [3]. Using model-based systems engineering (MBSE) as a rigorous tool (Cameo) allows for systemic modeling of complex architecture such a as a flight control system, UAV subsystems, and enabling systems. By applying systems principles (3-systems principle in particular), MBSE helps to improve system architecture. The interaction between these tools and the principles of the systems ensures that we develop an effective flight control system, which leads to better performance and enhances design at various stages of development.

3.9 Physical Viewpoint (PV) Architecture of the SFC

As per MBSAP, the Physical Viewpoint (PV) Architecture is constructed to accommodate the Logical Viewpoint architecture and operational scenarios. The physical viewpoint architecture continues to prioritize the purpose of the mission of increasing the range of the UAV.

3.9.1 SFC Physical Architecture Evaluation

A Model Based Systems Engineering approach (MBSE) has been utilized to architect the SFC for the Wildfire UAV.

SFC Domain Diagram with Hierarchy

The top-level partitioning of the surface-less flight controls (SFC) is done in an MBSE tool, Cameo in this case, to establish the hierarchy of the architecture. The SFC is decomposed into domains or a subsystem hierarchy, captured in Figure 3.11 in a block definition diagram (BDD). Figure 3.11 shows how the UAV SFC is categorized into five main domains or subsystems. Further details can be added in a domain specification containing information for owner, description/general, definitions, operations, data, interfaces, and allocated requirements. Wind impacts the flight control surfaces significantly and is considered as an external disturbance element.

3.9.2 Physical Viewpoint PV Sequence Diagram of a Subsystem to SFC

Development included analysis of the operational challenges of the thrust vector nozzle (TVN), a subsystem of SFC. A sequence diagram based on MBSAP concepts was used for the timing analysis, flow of command, and status. TVN contains a controller, thrust vector control (TVC),

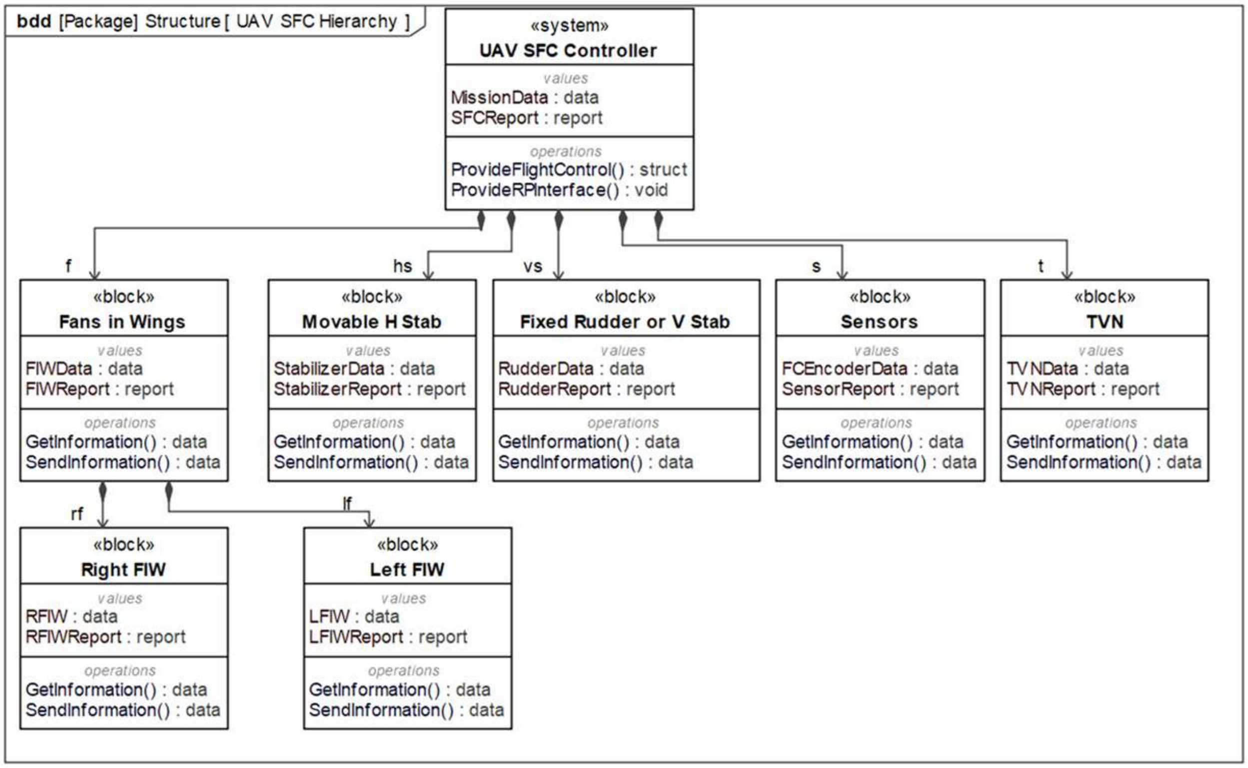


Figure 3.11: UAV SFC Domain Diagram with Hierarchy (BDD)

which is physically allocated inside the SFC controller. TVN consists of the four major modules: TVC modules (two modules, A and B), motor gearbox, linear variable differential transformer (LVDT) sensor, and Thrust Vector Launcher (TVL) Multi-directional nozzle. TVN controller (SFC controller), shown in Figure 3.12, is partitioned from the onboard computer (outside the scope of SFC), which performs other aircraft operational tasks. Physically these controllers all can be housed in the same box or line replaceable unit (LRU). Onboard computer will interface with multiple logical controllers such as (TVN) controller, FIW controller, and elevon controller. Figure 3.12 also shows how the onboard computer communicates with TVN controller (SFC controller) within 0.1ms to 1ms. Also, the entire TVN motor control command and feedback process should be between 1ms to 10ms.

Onboard computer (or SFC controller) processes TVN controller between 0.1ms to 1ms (time constraint). TVN controller expects an LVDT sensor feedback within 1ms to 10ms (duration constraint). These timing requirements are needed to have a scheduler that runs all the tasks for the

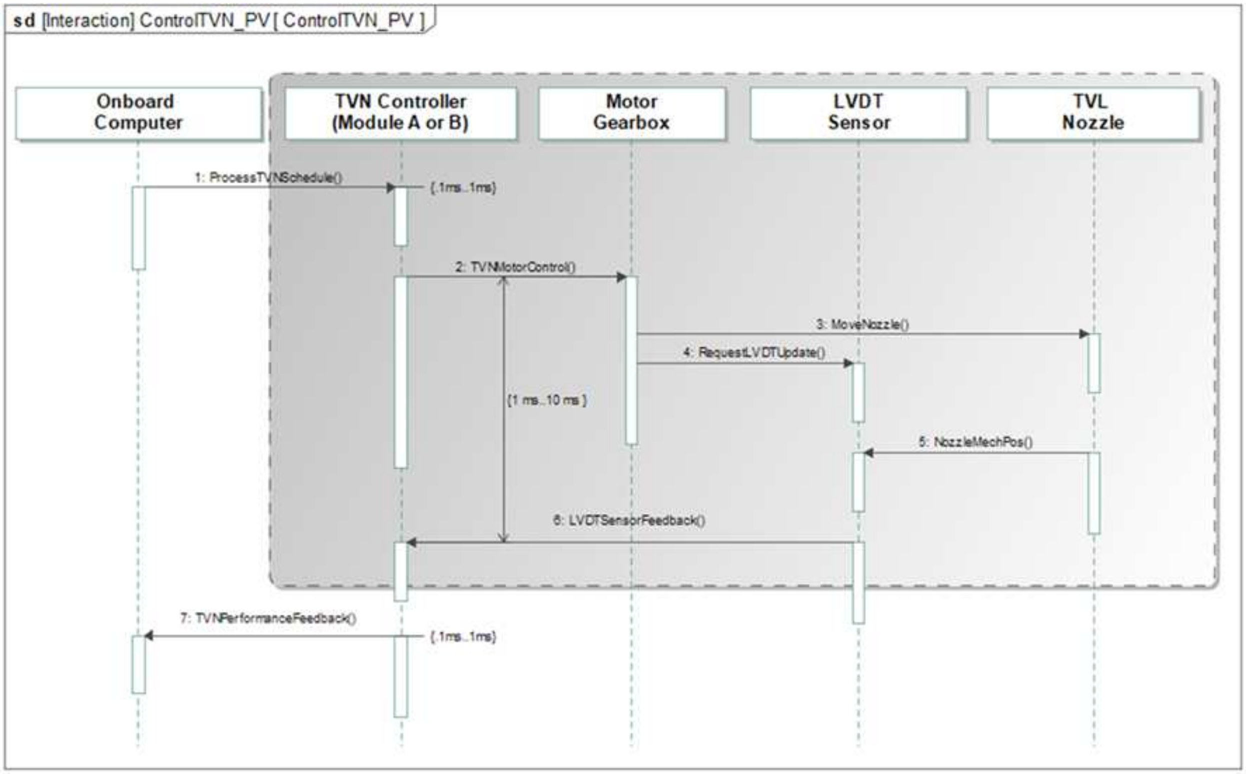


Figure 3.12: SFC TVN Physical Viewpoint Sequence Diagram

actuation systems. Also, timing wise this system is predictive. If a message is not received on time, it can trigger a potential issue with the system.

3.9.3 Comparison among Subsystems Solutions and Architectures

A total of four different flight control architecture options are considered for the trade study. The critical items for the trade study are weight, technical feasibility, performance, cost, and operational parameters. The breakdown of these parameters and the scoring system is within Table 7, with more trade details. An extensive qualitative trade has been conducted for flight control architectures, trading almost half the number of options as there are major performance trade variables. Table 3.1 shows a comparison among four architecture options based on seven major parameters. The first option is the baseline option, traditional flight controls without SFC, to be compared with the three other novel architectures. Traditional Flight controls consist of a set of movable ailerons and a set of movable elevons. This approach to flight control includes traditional elevons for roll and pitch axis maneuvering. Also, this flight control approach includes split rudder for yaw-axis maneuvering. All four of these options require autonomous flight control algorithms and require an elevator or fixed elevon.

Table 3.1: Physical Architectural Variants of the SOI

Flight Controls Options	**Large FIW**	**Fan Doors**	**Single-TVN**	**Multi-TVN**	**Aileron**	**Rudder**	**Elevator /Elevon**
1) Traditional Flight Controls with ailerons, rudder & elevators					x	x	x
2) Flight Control with two large Lift Fans with doors & single axis TVN	x	x	x			x	x
3) Flight Control with two large Lift Fans without doors and (single/multi) axis TVN	x			x		x	x
4) Flight Control with four large Lift Fans without fan doors and No TVN	x						

The second option for flight control includes an SFC controller, two large lift fans/fan-in-wings (FIW), and a single axis thrust vector nozzle (TVN). This approach to flight control includes two large lift fans on the wings for primary means of lift, and a TVN powered by the Internal Combustion Engine (ICE). The third option includes the SFC controller, and two large lift fans / FIW without doors. Additionally, this option has a TVN for multi-directional movement, compared to the one-directional movement included in the second option. This approach to flight control includes two large lift fans on the wings for lift and multi-directional aiding available for TVN. The multi-directional TVN provides additional stability compared to single directional TVN. No doors are available on the FIW during horizonal motion/loitering of the aircraft. Fans may be operational to create enhanced aerodynamics of the wing.

The fourth and final option is a quadcopter like option with four large fans for FIW. In this architecture we evaluate a flight control system with four lift fans with equal torque capability. Each pair of diagonal lift fans moves in the same direction (front left and back right clockwise and front right and back left counterclockwise). This option replaces TVN and effectively uses quad copter concepts for the flight dynamics. A longer tail horizontal surface is needed to accommodate back lift fans.

3.10 SFC Measure of Effectiveness (MOE)

The essential measure of effectiveness (MOE) for SFC is the increased range for the UAV, at a reasonable cost, to provide more coverage for wildfire monitoring purposes.

3.10.1 Flight Control Trade Studies Methodologies

A comprehensive trade study has been done with and without SFC as shown in Table 2 below. The overall score for SFC with the FIW option (Option 3) is the highest, while the traditional flight control (TFC) option (Option 1) score is lowest, showing SFC facilitates about a 17% improvement. The dominance factor (DF) in this trade matrix derives the quality of the trade for the specific application of an UAV. Our research covers the determination of the Dominance Factor from both qualitative and quantitative perspectives.

Dominance Factor - “Dominance Factor” refers to how important the item is on a scale from 1 to 5. The most dominant item is rated 5 and least dominant item is rated 1. This dominance factor can be evaluated using a causal loop diagram (CLD) and the rating can be validated. The value in the dominance factor has been substantiated either qualitatively or quantitively when possible.

Option Score - This is to determine if the trade option is favorable or not. The most favorable item is rated 5 and least favorable item is rated 1.

Subtotal Option Score - Subtotal score for each of the option items. This score is calculated by multiplying “Dominance Factor” with “Option Score.”

Total Score - Total score is the final score and is influenced by both "Dominance Factor" and "Subtotal" score.

Table 3.2: Physical Architectural Variants of the SOI

Class of Parameters	Parameters to Trade	Dominance Factor (DF) (1 to 5)	OPTION-1 Traditional Flight Control (TFC)	OPTION-2 SFC with 2 FIWs with Doors	OPTION-3 SFC with 2 FIWs without Doors	OPTION-4 4 Lift Fans & No TVN	OPTION-1 Traditional Flight Control (TFC) SUBTOTAL	OPTION-2 SFC with 2 FIWs) SUBTOTAL	OPTION-3 SFC with 2 FIWs without Doors SUBTOTAL	OPTION-4 4 Lift Fans & No TVN SUBTOTAL
Weight	Take off Weight	5	2	4	5	4	10	20	25	12
	Battery Weight	1	3	2	2	2	3	2	2	6
	Fuel Weight	1	3	2	2	2	3	2	2	6
Technical Feasibility	Signal Architecture Complexity	2	4	2	2	3	8	4	4	9
	Power Architecture Complexity	2	3	3	4	3	6	6	8	9
	Complexity of Control Laws	1	4	2	1	3	4	2	1	9
	Aircraft Sizing	3	3	3	3	3	9	9	9	9
Performance	Horizontal Speed	3	3	4	4	1	9	12	12	3
	Verticle Speed	2	3	4	4	3	6	8	8	9
	L/D (Drag/Aero Dynamic)	2	3	4	4	3	6	8	8	9
	Battery ED/Energy Efficiency	1	3	4	4	3	3	4	4	9
	Flight Range	5	3	5	4	4	15	25	20	12
Cost	Initial Cost	4	4	2	3	3	16	8	12	9
	Final Unit Cost	4	3	3	4	3	12	12	16	9
	Per Square Mile Cost	4	3	4	4	3	12	16	16	9
Operational Parameters	Maintainability	3	3	3	3	3	9	9	9	9
	Reliability (MTBF)	3	4	2	3	3	12	6	9	9
	Producibility	3	3	3	3	3	9	9	9	9
	Security/Cybersecurity	5	3	4	4	4	15	20	20	12
	Harsh Environmental Tolerance	4	3	4	4	4	12	16	16	12
	TOTAL SCORE						179	198	210	180

The trade study indicates that SFC options certainly benefit the architecture of the Wildfire UAV.

3.11 Results and Observations from SFC Architecture Design Process

We observed a very interesting and possibly serendipitous outcome when we integrated systems architecture modeling with architectural trade-study for flight controls of the UAV. From previous work by Crawford, we already knew the most important factors that impacted Range (km) and specific cost ($\$/(kg\ payload \times Range)$), for the configuration of a hybrid electric/Gas turbine propelled UAV which matched option 2 in our architectural trade study (Table 3.1), [6]. The known information from Crawford is summarized in Figure 3.14 [6], [173].

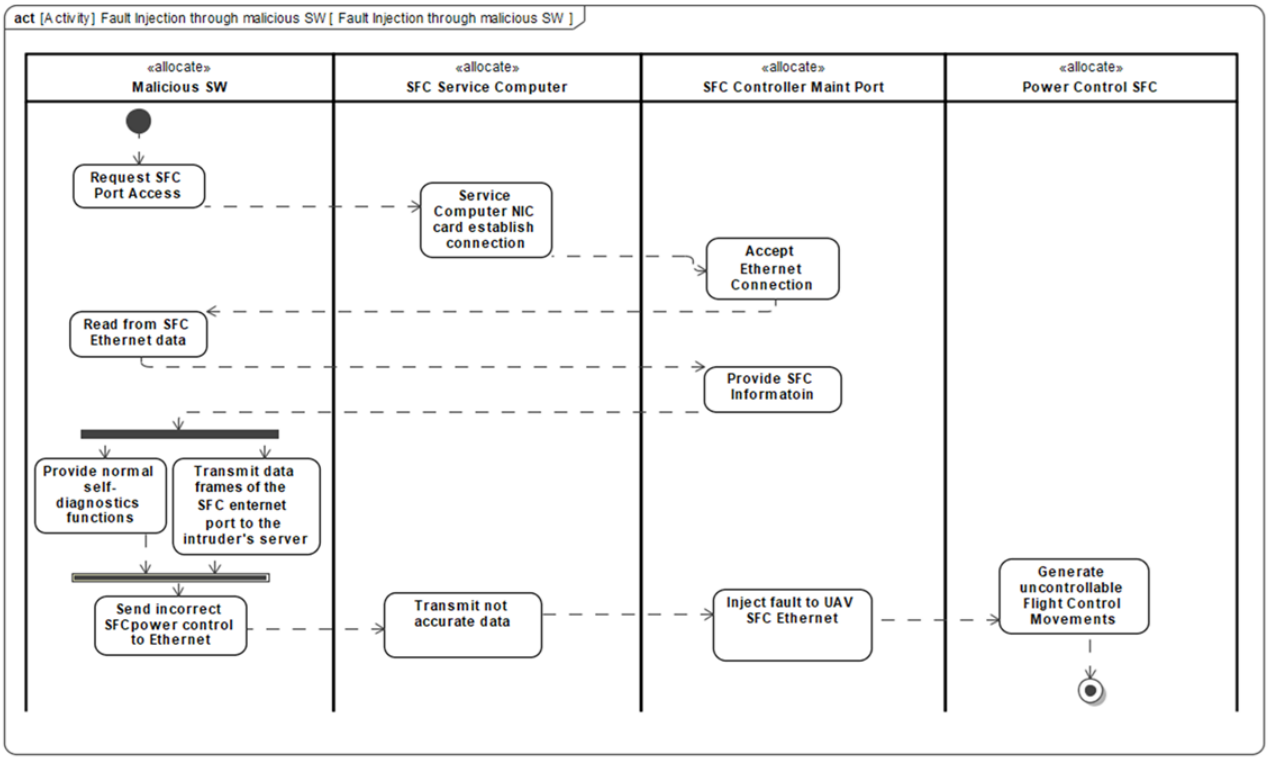
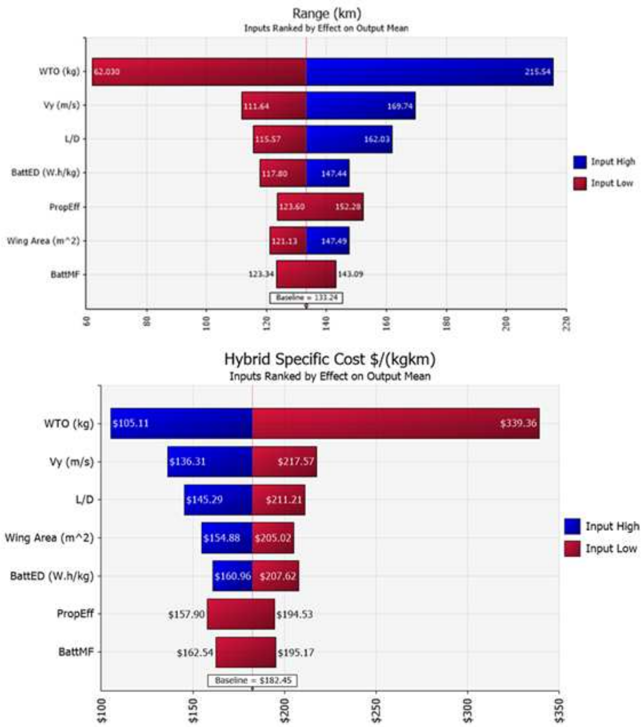


Figure 3.13: SFC Cybersecurity Attack Scenario (malicious SW)

The sensitivity analysis ranks the parameters by their importance in the range, which are maximum takeoff weight (WTO), cruise velocity (Vy), lift-to-drag ratio (L/D), battery energy density (BattED), propeller efficiency (PropEff), wing area, and battery mass fraction (BattMF), shown in the top left of 3.14. The sensitivity analysis ranks the parameters by their importance on the hybrid specific cost, which are maximum takeoff weight (WTO), cruise velocity (Vy), lift-to-drag ratio (L/D), wing area, battery energy density (BattED), propeller efficiency (PropEff), and battery mass fraction (BattMF), shown in the bottom left of 3.14.

This figure represents information about the system context (i.e., airframe sizing, performance, and weight allocations) that flowed down to our system of interest (flight control system). Figure 3.14 shows that if there is a way to reduce weight and vertical take-off speed, and to modify the lift-to-drag ratio as needed, we can potentially double the range, reduce survey time, and halve the specific cost of the UAV. A very simplistic explanation is to look at the weight breakdown in Figure 3.14. The fuel mass is approximately 7 kg, giving a range of 133 km with classical flight



Total Weight (kg)	46.64
Fuselage Mass (kg)	2.17
Wings Mass (kg)	3.86
Empenage Mass (kg)	0.342
Landing Gear (kg)	4.77
Airframe Mass (kg)	**11.14**
Fuel Mass (kg)	7.08
Battery (kg)	1.87
Storage Total	**8.96**
Gasturb Mass (kg)	2.29
Lift EM (kg)	1.44
Lift Props (kg)	0.19
Ducting (kg)	4.00
Propulsion Mass (kg)	**7.92**
Flight Controls Mass (l	**12.62**
Payload Mass (kg)	**6.00**

Figure 3.14: Ranked Sensitivities of Range, Specific Cost, and Weight breakdown

Note:

[1] The sensitivity analysis ranks the parameters by their importance on range on top left.

[2] The sensitivity analysis ranks the parameters by their importance on bottom left).

controls using the aileron, rudder and elevator. The mass of the flight control system is 12.6 kg, of which the majority is the mass of the mechanical fixtures of the aileron, rudder, and elevator control surface and their actuators. The removal of the actuators and associated fixtures would easily enable doubling of fuel while reducing the count of parts and the cost.

In a classical approach to systems architecting, where SOI optimizations occur in isolation from the context, we would work under the requirement that the flight control system mass not exceed 12.6 kg while delivering the required roll, pitch, and yaw rates for the specified classical flight control architecture. However, since the process of architecting the flight controls addressed stakeholder concerns, mission, operational scenarios, and context diagrams in MBSAP, an innovative flight control system architecture emerged, which was option 3 in the trade study (Table 3.1).

Specifically, this solution dropped the lift fan doors and all classical flight control actuators and fixtures, controlling pitch, yaw, and roll by differential control of the lift fans, together with the thrust vectoring nozzle of the gas turbine. It uses the lift fans in forward flight to modify the (L/D) ratio of the FIW, thereby optimizing the wing area and mass and potentially reducing them. In this way, we shed the weight and cost of fan door, actuators, control surfaces, and mechanical fixtures. Hence, the lift fans are no longer a purely vertical take-off and landing means; they are now also a key enabler for L/D optimization in forward flight, in addition to being an element of flight controls.

Given that the Wildfire UAV will fly autonomously in very harsh gusty conditions, we still need to verify that this innovative approach to flight control still meets all stability, performance, reliability, and forward flight control electric power requirements, so that the UAV battery, for example, still holds enough charge for a vertical landing at the end of the flight mission. Further research can be conducted for future commercialization.

The main systems thinking take-away of this chapter is that the inter-connectivity of components of the SFC is having an emerging impact at the context system level [9], [19], [121]. However, we believe that integrating the trade study with the systems architecting process was the key enabler for the serendipitous identification of a drastically improved architecture for the system of interest. Without it, we would likely have focused solely on meeting the stated requirements for classical flight controls, as is often the case elsewhere, and would have been unlikely to leverage the system context's existing architecture.

The next section summarizes some FIW aerodynamic results that are not 100% applicable to our precise UAV airframe design. However, the section is included because the results are encouraging, showing a significant ability to control the lift-to-drag ratio of the wing by adjusting the airflow through the fan in forward flight.

3.11.1 Performance Consideration: L/D for FIW (No Doors vs Doors)

Lift-to-Drag (L/D) ratio is a critical parameter to be traded in the trade matrix. We evaluate if FIW architecture should or should not include doors. In our early analysis we investigated the impact between the door being closed for horizontal flight and the no door op-tion. The no door option also has two possible operating conditions: a) Fans are not operational with no door and b) Fans are operational with no door. The research paper, "Aerodynamic In-vestigations on a Generic FIW Configuration" [4] by Thouault, Gologan, Adams focus-es on aerodynamics of FIW for lift and drag.

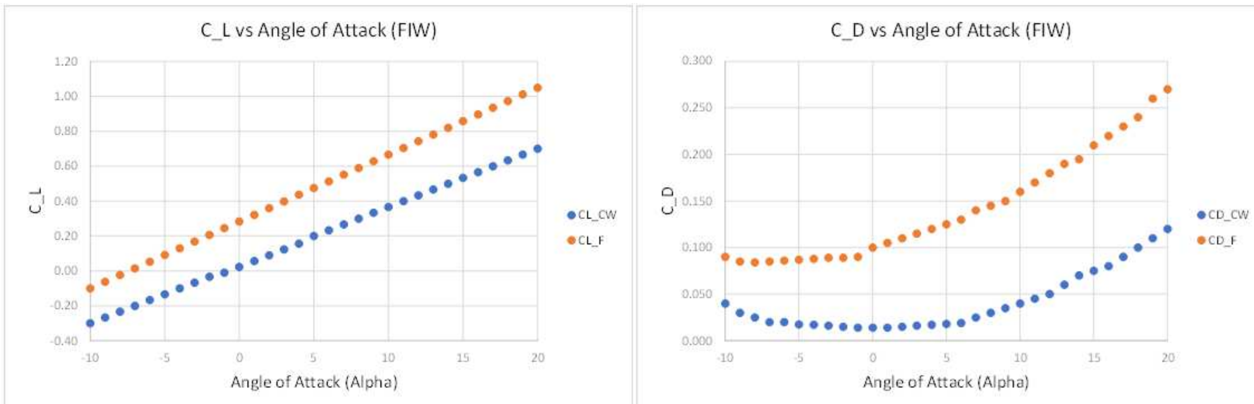


Figure 3.15: Impacts of Open FIW and Closed FIW/No FIW

Notes:

[1] An L/D have been calculated from "Aerodynamic Investigations on a Generic Fan-in-Wing Configuration" [4] and applied to Wildfire UAV calculation [1].

For a low lift scenario, open fan in wing has some advantages. An L/D between 10 and 20 may be desirable for this size of aircraft for this application. Initial results show better aerodynamics with the door closed, if the fan is not operational for the no-door option. We compare L/D for FIW with closed doors and FIW without doors to reduce weight of the overall aircraft. The researchers demonstrate that closed FIW has better aerodynamics. Future work will include more detailed analysis of when the door is open or not available, and performance of the FIW with respect L/D if the fan is operating at a certain speed at typical operational angle of attack.

3.11.2 Anticipated Issues and Potential Unknowns

Approach to discovery of Unknowns and Unknown Unknowns of the trade parameters

The approach to the discovery requires a detailed feasibility analysis of the surface-less UAV flight control system (including control algorithm design, airframe dynamics, and wing aerodynamic considerations) for energy efficient light weight control of pitch, yaw and roll. If we can reduce component weights of the UAV, then the size of the battery and/or the amount of fuel carried can be increased. One major feasibility consideration is, for example, the level of required power from the fans incorporated in the wing in forward flight without fan doors, such that the L/D breaks even with the closed fan doors in the classical flight control architecture.

If surface-less flight control is still promising after detailed feasibility analysis, then it is important to identify any associated unintended consequences or adverse emergent behavior resulting from the interaction of SFC with other major systems in the context system and enabling systems.

Unknown Unknowns

Wildfire occurrences often coincide with high gusty winds, so flying through rough weather (with a prototype) may be the best way to identify the unknown unknowns. The reason is that very little is currently known about the aerodynamic impact of incorporating large fans inside a wing that experiences a large range of positive and negative angles of attack. Several battery characteristics are also considered "unknown" currently, including discharge rate, energy density, and battery mass overhead. Slow discharge will not fit the application, as during takeoff and landing battery is assumed to be used. An extremely fast discharge may negatively impact the total energy supply.

3.11.3 Path to Reducing Risks of Causing Wildfire

Path for Reducing Risks

Quantification of Risk and Mitigation efforts enables SFC to achieve the safety margin that is required. The SFC implementation of the flight control for UAV takes the risks into consideration and makes potential mitigation efforts. Inadvertent Use Case / Misuse case identifies the risks and assists in developing mitigation efforts. The risk of the UAV SFC is the function of Threat to the SFC and Vulnerability of the SFC. This can be identified using the equation 3.1 [2]:

$$SFC_{Risk_n} = f(SFC_{Threat_n}, SFC_{Vulnerability_n}) \tag{3.1}$$

where n[th] risk for SFC can be quantified from n[th] threat relevant to n[th] vulnerability. This vulnerability can be either from system failure due to SFC or cybersecurity breach due to SFC.

SFC System Failure

The reliability of the system shall be sufficient for safe operation of the aircraft, ensuring UAV does not become part of the problem due to malfunction or failure of the SFC. Failure conditions, in addition to inadvertent conditions, are identified in the use cases covered in 3.7. The goal of the SFC is to reduce UAV vulnerability utilizing MBSAP, by including capabilities like detecting when an incorrect calibration factor is introduced.

SFC Cybersecurity

The misuse case (such as cybersecurity breach by intruder) can be analogous to the inadvertent use case (incorrect calibration during SFC maintenance by SFC Support personnel). The details of cybersecurity are discussed Section 8. The SFC cybersecurity vulnerability utilizing MBSAP by having capability like detection intruder activities mapped in activity diagram Figure 3.13. The SFC single loss expectancy can be calculated using equation 3.2:

$$SFCLossExpectance = SFCAssetValue \times SFCExposureFactor \tag{3.2}$$

The SFC asset value can be determined using this equation, based on a detailed analysis of the values employed in cost calculations for this research study. The SFC is intended to reduce the weight and cost factors through the use of MBSAP.

3.12 Chapter Conclusions

In this chapter we showed how to integrate an Architectural Trade Study into a Model-Based Systems Architecting Processes (MBSAP) for the real-world application of wildfire detection using a fleet of locally owned and operated, cost effective hybrid electric/gas turbine-propelled UAVs. Our MBSAP included cases of inadvertent misuse and cybersecurity misuse to ensure the robustness of the architecture of the system of interest. We also showed how this approach uncovered a novel architecture for the system of interest, namely the surface-less flight controls (SFC) system. This flight control architecture trade study drops all classical flight control surfaces, actuators, and mechanical linkages to reduce weight and cost, while recognizing the potential of lift systems to also serve flight controls: FIW and thrust vectoring nozzle (TVN). We have demonstrated that, by applying principles of system thinking such as *3-systems Principle*, mental models can be transformed from mission goals to effective MBSE models. Classical flight control does meet the requirements and is feasible for Wildfire detection. However, the novel architecture developed during our integrated model-based systems engineering (MBSE) approach appears very promising, as it can halve the specific cost of the UAV. This is very intriguing, as classical flight controls are normally not the go-to system for factors improvement in aircraft performance (cost, time, risk-reduction capability, range/area coverage). We therefore listed anticipated issues, potential unknowns, and risks associated with the surface-less architecture that we will analyze in depth going forward.

3.13 Chapter Summary

The objective of this section of the MBSE research is to develop aspects of UAV design that address research question 2 (RQ2) and research question 3 (RQ3) as discussed in Chapter 7 and Chapter 8. This SFC design enhances the understanding of flight control design, enabling the bounding of flight control parameters within the decision support systems (DSS) optimization framework for UAV design and wildfire UAV fleet deployment. The architecture identified through trade study and MBSE implementation can be incorporated into subsequent optimization analyses that examine the trade space between UAV fleet deployment and UAV design. Chapter 4 characterizes the aerodynamics and control of the fan-in-wing (FIW) and vectored thrust, aiming to identify strategies that reduce cost, improve energy efficiency, decrease weight, and increase range.

Chapter 4

Systemic Architectural Optimization utilizing CFD Analysis for Flight Controls with Fan-In-Wings (FIW) for Wildfire UAVs VTOL

4.1 Preface

This chapter is derived largely from a computational fluid dynamics (CFD) paper [173], which was mainly authored by the author of this dissertation. The author's contribution has also been published in systems thinking book [42] and several paragraphs have been adapted for this chapter.

4.2 Overview

Wildfire has become a global concern that has grown with every new incident worldwide in recent years, with one of the most devastating occurrences in Hawaii on August 4, 2023. Numerous strategies are continuously being evaluated for wildfire detection and communication. However, one of the most effective methods is emerging to be the use of high-endurance hybrid electric/ interior combustion engine (ICE) propelled unmanned aerial vehicles (UAVs) equipped with vertical takeoff and landing (VTOL) capabilities, as detailed in our earlier publications for this research project. In this study, we utilize a systematic and holistic approach, deploying systems thinking principles to optimize the fan-in-wings (FIW) architecture using computational fluid dynamics (CFD).We have devised a three-phase methodology: starting with the preliminary concept of the architecture for flight controls, we continue to refine the airframe, as well as the FIW feature. Finally, we formulate the next-generation architecture for the specialized UAV for the wildfire fleet. In the previous study, we discovered that integrating the functions of flight controls, lift fans, and swivel nozzle improved the specific cost ($/kg x km) metric of the UAV because the need for classical yaw, roll, and pitch control surfaces was eliminated entirely. The feasibility of this concept required a system trade study of various airframe/flight control architectures incorporating a large FIW [17], [27], [28], for which minimal applicable aerodynamic data is available in the literature. From the CFD data analysis it is evident that, when aligned with the operational mission objective of wildfire applications, we can achieve an adequate lift-to-drag ratio (L/D), instrumental for the VTOL capabilities of the UAV. By introducing a gap wing concept, we not only retained the requisite lift-to-drag (L/D) ratio but also achieved a reduction in the overall weight of the UAV. This optimization of the systemic architecture efficiently benefits the ultimate goal of wildfire detection and communication given the constraints of operational and environmental parameters.

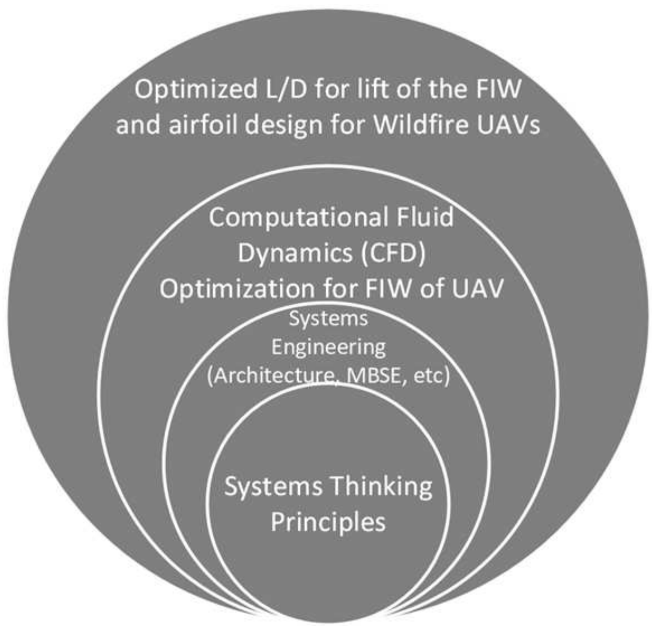


Figure 4.1: Systems Thinking Philosophy with Systems Principles for FIW for Wildfire UAV

4.3 Introduction

This chapter is geared to enhance lift-to-drag (L/D) ratio optimization for Fan-In-Wings (FIW) along with airframe design of a UAV that is wildfire application purposed. Traditionally, airframe design is done first, with requirements developed later for flight controls systems. In compare, our method adopts systems principles prioritizing FIW in the context of Surface-less Flight Controls

(SFC), previously published [3]. We leverage concepts of systems thinking [9], [5] to design an airframe to provide optimized lift for FIW [29], [30], [33], and is validated through CFD as depicted in Figure 4.1.

4.4 Methodology of Optimization via CFD

The systemic approach for the computational fluid dynamics (CFD) analysis of the fan-in-wings (FIW) architecture can be organized sequentially into three principal phases, as shown in Figure 4.2. The three primary phases are the preliminary architecture phase (Phase 1), the optimization phase via CFD (Phase 2), and the optimized flight control architecture phase (Phase 3).

In Phase 2 of our computational fluid dynamics (CFD) analysis, we scrutinize two key parameters: the lift-to-drag (L/D) ratio and range, applying principles of systems thinking [9]. This approach enables rapid performance evaluation at the UAV level. The next three sections will address each phase, with a focus on optimization. This phase covers both the subsystem level, with FIW as the SOI, and the system level, where the UAV serves as the context system. We have developed an efficient methodology to evaluate the lift-to-drag (L/D) ratio and range using CFD analysis, and subsequently update the corresponding color map.

We have developed a color map that facilitates the rapid visual representation of critical parameters for comparative analysis against innovative fan-in-wings (FIW) aircraft architectural concepts. The primary parameters of interest include:

- Lift-to-Drag Ratio (L/D) (CFD Analysis current scope)
- Range of the UAV (CFD Analysis current scope)
- Specific Cost (USD/kg-km) (Future scope)
- Cruise/Loiter Fan Power (Future scope)
- Roll/Pitch Control Torque (Future scope)

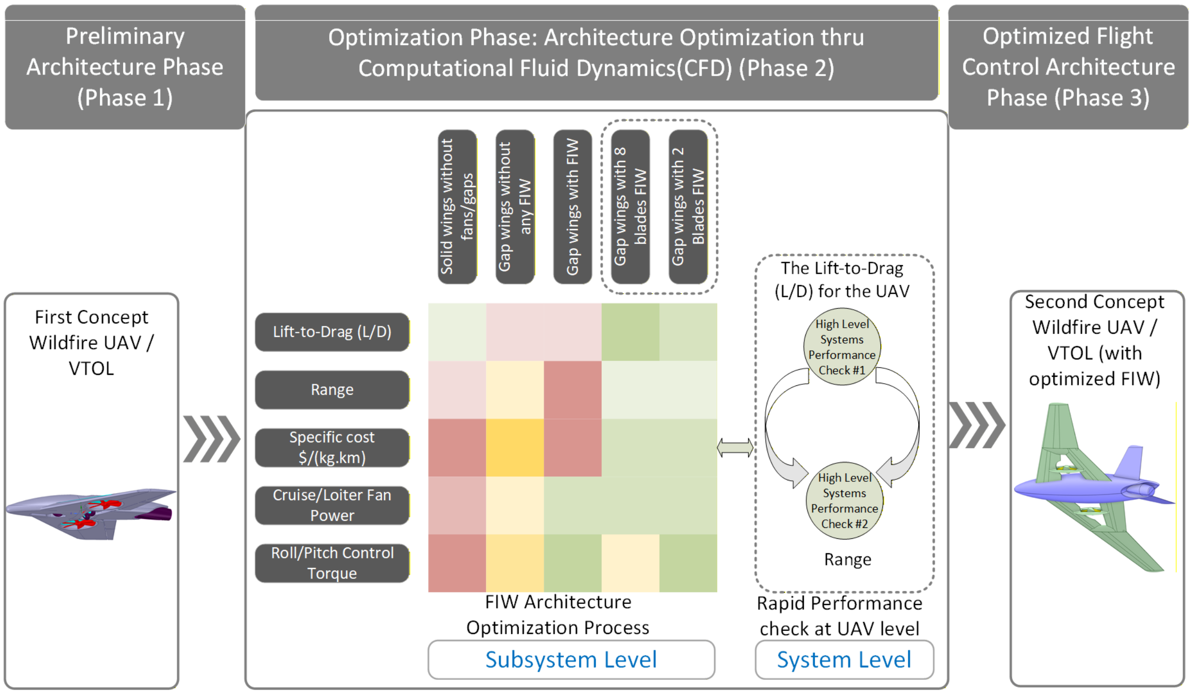


Figure 4.2: Systemic Method for CFD Analysis for Fan-In-Wings (FIW)

First two items (L/D and Range) are the most critical items and can be used for rapid performance check at the UAV level (system level) in Figure 4.4. This quickly evaluates the options that are feasible, and thus many possible options can be narrowed down to a few options. In this case, we narrow down 10+ different options to 5 options (using FIW) as following:

- Solid wings without fans/gaps
- Gap wings without any FIW
- Gap wings with FIW
- Gap wings with 8 blades FIW
- Gap wings with 2 Blades FIW

We do performance checks using CFD models for these five primary parameters against the five major FIW configuration options and develop the color map in Figure 4.3.

This color map serves as a visual conduit, translating our quantitative and computational findings into a graphical representation. We have focused on two major parameters lift-to-drag (L/D) and

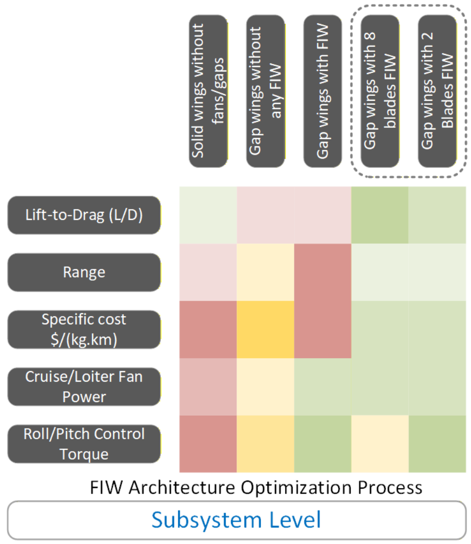


Figure 4.3: Color map of 5 parameters by 5 options trade at the Subsystem level

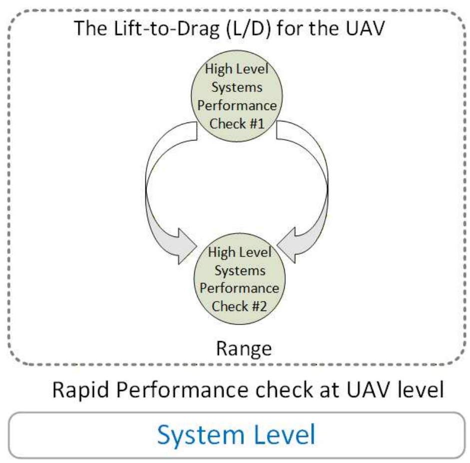


Figure 4.4: Rapid performance check at the UAV level (System level)

Range out of five. Remaining three parameters can be evaluated using similar systemic steps steps for Specific Cost, Cruise/Loiter Fan Power, Roll/Pitch Control Torque.

The Subsystem level color map evaluation in Figure 4.3 and System level rapid performance check in Figure 4.4 are integrated in the comprehensive Systemic Method in Figure 4.2. The overarching objective is to seamlessly utilize performance feedback loop as development process between the Subsystem (utilizing the color map) and System levels (rapid performance check), bypassing exhaustive analyses, yet converging on the most optimized solution.

4.5 Background - Context Systems Integration

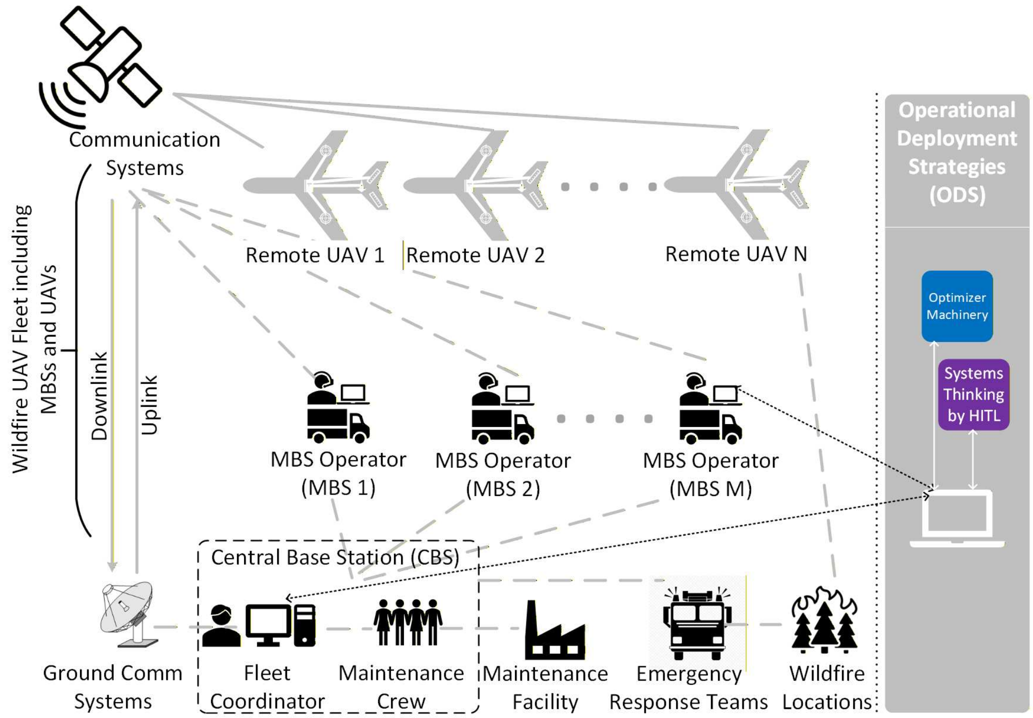


Figure 4.5: Wildfire UAV fleet context diagram

4.5.1 Operational Concept of the Enterprise System of the UAVs

The center of operation of the wildfire UAV fleet is a central base station (CBS) that dispatches a series of mobile base stations (MBS) and facilitates communication among and between them. The CBS is managed by a fleet coordinator who is part of the human-in-the-loop (HITL) strategy. The fleet coordinator manages the entire fleet, including all UAVs and MBS vehicles, and has access to multiple methods for MBS dispatching and UAV deployments. Each MBS carries up to three UAVs that are folded in large pieces and ready for rapid assembly and launch. The MBS is manned by an MBS operator (the launch crew) who is available whenever human intervention is required. The MBS Operator is capable of deploying different methods as needed for UAV launching and wildfire points planning.

Given the locations of most wildfire incidents, it is apparent that standard runways might not be always accessible in wildfire-prone areas. These wildfire UAVs, therefore, are equipped for vertical lifts utilizing fan-in-wings (FIW) [4] Surface-less Flight Control (SFC) concept [3] and are taken near the wildfire-prone locations using vehicles as mobile base stations. Each UAV maintains communication with its respective mobile base station (MBS). Figure 4.5 shows the fundamental concept of the use of specialized wildfire UAVs for wildfire detection and communication.

Individual UAVs can communicate directly with the CBS as necessary for the overall operations. The UAVs can also form their own mesh communications network while operating in the sky. In the event of satellite communication disturbances, the UAVs can intercommunicate using their mesh network. This provides redundancy and strengthens the overall system.

Response time to fire departments is also a factor that needs to be considered for this operational concept of the enterprise system of the Wildfire UAVs. Depending on circumstances, including availability and location of firefighting resources, there may be need to use sirens to alert nearby inhabitants of the rapid spread of wildfires from uninhabited areas to human habitat.

4.5.2 Wildfire UAV Mission Profile

There are a total of nine mission flight segments considered for wildfire detection and communication as shown in Figure 4.6 [3]. The two most critical bounding segments are initial Hoover/Climb and Loiter Flight. The most significant factor of the Climb segment is the battery size and weight requirements. Loiter segment is the other bounding segment because exploration and optimization would yield a UAV system fuel weight that meets the required loiter range.

Remaining segments of the flights are Transition/Climb (Fan Lift Flight), Transition/Climb (Wing Borne Flight), Pre-Loiter Dash Flight, Post-Loiter Dash Flight, Descend, Transition/Descent (Fan Lift Flight), Hoover/Land. These 7 segments of flight are not optimized because results would not appreciably affect the UAV sizing methodology or design analyses [6]. The results of the bounding segments are used to approximate the inputs required to arrive at an optimal UAV configuration to achieve mission requirements.

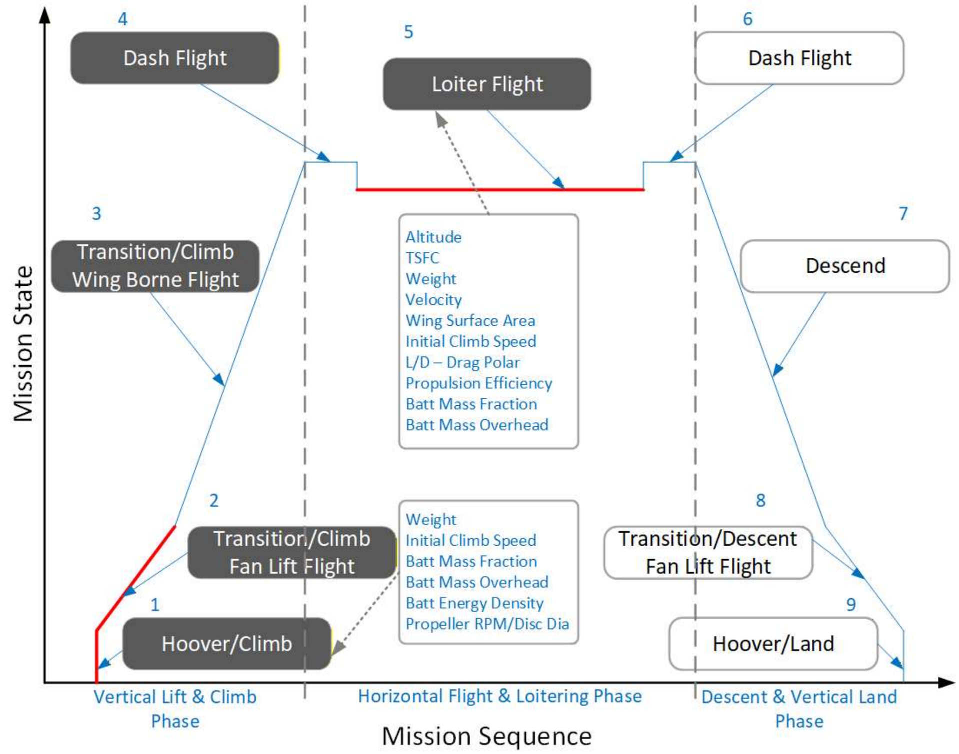


Figure 4.6: Typical Wildfire UAV Mission Profile

4.6 Preliminary Architecture Phase (Phase 1): First Concept

The Preliminary Architecture of Wildfire UAV offers an opportunity for further weight reduction. Additionally, there are plans to reposition the doors originally located on the FIW. Initial FIW concept was introduced in this airframe architecture of the wildfire UAV. As reported in prior publication [3], the flight control strategy encompasses a specific controller, complemented by two prominent fan-in-wings (FIW) without doors. Concurrently, this configuration incorporates a Thrust Vector Nozzle (TVN) to facilitate multi-directional motion, compared to the unidirectional movement inherent to the alternative option. This flight control modality integrates two lift or FIWs, and the multi-directional capabilities endowed by the TVN. The multi-axial orientation of the TVN proffers superior stability in comparison to its single-axis counterpart. During horizontal navigation or loitering phases of the aircraft, the FIWs remain unobstructed in absence of any doors.

Results from hybrid configuration loiter range simulation indicate that the ideal weight for the UAV   46.7 kg to achieve the range requirements specified. We systemically make attempt to reduce weight and architect FIW to generate sufficient L/D for this purpose as shown in Table 4.1.

Table 4.1: UAV Components Weight

UAV Sub-Systems and Component	Weight (kg)
Airframe Mass • Fuselage Mass – 2.17 kg • Wings Mass – 3.86 kg • Empennage Mass – 0.342 kg • Landing Gear – 4.77 kg	11.14
Energy Storage Total (Fuel 7.08 and Battery 1.87)	8.95
Propulsion Mass	7.92
Flight Control Mass • Fan-In-Wings (left) – 1.95 kg • Fan-In-Wings (right) – 1.95 kg • Thrust Vector Nozzle – 2.62 kg • Elevon (left) – 1.2 kg • Elevon (right) – 1.2 kg • Controller unit – 2.1 kg • Cables – 0.4 kg • Miscellaneous – 1.2 kg	12.62
Payload Mass	6.00
Total UAV Weight (kg)	46.64

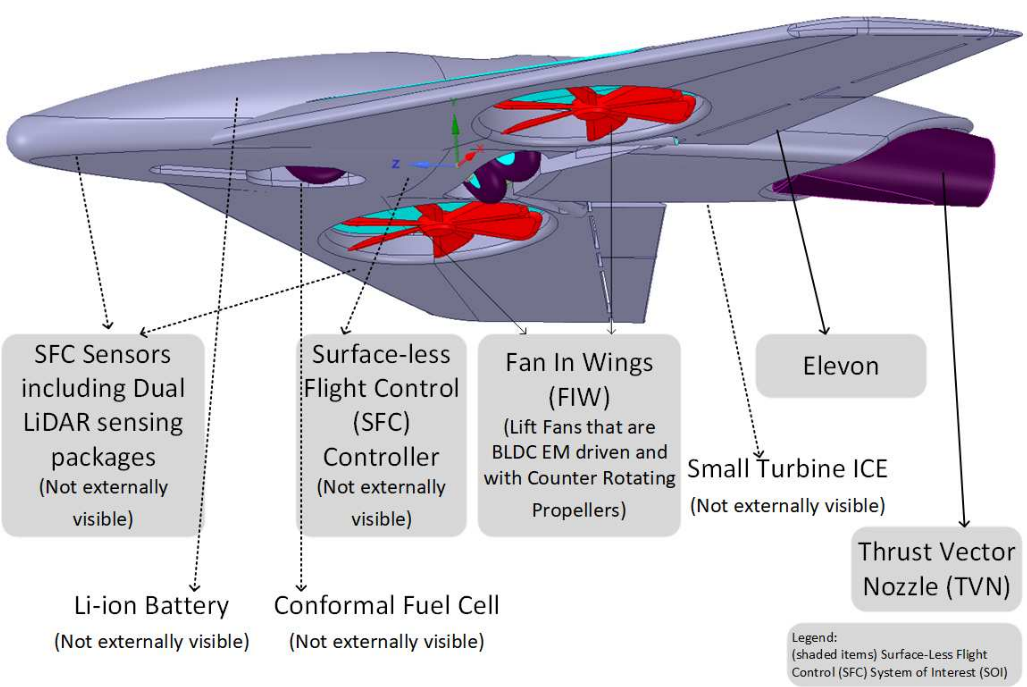


Figure 4.7: Preliminary Wildfire UAV with Flight Controls utilizing FIW

4.6.1 Architecture Optimization Goals

As ongoing research, it is critical to evolve this preliminary concept to establish a functional flight control mechanism for the UAV. Within the context of Vertical Takeoff and Landing (VTOL) capabilities part of the Flight Control Strategy, FIWs synergistically operate with the Thrust Vector Nozzle (TVN) based on a tri-pod conceptual model. This configuration necessitates that the FIWs collectively produce roughly two-thirds of the L/D force, distributed such that 60% is attributed to the two FIWs and 40% to the TVN. We have determined that the FIW presents a significant opportunity, and we intend to leverage the computational fluid dynamics tool, ANSYS CFX, for optimization and analysis.

4.6.2 Identification of 3-Systems with respect to FIW

Holistic systems adhere to a triadic architecture: System-of-Interest (SOI), System Context, and Enabling System. Our research utilizes the proposed optimization of FIW through the lens of this tripartite systems principle.

System-of-Interest (SOI). The designated system-of-interest (SOI) intrinsically encompasses the fan-in-wings (FIW) [4], [17], followed by the wing surface area, and ultimately, the airframe geometry of the aircraft. Although the FIW constitutes our primary emphasis, there is a simultaneous endeavor to holistically optimize the airframe in alignment with these focused objectives. At this stage of the research, elements related to the Thrust Vector Nozzle are omitted from our analytical purview.

Context System. The contextual framework surrounding the System-of-Interest (SOI) is the UAV airframe as well as all electrical and sensor equipment. This includes the Mission On-Board Computer, with components from the UAV's More Electric Aircraft (MEA) interfacing beyond the flight controls, as well as residual aircraft sensors amenable to auxiliary sensor fusion operations. Further system context considerations encompass adverse environmental factors such as gusty conditions, diminished visibility scenarios, and the inherent challenges posed by wildfire environmental conditions.

Enabling System. There are several enabling systems to FIW are TVN, Surface-less Flight Controls (SFC), electrical controller and these enabling systems essentially facilitate the FIW to perform its mission objective.

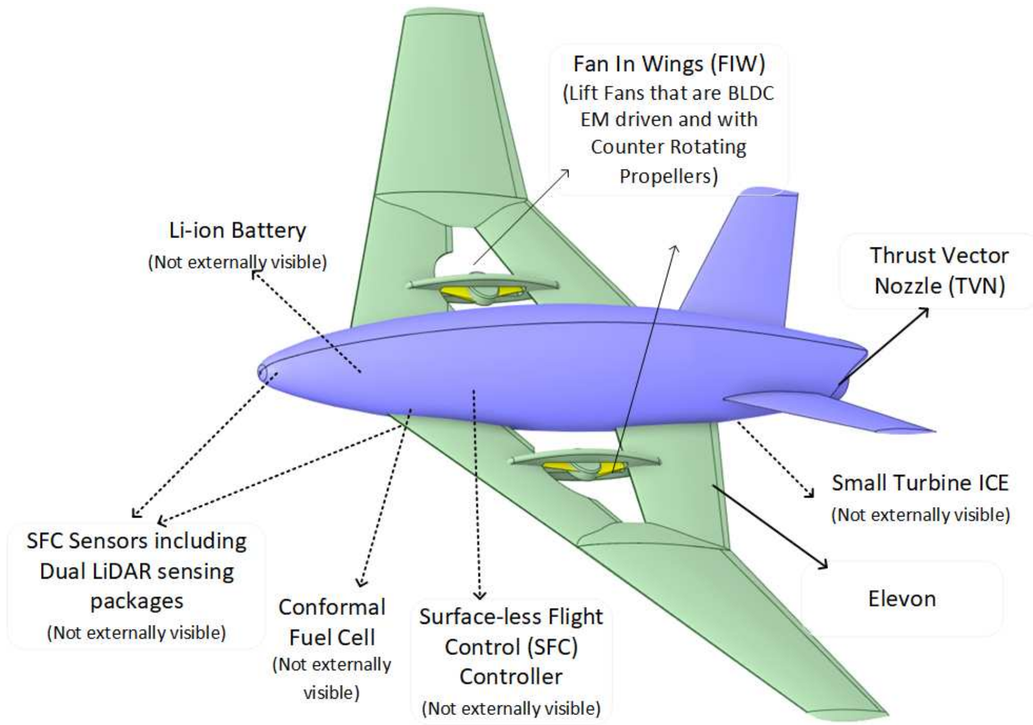


Figure 4.8: Second Generation Wildfire UAV with FIW Concept

4.7 Optimization Phase: Architecture Optimization thru CFD (Phase 2)

Within the three-phase systemic methodology, the second and primary phase is dedicated to the optimization of the FIW (predominantly for wildfire UAV applications) via computational fluid dynamics (CFD) analysis.

4.7.1 Subsystem Level Considerations

Our CFD analysis has been conducted using ANSYS CFX, we considered the subsequent parameters deemed pivotal for our objectives as shown in Table 4.2.

Table 4.2: Aircraft Parameters for CFD Calculation

Parameters	Values	Descriptions
Velocity	100 mph or 160.93 kph	Optimal velocity for the application for wildfire detection and communication
Pressure	14.7 psi	Assumed nominal pressure
Temperature	20 C or 68 F	Assumed nominal temperature
Total UAV Weight	46 kg or 101.41 lb.	Airframe, wings and FIWs are opportunities to reduce weight of the aircraft
Fan speed	0 krpm or 6 krpm or 10 krpm	We consider three points for fan speed to gather analysis data
FIW Blade Count	2 blade or 8 blade	We consider 2 blade fan or 8 blade fans for comparisons purposes
Wing Span	144 in, or 3.7 m	Wing span can be varied from 142 in to 145 in depending on the varying parameters
Fuselage Length	105 in, or 3.8 m	Optimal fuselage length
Distance to fan centerline	17.4 in, or 0.442 m	Optimal distance from body to fan centerline

In this ANSYS CFX-based computational fluid dynamics (CFD) analysis, we incorporated specific parameters identified as crucial for our intended objectives, such as velocity, pressure, temperature, UAV total weight (see Table 4.1), fan speed, and FIW blade count. We have used parameters at 0ft sea level altitude (14.7 psi). We can use the same process and run additional simulations at 10,000 ft, the UAV operational altitude (approximately 9.7 psi), to get even more realistic results.

4.7.2 System Level Considerations: Rapid Performance Check

The aerodynamic efficiency of the wildfire UAV can be quantified using two primary metrics: the moment coefficient (C_m) and the lift-to-drag ratio (L/D). The lift coefficient (C_L), drag coefficient (C_D), and pitching moment coefficient (C_m) collectively describe an aircraft's aerodynamic performance, efficiency, and longitudinal stability.

The Lift-to-Drag (L/D) for the UAV. Maximum (L/D) or the best glide speed will extend the range of the UAV. The lift-to-drag ratio is calculated as follows, and the ratio is the same as lift coefficient-to-drag coefficient [18], [32].

Two major interesting aspects of L/D considerations are as follows:

1. Identifying maximum L/D for application specific UAV design
2. L/D control range (from design optimization perspective).

Equation 4.2 gives the mathematical derivation of the lift-to-drag (L/D) ratio.

The UAV Range Considerations. We calculate the range of the wildfire UAV using both fuel and battery. Thus, we need to consider UAV range using a fuel energy source as the sum of equation 4.3 and UAV range using a battery energy source using equation 4.4.

4.8 Optimized Architecture Phase (Phase 3): Second Concept Wildfire UAV

For the optimized concept of FIW architecture, we adopt a comprehensive approach, targeting both weight reduction and enhancement of the L/D ratio. While our primary focus is on the FIW, we also extend our efforts to optimizing the overall airframe to align with these objectives. At this juncture, the Thrust Vector Nozzle remains outside the scope of our analysis.

4.8.1 Next Generation Evaluation Process

In the conceptual design for the next-generation aircraft, we propose a gap-wing configuration aimed at reducing wing mass without compromising its aerodynamic efficacy, as illustrated in Fig

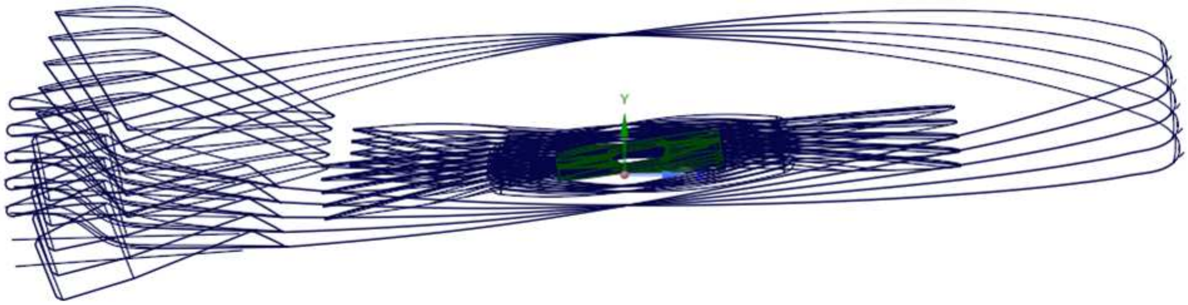


Figure 4.9: Reference image showing overlay of Angle of Attack (AoA)

4.6. Our investigations predominantly focused on the comparative performance of a 2-blade fan configuration versus an 8-blade fan configuration.

Although the 8-blade concept yielded a significant L/D ratio, the data for the 2-blade concept proved to be sufficient, especially considering its weight reduction benefits. Reference visualization presenting overlays of 0°, 2.5°, 5°, 7.5°, and 10° angles of attack (AoA)in the CFD analysis as shown in Figure 4.9.

Modulation of fan rotational velocity to attain the requisite lift for the FIW concept employing both fan configurations as shown in Figure 4.10.

Adjustment of fan rotational speed to achieve the targeted lift for the FIW concept, utilizing both fan configurations, as shown above The illustration in Figure 4.11, presents a cross-sectional representation of a Course CFD mesh far away from the drone geometry overlayed with cross section of Fine CFD mesh on and near the drone geometry.

In the presented dynamic analysis, thew above figure shows a rough grid (called a coarse CFD mesh) that's not close to the drone is layered with a detailed grid (called a fine CFD mesh) that's right on and around the drone. The consistency or coarse mesh and fine mesh provide evidence that the gap in wings with this architecture is fully aerodynamics.

4.8.2 System Level Considerations: Rapid Performance Check

In our investigation, we examined five distinct configurations for FIW and assessed their performance based on data derived from computational fluid dynamics (CFD) analysis as depicted

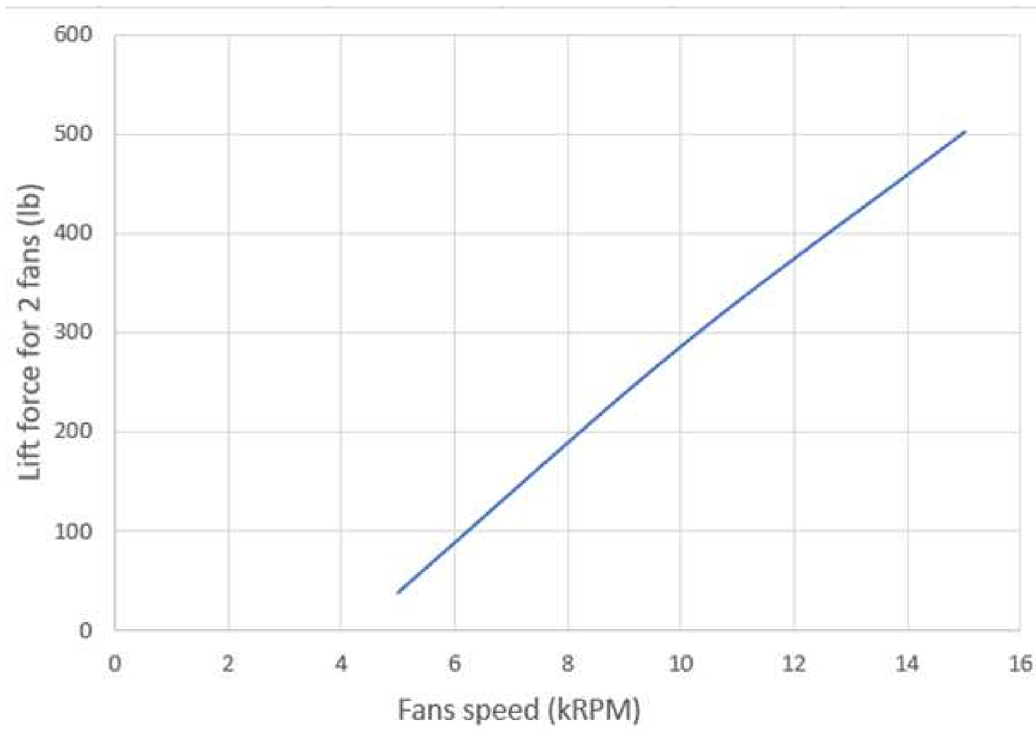


Figure 4.10: Relationship between lift force and FIW fan speed

in Figure 4.12. We run the simulation for half of the airframe to capture half of the drag and half of the lift for a given angle of attack and set of the UAV parameters. From the raw CFD data we calculate overall L/D.

Our findings indicate that the gap in the wing exerts minimal influence on performance, and both the 2-blade and 8-blade fan configurations can generate sufficient lift for (VTOL) applications.

The results suggest that the wing gap has a negligible impact on aerodynamic performance. Both the 2-blade and 8-blade fan designs can provide the requisite lift for VTOL operations.

4.8.3 Numerical Background for CFD Analysis

The required thrust of the UAV is the ratio of UAV weight (W) and L/D. Therefore, the goal is reducing weight and increase L/D given minimal energy usages by monitoring and controlling L/D control parameters. The reason it is a complex problem because too much thrust will waste energy but just enough thrust given weight optimizes energy usages. The required thrust is calculated as following [18], [32]:

$$T_R = \frac{W}{L/D} \tag{4.1}$$

The L/D is calculated as following: [18], [32]

$$\frac{L}{D} = \frac{\frac{1}{2}\rho_\infty V_\infty^2 S C_L}{\frac{1}{2}\rho_\infty V_\infty^2 S D_L} = \frac{C_L}{C_D} \tag{4.2}$$

Where both C_L and C_D are functions of the angle of the attack of the airplane, α and thus L/D is also a function of α and ρ is the air density, V is the velocity of the UAV relative to the air, S is the surface area (the wing area). [6]

$$R = \frac{2}{c_t}\sqrt{\frac{2}{\rho_\infty \times S} \times \frac{C_L}{C_D}\left(\frac{1}{W_0^2} - \frac{1}{W_1^2}\right)^{-1}} \tag{4.3}$$

Where ct is the Thrust Specific Fuel consumption, [N/N-s]. Additionally, note that W_0 represents the weight of the UAV at the beginning of the flight segment, while W_1 denotes the weight of the UAV at the end of the flight segment. Therefore, the difference between W_0 and W_1 corresponds to the fuel consumed during the flight segment, also known as the range fuel. Range (battery) equation can be calculated as the following: [6]

$$R = \text{Batt}_{\text{CE}} \times \eta_{\text{total}} \times \frac{1}{g} \times \frac{L}{D} \times \frac{\text{Batt}_{\text{sys.W}}}{\text{WTO}} \tag{4.4}$$

Where Batt_{CE} represents the battery energy capacity, η_{total} is the total system efficiency, g stands for gravitational acceleration, L/D is the lift-to-drag ratio, $\text{Batt}_{\text{sys\_W}}$ represents the battery's weight fraction, and WTO is the aircraft's take-off weight. Total fuel consumption of the wildfire UAV is ($W_0 - W_1$) and goal would be maximizing the R while ($W_0 - W_1$) is close to zero. [6]

$$W_1 = \left(\frac{R}{\frac{2}{c_t}\sqrt{\frac{2}{\rho_\infty \times S} \times \frac{C_L^2}{C_D}}} - W_0^{\frac{1}{2}}\right)^2 \tag{4.5}$$

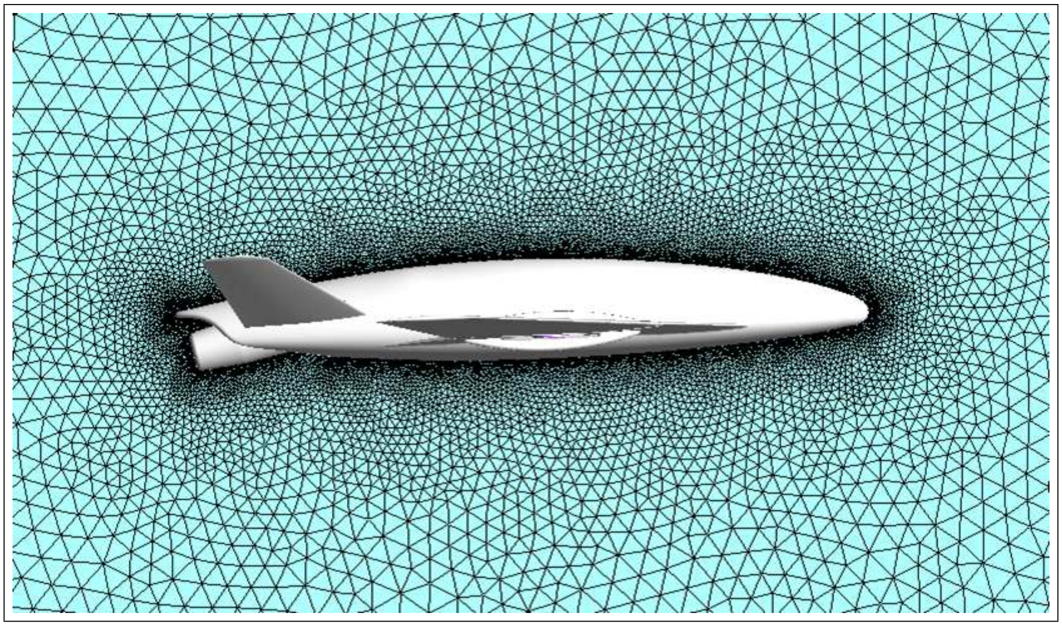


Figure 4.11: CFD mesh analysis

4.9 Results and Observations From Fan-In-Wings (FIW) CFD Study

In our research of CFD Modeling with Architectural Trade-Study of the wildfire UAV flight controls, we identified a potentially effective outcome for flight controls for UAV, especially designed for wildfire detection and communication application. Drawing from the prior work by Crawford, we had pre-existing knowledge on key factors influencing the Range (km) and Specific Cost ($/ (kg payload X Range)) for the configuration of a hybrid electric/gas turbine-propelled UAV [6]. This configuration corresponds to from our prior architectural trade study [3].

4.9.1 Direct Analysis and Observations From CDF Model

The primary insight from systems thinking derived from this paper is our assertion that the confluence of the trade-study with the systems architecting process served as a pivotal catalyst for the serendipitous recognition of a substantially enhanced architecture for the targeted system. In the absence of this integration, our focus might have been confined to fulfilling the explicit requirements for conventional flight controls, a commonplace approach. Such a narrow focus would likely preclude the exploitation of the inherent architectural features of the system context.

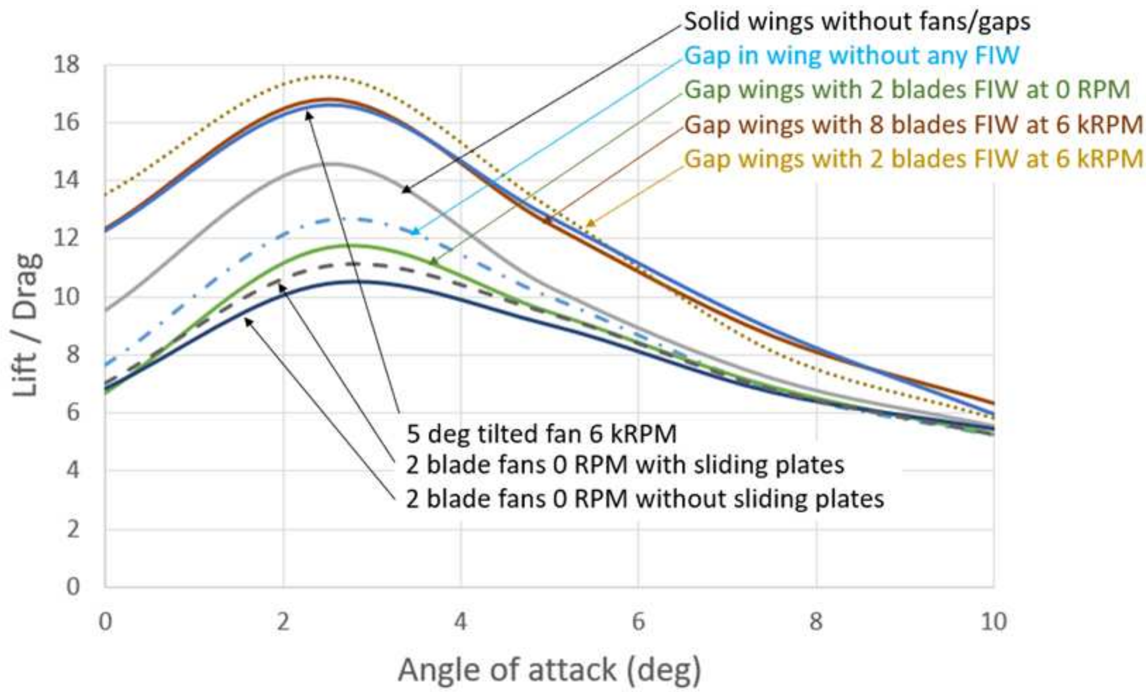


Figure 4.12: Lift-to-drag ratio over angle of attack analysis)

4.9.2 Computational Fluid Dynamics (CFD) Result Analysis

While our computational fluid dynamics (CFD) study outlines certain fan-in-wings (FIW) aerodynamic results not wholly relevant to our specific UAV airframe design, they are incorporated due to their indicative value. These results suggest a notable capability to modulate the wing's lift-to-drag ratio by managing the airflow through the fan during forward flight.

Utilization of Holism Principle - Holistic Thinking

The Holism Principle identifies, " *(Complex) Systems are (much) more than the sum of their parts - elements, interconnects, and purpose*" [42].

Our goal expanded beyond simply meeting the pitch, roll, and yaw control requirements or simply reducing weight. Instead, we adopted a holistic systems approach to comprehensively evaluate the overall system.

As illustrated in Figure 4.2, we identified opportunities to eliminate certain flight control components from the preliminary design (left side of the figure) and implemented a new design (right side of the figure) that significantly reduced weight while enhancing the performance of the system.

In addition, we optimized the use of SFC's fan-in-wings (FIW) for pitch, roll and yaw functions. By strategically positioning the FIWs to maximize lift, we achieved improved aerodynamic efficiency. This repositioning also allowed us to reduce wing surface area, further decreasing weight without compromising performance. Also, we introduced a gap at the wing root, an area less sensitive to aerodynamic contributions, which positively influenced the lift-to-drag (L/D) ratio, further enhancing overall system performance. Using CFD (Ansys CFX) as a rigorous tool, the design process becomes more rigorous, allowing us to optimize airfoil and wing design and essentially improve the overall efficiency of the UAV. Combining holistic thinking with aerodynamics and CFD modeling ensures an integrated approach to system design and performance optimization.

Utilization of Evolution Principle - Evolutionary Thinking

The Evolution Principle says that "*Systems have life cycles and evolve*" [42].

The evolution of UAV design reflects a move toward a lighter, more mission-oriented architecture based on wildfires. By improving UAV adaptability and minimizing its weight, the design evolved from traditional flight control architectures to an innovative surface-less flight (SFC) control concept with a fan-in-wing (FIW) design. This approach not only reduced the aircraft's weight but also effectively increased its range and payload capacity.

In Figure 4.2, the principles of evolution are evident. We reviewed the initial preliminary design to identify the changes required to refine and advance the concept. The key evolutionary breakthrough was the redesign of the flight control system and its integration with the fan-in-wing concept. This redesign provided an opportunity to collaboratively develop and validate a computational fluid dynamics (CFD) model, addressing gap wings with FIW functionality, FIW locations, and aerodynamic objectives. Using rigorous tools such as CFD, simulating scenarios such as virtual wind tunnels, helps to model and evaluate the aerodynamic design of the UAV. By applying systems thinking principles (holism principle, evolution principle), such as feedback loops and optimization, we can evolve the preliminary architecture of the UAV;s flight control system. Through this process, the design evolves to become more efficient and the flight controls are optimized. The combination of evolution and holistic thinking ensures that the UAV's design is optimized across various stages of development. When we step back and observe the entire complex problem wildfire, it becomes evident that the unique needs of wildfire detection and communication call for UAVs designed specifically for that use. Our game-changer design includes an airfoil and flight control design to minimize weight and cost. It specializes in early detection, extended loitering range, instantaneous motion, accessibility to rugged terrains, extended operation time, extended communication availability, data collection, safety, and rapid deployment.

4.10 Chapter Conclusions

Using a systemic approach, our research study has identified an advanced and efficient fan-in-wings (FIW) UAV design that offers a high lift-to-drag (L/D) ratio while reducing weight, thus optimizing its aerodynamic characteristics for wildfire scenarios. We have demonstrated that by applying principles of system thinking, such as the *Holism Principle* and *Evolution Principle*, mental models can be transformed from mission goals into effective aerodynamic models, keeping both fleet deployment and UAV design coupled together.

Using CFD within a holistic systems-oriented design optimization approach, we found a detailed 3D design of the airframe that can reach the high lift-to-drag ratio targets determined during preliminary design optimization and sizing for the Wildfire detection and communication mission. We could quantify the significant sensitivity of the lift-to-drag ratio to fan speed, number of fan blades, and angle of attack (AoA). This high level of sensitivity leads to the conclusion that surface-less flight controls (SFC) may indeed be feasible for our long-endurance hybrid electric or gas turbine-propelled wildfire detecting and communicating UAV. This is exciting because any structural weight saved by removing ailerons/rudders and the associated actuation systems would allow more fuel or payload to be carried onboard to improve endurance, range or coverage area, or the specific cost metric $/(kg.km). Of course, this gain would also imply a more complex advanced primary flight control strategy that uses differential fan speed, differential fan acceleration, angle of attack, and variable nozzle angle to control roll, yaw, and pitch. A caveat is that we have not yet included FEA-based structural optimization in our holistic design optimization approach. Joint optimization of the structure and aerodynamics would produce more realistic results. We have also not flown this configuration into the harsh gusty flying conditions typical of major wildfires.

4.11 Chapter Summary

This study utilizes a systemic approach, our research study has identified an advanced and efficient Fan-in-Wing (FIW) UAV design that offers high-performance lift-to-drag (L/D) ratio while reducing weight, optimizing its aerodynamics characteristics for wildfire scenarios. In Chapter 6, Chapter 7 and Chapter 8, we will discuss the uncertainties, and risks associated with UAV deployments and trajectory control strategies. Our research object is to study whether UAV fleet deployment and trajectory control strategies (i.e., the systemic way the UAVs are operated) impact the optimal design of the UAV airframe that is specifically designed for wildfire detection and communication.

Chapter 5

Systems Dynamics Approach for Rapid Prototypes Integrating Model-Based Systems Thinking (MBST)

5.1 Preface

This chapter serves as the systems thinking and rapid prototype building block for this research on wildfire detection and communication using a fleet of UAVs. We apply system dynamics and model-based systems thinking (MBST) to identify the critical components of the overall fleet deployment problem.

5.2 Overview

In this chapter, we discuss the implementation of system dynamics (SD) for a management flight simulator (MFS) for a fleet of unmanned aerial vehicles (UAVs) to detect wildfires and gather surveillance data to predict and prevent wildfires [26]. The UAV under consideration is a hybrid aircraft that uses power from both the Li-ion battery and the fuel cell and is hauled to the launch site on a mobile base station (MBS). We optimize fleet operation by considering a wildfire topology map, geographic locations, operational constraints, communication requirements, and essential wildfire detection and communication constraints.

5.3 Introduction

The proposed systemic approach includes the first phase of development of the concept of operation (ConOps) of a rapid prototype model (using SD) according to model-based systems thinking (MBST). The MBST model's results emphasize the importance of efficient time management between UAV deployments to enhance or maintain coverage while navigating the system's complexities for optimal outcomes. The goal is to efficiently cover a region with minimal resources, addressing the dynamic hurdles posed by environmental factors and UAV and MBS limitations. As part of the model, we utilize real wildfire data from Colorado as a case study, and Textron Bell 206 [14] helicopter aerodynamics data to develop realistic parameters for the management flight simulator (MFS) [14], [169].

5.3.1 Background

The deployment of a fleet of UAVs for wildfire detection and monitoring is a complex problem due to dependencies, feedback loops, and other interconnected behaviors. Based on our previous work in model-based systems engineering (MBSE), systems architecture, and computational fluid dynamics (CFD), we consider the aerodynamic impacts of UAVs on deployment time. Therefore, performance parameters such as lift-to-drag (L/D) and rate of climb are related and can affect climb time. Also, fleet-related operational issues need further evaluation, as they are complex and depend on both aerodynamics and operational logistics. This complexity is particularly evident in two major areas directly impacting deployment scenarios. First, managing the climb time or rate of climb (ROC). Second, launching the fleet due to UAV failure rates, unscheduled maintenance time, and the total time required to perform logistics tasks between deployments.

Systems Dynamics to Address Performance Complexities

The performance area of complexity is the ROC. Getting the right balance in the climbing time is crucial to achieving the desired altitude. While higher altitudes allow UAVs to cover larger geometric areas, the climb is influenced by temperature and air density variations, demonstrating the interconnections between environmental conditions and UAV performance. Also, the dynamic nature of these environmental factors means that climb rates (climb time) vary throughout the year, impacting the UAVs' deployment efficiency and predictability. Another layer of complexity arises from the feedback loops between different elements of UAV operations. For instance, rapid climbs can save time but might deplete the power needed for effective loitering, whereas slower ascents can limit the time available for surveillance. This scenario illustrates the intricate feedback loops between environmental phenomenon, climb time, and surveillance efficacy.

Systems Dynamics to Address Operational Complexities

The operational area of complexity of the interconnectedness of the system is further highlighted in fleet management. Increasing the number of UAVs can seem advantageous for coverage, but can also lead to repair capacity bottlenecks and more frequent UAV failures, especially if deployments start early in the year. This aspect demonstrates the importance of balance in managing fleet size against repair capabilities.

5.3.2 Systems Method for Systems Dynamics Models

We employ the *Model-Based Systems Thinking (MBST) framework* and *Systems Dynamic Modeling Process* to explore the complexities involved in deploying a fleet of UAVs (Unmanned Aerial Vehicles) for wildfire detection and monitoring as shown in Figure 5.1.

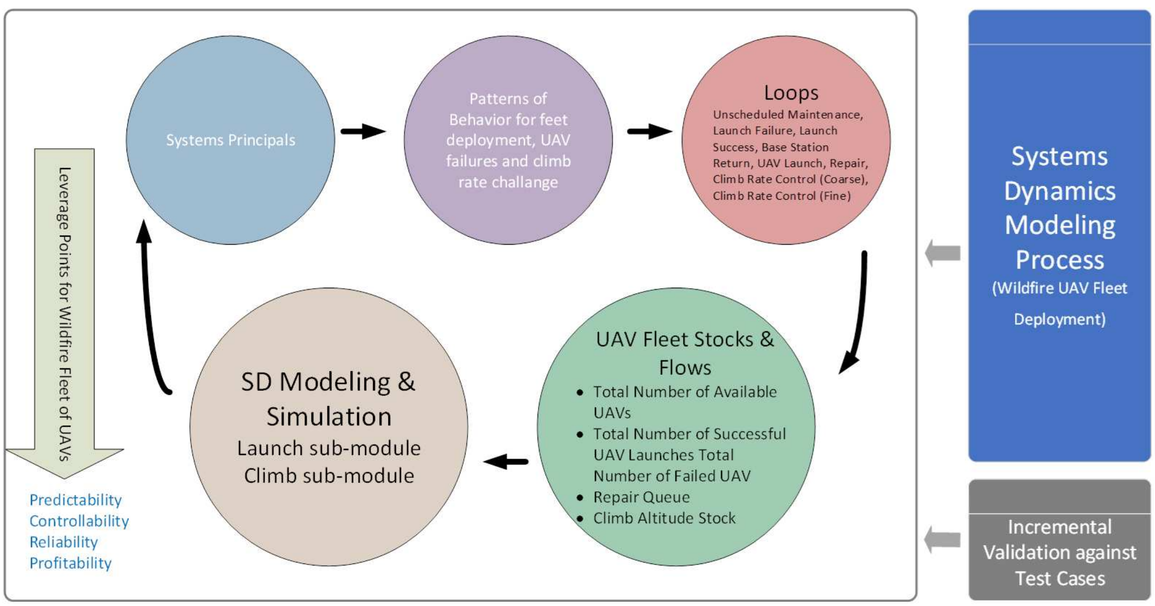


Figure 5.1: Integration of MBST Framework and Systems Dynamic Modeling Process

The bottom-right part of Figure 5.1 depicts the stock-and-flow diagram for the UAV fleet deployment model, illustrating the interrelationships among the stock and flow variables. Through MBST, we systematically dissect and understand the various components and their interactions within this intricate system, facilitating more informed decision-making leverage points in the systems and strategy development for effective UAV deployment.

5.3.3 Gap Analysis for Deployment Using Systems Dynamics

One of the most important deployment components of wildfire UAVs is the altitude capability. General-purpose small UAVs are designed with low altitude capability and range. The existing small UAVs identified in the literature search [10], [16] had altitude ranges of 50 to 200 m, the best case being 1000 m. This altitude is not sufficient for the detection of wildfires in many parts of the world, where the mountains can easily exceed 3000 m. The UAVs proposed in our project are typically 2x to 10x larger and able to fly 10x higher (10,000 ft/3048m flying altitude with a 15,000 ft/ 4572m ceiling) to navigate high mountain areas. Several key deployment questions also remain about the proposed MBS component of our solution.

1) High Risk Terrain Consideration - How to optimally send Mobile Base Stations (MBS) to High Risk wildfire prone locations, considering the complicated terrain in wildfire areas.

2) Access Roads Consideration - Whether and how to consider access roads as part of MBS vehicle route planning.

Another additional component of deployment is how to optimize the size and design of the UAV for efficient energy use while also accommodating the need to carry the necessary amount of fuel. All these items can be considered for optimization problem formulation parameters.

5.3.4 Systems Thinking Principles – Human Principle and 3-Systems Principle

We consider several Systems Thinking Principles as the fundamental to building the SD model for Wildfire Fleet deployment.

Utilization of Human Principle

The Human Principle, "*Humans impact and are impacted by the (wanted/unwanted) emergence of all reachable systems*" [42]. While we explore the key factor for UAV design and UAV fleet deployment, we evaluate the most critical man-made impact, as well as the environmental impact.

Utilization of 3-Systems Principle

Additionally, we also consider, 3-Systems Principle, "*Systems come in (at least) three – context systems, systems of interest (SoI), and enabling systems*" [42]. We utilize this core principle to approach the deployment architecture.

The SOI: The system of interest (SOI) is a fleet of wildfire UAVs for wildfire detection and communication that are launched from a mobile base station (MBS), which serves as a launcher. The central base station (CBS) is where the MBSs are dispatched from. The focus in this chapter is the systems dynamics of the environmental impacts and repair system, demonstrating deployment and aerodynamic design.

Context System: The context systems are the overall system that includes wildfires, geographical locations, the environment, wildfire, population, and related elements.

Enabling System: Here are some enabling systems to consider:

· *Road and path infrastructures*: Road and path infrastructures for MBS vehicles to travel with a UAV.

· *Satellite Communication System*: Satellite communication to be used for deployment and communication with UAVs.

5.3.5 Wildfire Fleet Deployment Realistic Case Study

In the dynamic system model, we use the state of Colorado as a case study and examine how climb time, maintenance, and repair loops influence deployment rates. The goal of the model is to essentially understand the parameters that can impact the number of days it takes to cover the entire state of Colorado by essentially increasing loitering time, decreasing climb time and managing failure and repair issues.

Colorado Environmental Data

As an approach to address this complex problem, we consider environmental parameters in state of Colorado for temperature fluctuation over a year [12] in particular and develop the systems dynamic model to demonstrate real world scenarios. Part of the problem-solving approach we divide Colorado's terrains into a grid for strategic deployment, with each UAV designed to cover a specific range. The objective of the model is to understand how variables such as loitering time, climbing time, and maintenance issues inter-play to affect the number of days needed to cover the state.

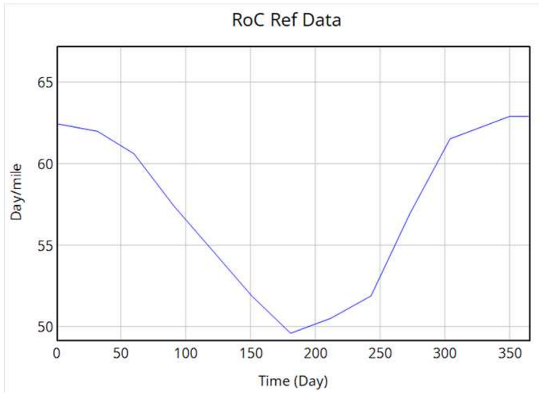
5.4 MBST Framework Applied to UAV Fleet Deployment

The model-based systems thinking framework (MBST) integrates the utilization of mental models, a foundational element of Systems Thinking principles to facilitate a holistic system. This integration facilitates the identification of behavior patterns. From these discerned patterns, it is possible to construct causal loop diagrams, which serve as a foundational step towards developing comprehensive stocks and flows dynamics models.

5.4.1 Reference Data: Matching Ref Data to Incorporate Actual Data

Additionally, the model compares reference data from Bell 206 helicopter [14] data to understand the impact of temperature on altitude and air density. This comparison highlights the dynamic nature of the environment and its influence on UAV performance, especially the climb rate, which varies with temperature changes throughout the year.

Ultimately, the model's results emphasize the importance of efficient time management between UAV deployments to enhance or maintain coverage while navigating the system's complexities for optimal outcomes. The aim is to effectively cover the state with minimal resources, addressing the dynamic hurdles posed by environmental factors and UAV limitations. According to our model, significant benefits of up to 20% are achievable by managing temperature over a day and variations in air density, which vary depending on the time of year and the specific topography of the launch



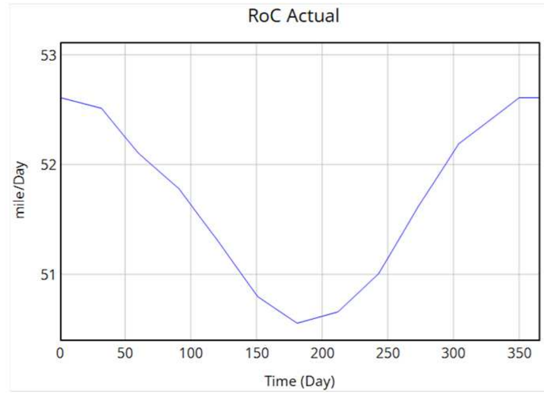


Figure 5.2: Comparison of Reference Data to Actual Rate of Climb (ROC) or Climb Rate in model

site. In Colorado, ideally deploying about 10 UAVs over a span of 6 to 8 days we can cover the entire state. This time can be shortened by finding relatively high air density site and suitable time in a day when temperature is favorable. Also, increasing the fleet size substantially could overburden repair capacities, thus undermining the benefits of having more UAVs. This careful balance between fleet size and repair resource management is crucial for the successful implementation of this strategy.

5.4.2 Stocks and Flows as Per MBST Framework

The stocks and flows of the MBST model form the basis for system dynamics modeling and simulation. This sequential progression from mental models to dynamic simulations embodies the essence of MBST framework. The elements in the MBST framework help identify leverage points within complex systems.

Table 5.1 shows the stocks incorporated in the UAV fleet deployment system dynamics (SD) model. The major stock variables include the total number of available UAVs, the total number of successfully launched UAVs, the failed UAV repair queue, the climb altitude stock, and the time stock. The climb altitude stock quantifies the cumulative altitude gained by UAVs during flight, whereas the time stock is utilized for time-related calculations within the simulation model.

Table 5.2 shows the flows within the UAV fleet deployment model. In SD models, stocks denote accumulations, while flows represent rates of change. The principal flow variables in this model are the base station arrival rate, launch rate, successful launch rate, failed UAV rate, incoming

Table 5.1: Stocks in the UAV Fleet Deployment Model

Parameter Name	Unit	Sub-module	Comments
Total Number of Available UAVs	uav	Launch	Base Case Test consists of 10 UAV with 4 launches per day for 365 days.
Total Number of Successful UAV Launches	uav	Launch	This stock excludes any failed attempt of UAV launches.
Total Number of Failed UAV	uav	Launch	Test stock is to monitor total number of failed UAVs.
Repair Queue	uav	Launch	This stock is for UAV repair queue and repair logistics purpose.
Climb Altitude Stock	mile/day	Climb	This stock is for accumulation of altitude gains.
Time Stock	timeslice	Climb	This is for time calculation purposes.

Note:

[1] In this table, "UAV," "timeslice," and similar terms are custom units used in the Vensim software implementation for system dynamics modeling. These units are required to maintain meaningful units for the elements, tasks, and time within the software.

[1] Overall wildfire deployment module (system) has launch sub-module (subsystem) and climb sub-module (subsystem).

repair rate, outgoing repair rate, and UAV climb rate. These flows regulate the transitions of UAVs between operational states and shape the overall behavior of the system.

5.4.3 Integration of Systems Thinking Principles and Mental Models

model-based systems thinking (MBST) proves to be highly effective in the conceptual systemic design and development of UAVs, especially for specific purposes such as wildfire detection and communication. This approach begins with analyzing flight control strategies, deployment, and trajectory control using tools like Vensim, before progressing to detailed airframe design. Employing Systems Thinking within a model-based environment can lead to significant time savings during the development process. For example, by identifying flight controls and deployment strategies as leverage points in the design process of a wildfire UAV, we can make critical design decisions

Table 5.2: Flows in the UAV Fleet Deployment Model

Parameter Name	Unit	Sub-module	Comments
Base Station Arrival Rate	uav/Day	Launch	After a success launch and land or from repair facility.
Launch Rate	uav/Day	Launch	This can include both failed and successful launches.
Successful Launch Rate	uav/Day	Launch	Launches that complete the missions.
Failed UAV Rate	uav/Day	Launch	As per predicted failure mechanism.
Incoming Repair Rate	uav/Day	Launch	This depends on the MTBF of the UAVs.
Outgoing Repair Rate	uav/Day	Launch	This depends on the repair capacity.
UAV Climb Rate	mile/day	Climb	Rate of Climb (ROC) or climb rate determines climb time which is critical from fleet deployment efficiency.

supported by Systems Thinking. This leads to more targeted designs, using tools such as ANSYS, Cameo/MBSE, and Monte Carlo. Utilizing this framework ensures the integration of Systems Thinking in our wildfire UAV design process.

Utilization of reference data and base test cases

Firstly, we use any data as available part of the model (Bell ROC data, repair data, Colorado fire data) and then, we develop several base case test scenarios as we step by step develop the model.

Base Test Case - No Failure Scenario Test Case: As we develop the loops, stocks and flows, we establish a base case of 10 UAVs without any failure scenario.

Base test Case - Launch Failure Scenario Test Case: Then, we can consider launch failure test case and use spreadsheet to track the model behavior and establish the correctness of the launch case scenario.

Climb Scenario Test Case: Finally, we consider a climb test case scenario and analyze the impacts of the climb rate to the deployment rate.

5.4.4 System Performance Parameters for the UAV Fleet Deployment

The main goal is to improve performance parameters such as predictability, controllability, reliability, and profitability as discussed in Table 5.3. This table lists the performance parameters of MBST applied to evaluate the system, including profitability, reliability, deployability, and controllability. These parameters serve as the foundation for implementing and assessing the SD model. Incorporating these performance measures enables a comprehensive analysis of system behavior and supports the evaluation of UAV fleet deployment performance under varying operating conditions.

5.5 UAV Deployment Management Flight Simulator (MFS) for as Human Focus Design

The UAV deployment management flight simulator (MFS) for human interaction is used to evaluate the implementation of the SD model or MBST model for wildfire UAV fleet deployment and UAV aerodynamics analysis. The SD model includes both an input dashboard and a visualization dashboard. These dashboards enable users to access several key input parameters, selected from among numerous model parameters, that significantly influence the UAV deployment strategy.

5.5.1 Implementation of Management Flight Simulator (MFS)

The MFS effectively assists human decision making and helps with human-in-loop (HITL). We consider eight parameters as primary performance input, and the second set of eight parameters is secondary performance input, as shown in Figure 5.3. This dashboard shows the performance input controls for the MFS utilized in the wildfire UAV deployment model. The interface displays a representative subset of the numerous input parameters that influence the deployment strategy within the SD model, integrating UAV performance characteristics and deployment variables.

Primary performance inputs include the maximum number of UAVs, the repair capacity factor, loiter time, air density, the performance degradation factor, the average repair time, the descent

Table 5.3: MBST Performance Parameters for the Wildfire UAV Deployment

Performance Parameter	Vensim Model Elements	Explanations
Profitability	• Time to Cover State of Colorado	Increased favorable benefit is expected if we can reduce the time to cover the designated area that is under surveillance.
Reliability	• Average Repair Time • Repair Capacity	A reliability metric, mean time between availability (MTBA), is highly dependent on average repair time and repair capacity. By decreasing the average repair time and increasing the repair capacity, we can increase the deployment rate for the fleet of UAVs.
Predictability	• Unplanned Delay Due to Road Access • Unplanned Delay Due to Weather Conditions • Unplanned fluctuation in Temperature and air density	The model's input parameters allow to manage these unplanned models and assist to make best decisions and navigate the complex problem.
Controllability	• Loiter Time • Loiter Altitude • Descent Time • Ave Logistics Time Between Launches	Controllability of the deployment can be established with these set of parameters.

Note:

[1] Overall module has launch sub-module and climb sub-module.

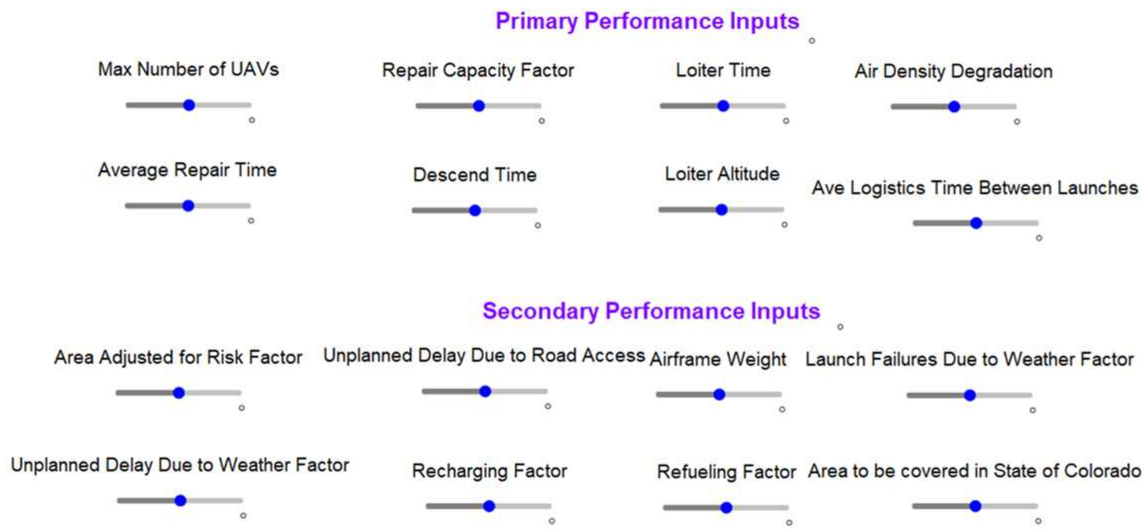


Figure 5.3: Performance Inputs to the Wildfire UAV Deployment Model (Controls)

Note:

[1] Performance Inputs to the Wildfire UAV Deployment MFS Model (Controls)

time, the loiter altitude and the average logistics time between launches. These variables directly influence fleet availability, mission endurance, and overall effectiveness of deployment.

Secondary inputs comprise the area-adjusted risk factor, road access delays, aircraft weight, weather-related launch failures and delays, recharging and refueling factors, and the total area to be covered in Colorado. These parameters improve operational realism by representing environmental conditions, logistical constraints, and aircraft characteristics that affect mission performance.

Collectively, these controls allow for the evaluation of a wide range of operational scenarios and the execution of sensitivity analyzes. The simulator illustrates how variations in environmental conditions, maintenance capacity, logistics, and aircraft characteristics can significantly impact fleet performance and deployment effectiveness. Representative visualizations of the management flight simulator are provided in Figure 5.4.

According to the simulator, we can examine that the UAV climb rate or ROC significantly impacts the performance of the rest of the parameters. This can significantly increase the total flight

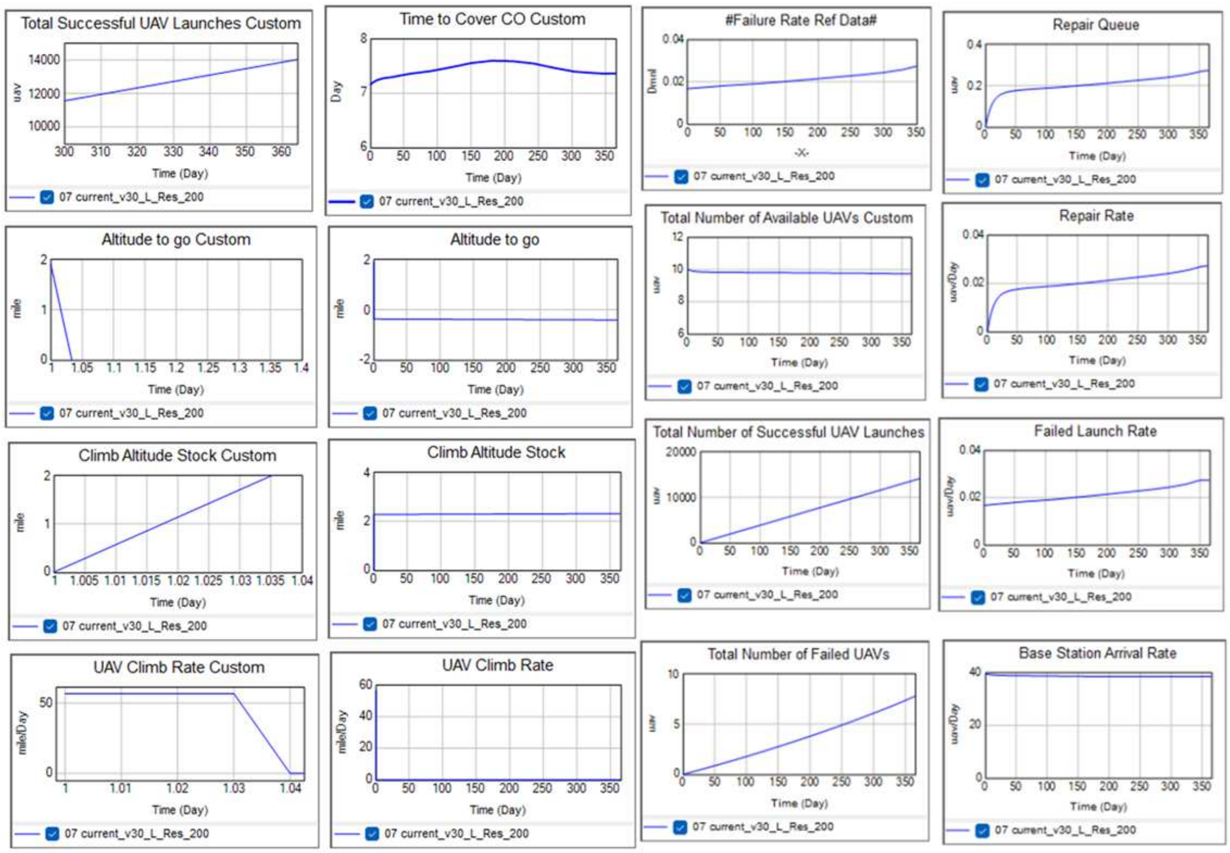


Figure 5.4: Management Flight Simulator (MFS)

Note:

[1] MFS gives a SD dashboard control and look for the wildfire UAV fleet deployment and strategies planning.

[2] We take the findings from this SD model and will plug into DSS optimizer machinery.

time of the UAV. In general, we can simulate more highly impactful parameters and try to address those parameters as part of the UAV design and/or UAV fleet deployment.

The management flight simulator (MFS) serves as a comprehensive dashboard to monitor and manage the UAV fleet. The dashboard displays key logistical, operational, and environmental parameters that facilitate fleet management, maintenance, repair scheduling, and aerodynamic performance analysis. Given that the primary focus of this research is the management of the UAV fleet, repair optimization, and aerodynamic design to improve deployment efficiency, the MFS provides real-time insight into these domains.

The dashboard tracks several critical performance indicators, such as the number of successfully operating UAVs, mission completion times, UAV failure rates, repair queues, repair rates, climb altitude, operating altitude, elevation, environmental impact, customized UAV configurations, climb performance, the cumulative number of failed UAVs, and the arrival rate of UAVs at the base station. These metrics enable a comprehensive evaluation of fleet performance, resource utilization, maintenance efficiency, and operational reliability.

By integrating operational and environmental parameters into a unified visualization platform, the management flight simulator enables detailed analysis of system behavior and supports informed decision-making regarding UAV deployment and maintenance strategies. Additionally, MFS functions as a verification tool for assessing the integration of UAV deployment and aerodynamic design methodologies, with results presented and discussed in Chapter 8.

5.5.2 Simulation Results Using SD Model

This SD model has two major sub-modules (subsystems), and the first is the "Climb Time" sub-module which analyzes the complexity of the climb rate of the UAV and evaluates environmental impacts. The second module is the "Launch Time" sub-module that models launch rates, failure rates, and the impacts of maintenance issues.

Minimizing Coverage Time

As part of the formulation of the concept of operation, our study looks at minimizing coverage time considering environmental, aerodynamics, and operational constraints.

The MBST Vensim model, in Figure 5.5, shows that the climb rate of the UAVs can impact the time it takes to cover the state of Colorado with a specific number (10 UAVs used in the case study model) of UAV fleet. This simulation takes into account the environmental parameters that affect the aerodynamics of the UAV. Essentially, given environmental parameters such as temperature, altitude / elevation, and pressure, we can try to minimize the coverage time.

In Colorado, the impact of changes in monthly temperature, air pressure, and air density (environmental constraints) on UAV climb rates (aerodynamic constraints) is analyzed, aiming to

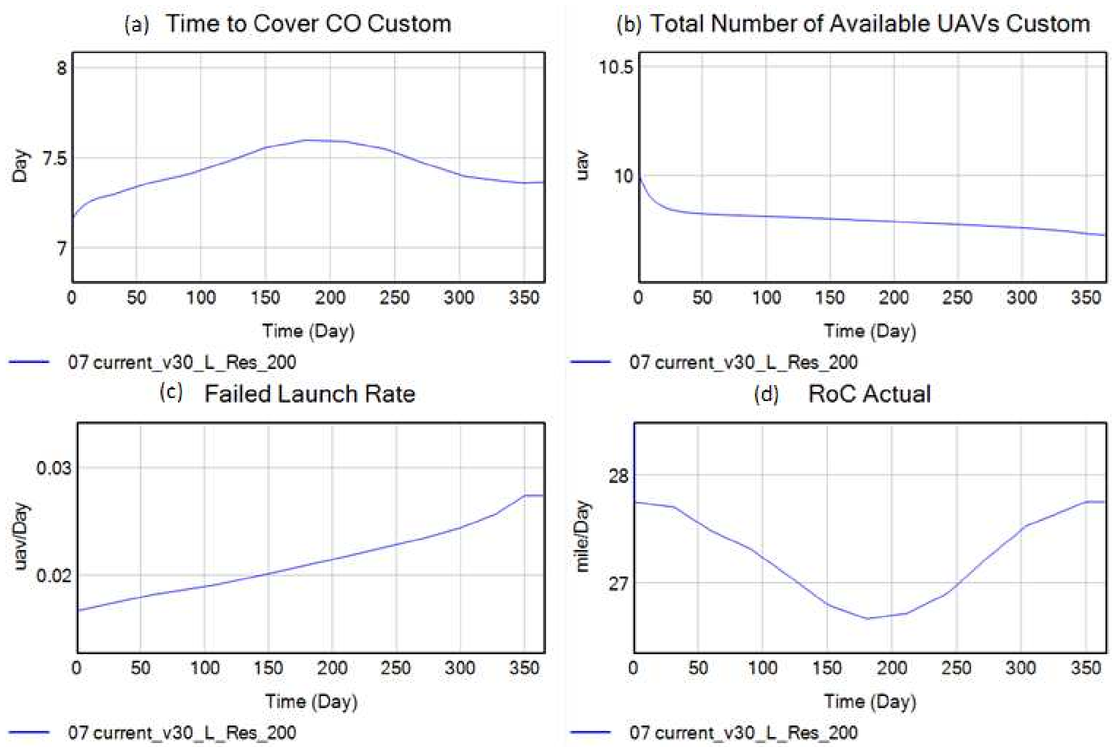


Figure 5.5: Systems Dynamics and systems operation Optimization using MBST model

achieve comprehensive coverage of the state with minimal resources, carrying out surveillance of the entire state within 6 to 8 days. The findings highlight that in wildfire-prone areas, high temperatures and low air density adversely affect climb time. In addition, factors such as unscheduled maintenance (operational constraints) can cause significant delays, emphasizing the critical role of strategic planning in the deployment of UAV. We discovered that clomb time significantly impacts the overall flight time and impact deployment time.

Vensim Running Configurations

To handle varying time ranges, our model runs in two configurations: "Debug" and "Simulation." The "Debug" configuration operates in low-resolution mode with a time-step of 0.01 (Day) in Vensim model setup, facilitating rapid testing and debugging of variable impacts. In contrast, the "Simulation" configuration runs in high-resolution mode with a finer time-step of 0.001 (Day) in Vensim model setup, offering greater accuracy.

Table 5.4: Major Loops in the UAV Fleet Deployment Model

Parameter Name	Sub-module	Details
Unscheduled Maintenance Loop	Deployment	B Loop
Launch Failure Loop	Deployment	B Loop
Launch Success Loop	Deployment	B Loop
Base Station Return Loop	Deployment	B Loop
UAV Launch Loop	Deployment	R Loop
Repair Loop	Deployment	B Loop
Climb Rate Control Loop (Coarse)	Climb	B Loop
Climb Rate Control Loop (Fine)	Climb	B Loop

Note:

[1] Overall module has launch sub-module and climb sub-module.

Causal Loop Diagrams

As per the MBST framework, we identify the major causal loop in the SD model. Then we characterize whether they are balancing loops (B) or negative feedback causal loops, reinforcing loops (R) or positive feedback causal loops, as shown in . The major loops that we examine are "unscheduled maintenance loop", "launch failure loop", "launch success loop", "base station return loop", "UAV launch loop", "repair loop", "climb rate control loop (coarse)", and "climb rate control loop (fine)".

Our goal is to identify critical parameters by exploring causal loop diagrams. In the Figure 5.6, the top climb rate control loops (fine and coarse), and the bottom Repair loop are shown.

In the Figure 5.7, the top is the UAV Launch failure loop, and the bottom is the broader Unscheduled Maintenance loop. As we experiment with these loops, we notice that two loops in particular, such as the repair loop and the climb rate control loop (coarse), have a significant influence on the performance of the model. In particular, the climb rate has a tremendous influence, and we consider it carefully for our optimization models in Chapter 7 and Chapter 8 to focus further on it.

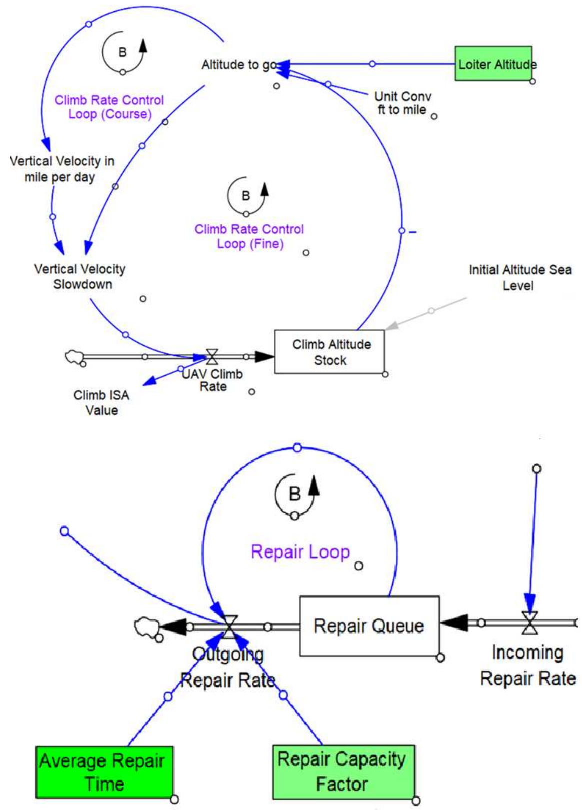


Figure 5.6: Investigating "Climb Rate Control" and "Repair" Loops

Control Policy Loop

The control policies within the deployment model considers several thresholds like "Average Repair Time", "Repair Capacity Factor" and these control policies help identify to items to monitor and control within the loops as show in Figure 5.8.

Managing and maximizing fleet size adds another layer of complexity that requires control policies to avoid bottleneck situations. While increasing the number of UAVs might seem advantageous for coverage, repair capacity limitations can lead to bottle-necks. A larger fleet can result in more frequent failures and potential UAV shortages, a concern especially later in the year if deployment starts early.

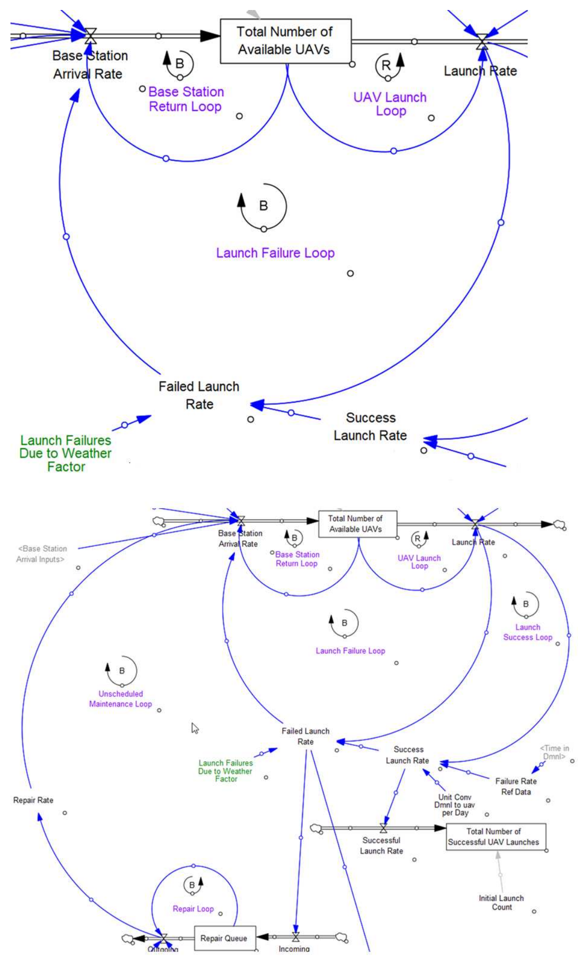


Figure 5.7: Predicting Unfavorable Case Test Cases – Failure Loops

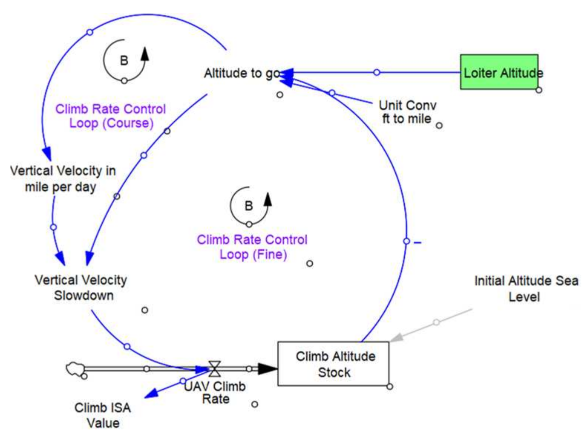


Figure 5.8: Control Policy for Repair Loop

5.6 Results and Observations from Operating Conditions Deployment

In the section, we discuss the observations of the scenarios from the deployment model and how a mental model can be developed.

5.6.1 Simulation-Based Identification of Critical Factor

The model in this Systems Dynamic study serves as a crucial guide for deploying wildfire UAVs through-out the year, concentrating on Rate of Climb and fleet launch dynamics. It underlines the necessity of efficiently managing deployment intervals to maximize area coverage and investigates the intricacies of fleet size management, noting that an increase in UAV numbers might lead to repair constraints and elevated failure rates. In Colorado, the impact of monthly temperature changes on UAV climb rates is analyzed, with the aim of achieving comprehensive state coverage with minimal resources, ideally using about 10 UAV flights in 6 to 8 days. The findings highlight that in areas prone to wildfires, high temperatures and low air density adversely affect the climb time. In addition, factors such as unscheduled maintenance can cause significant delays, emphasizing the critical role of strategic planning in UAV deployment. This model can be enhanced in future by incorporating additional elements such as fuel efficiency, battery performance, high-risk scenarios, and infrastructure availability. These additions are intended to enhance the model's accuracy and depth.

5.6.2 Formulating Mental Model to Address Complex Problems

Once we understand the scenarios of the complex problem, we can deploy an effective mental model to find highly optimized solutions.

MBST Critical Considerations for Systems Dynamics Model

These are key considerations for the DSS to achieve the mission goal of detecting wildfires, taking into account both fleet deployment and UAV design, especially parameters that are interconnected and can affect both.

- **Optimal Performance Consideration** - Efficient climbing is achieved using nominal temperature and air density, with an optimal number of UAVs that do not strain repair capacities.
- **Resource Constraint Consideration** - Resource constraints may limit an UAV's ability to reach higher performance. It also demands balancing aerodynamic parameters as resource constraints with environmental conditions to maximize efficiency. Such considerations encourage detailed analysis of the deployment environment, smarter resource use, and more effective wildfire monitoring.
- **Inefficient Utilization Consideration** - Deploying from locations with unfavorable air density or temperature conditions hampers wildfire monitoring and detection. A critical finding from the model is that under utilization of the available repair capacity can also diminish overall efficiency.

Mental Model for Deploying Wildfire UAV Fleet

To achieve mission effectiveness with a wildfire UAV fleet, a mental model based on system principles is needed. Move beyond simple assumptions, such as the idea that faster climb rates or more UAVs automatically enhance effectiveness, especially in Colorado.

It is important for UAVs to be able to reach higher altitudes, such as 10,000 feet, quickly and efficiently, where air density is lower. In addition, in high temperatures, particularly during wildfire events, the air density is optimal. The climb time may increase substantially if the climb rate is inadequate. Insufficient climb performance constitutes a resource constraint, thereby establishing the climb rate as an important operational factor. The SD model in this chapter explicitly experiments with the climb rate and the climb time as critical parameters. This parameter can notably affect overall deployment time.

5.7 Chapter Conclusions

The principles of systems thinking are the critical philosophies for having an effective implementation of SD simulation for wildfire UAV fleet deployment. We have demonstrated that by applying principles of system thinking, such as the *Human Principle* and understanding different types of systems, including the *3-Systems Principle*, we can identify game-changing parameters in the MFS. The critical factors are environmental parameters, such as altitude or elevation, and temperature, which significantly impact UAV's flight dynamics and can also influence the overall time of wildfire deployment, thereby affecting overall mission performance.

This study also serves as a basis for extensive prototyping and for formulating the optimization problem for fleet deployment of the MBST model. The SD model demonstrated opportunities to minimize coverage time due to environmental aerodynamic and operational constraints, such as failure rate, maintenance, fleet sites, etc. After this MBST model, this research will detail the development and use of the wildfire detection and communication optimization machinery to identify additional efficiencies in the deployment problem.

5.8 Chapter Summary

This model serves as a critical and extensive systems thinking prototyping and formulating tool for the problem for fleet deployment of the app MBST model, the system dynamics model demonstrated opportunities to minimize coverage time due to environmental aerodynamic and operational constraints such as failure rate, maintenance, fleet sites, etc. that change and will be basis for Chapter 7 and Chapter 8 responding to research gap 3 and research gap 4.

Chapter 6

Research Question 1: Wildfire UAV Fleet Operational Deployment Strategies (ODS)

6.1 Preface

The mathematical specification of deploying the wildfire UAV fleet and the UAV design parameters have been discussed in Chapter 2, along with the theoretical concepts of system engineering. In this chapter, we take the mathematical form of the optimization problem, and we apply human-in-the-loop (HITL) and Pareto surface systems method approaches to solve the problem and respond to research question 1 (RQ1) and research gaps 1 and 2.

6.2 Overview

Operational deployment strategies (ODS) for a fleet of unmanned aerial vehicles (UAVs) for the detection and communication of wildfires, focusing on natural and anthropogenic (man-made) conditions that influence the operational effectiveness of such a fleet. We document the research study conducted to address the primary challenge of detecting and communicating wildfires using a fleet of UAVs. Scenario-based optimization of operating conditions within a mathematical framework for multi-objective optimization has demonstrated effectiveness, particularly when human-in-the-loop (HITL) approaches are incorporated. A system architecture consisting of a central base station (CBS), launchers or mobile base station (MBS) vehicles, and unmanned aerial vehicles (UAVs) supports a decision support system (DSS) for wildfire fleet deployment. The DSS is developed from the perspectives of the wildfire analyst, CBS coordinator, and MBS operators.

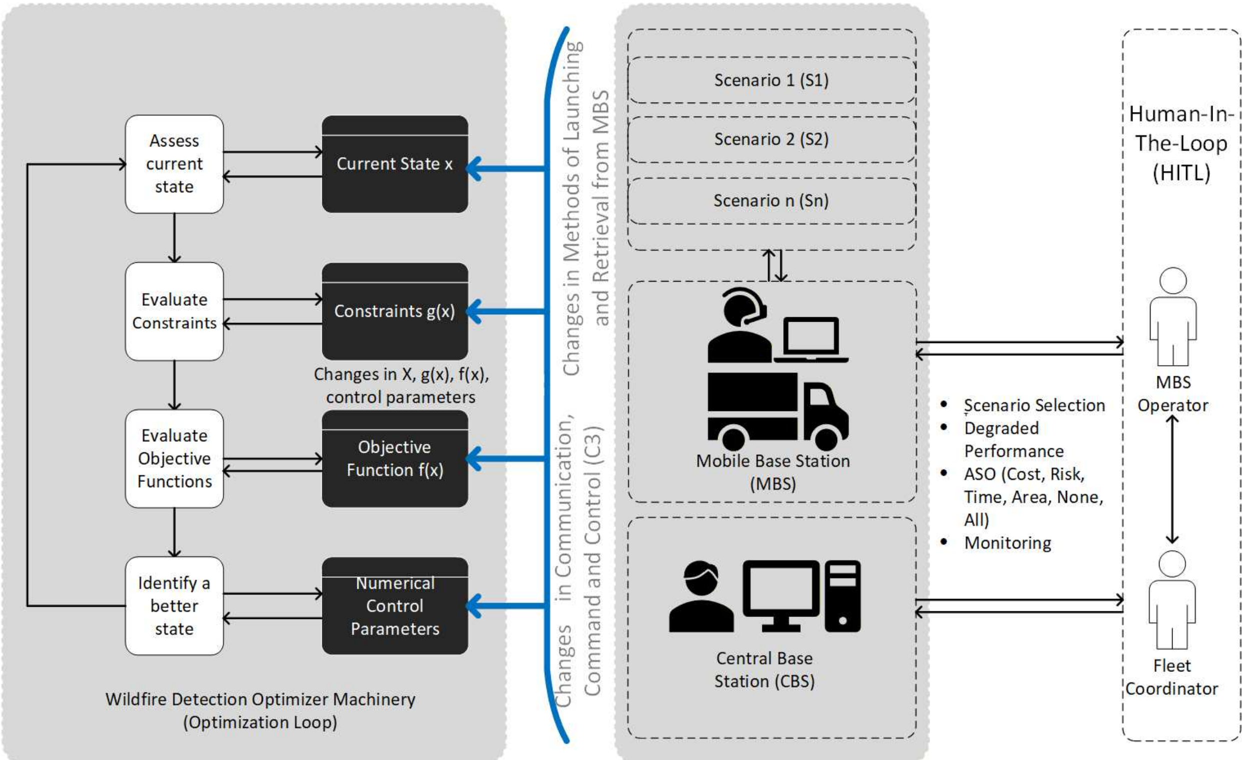


Figure 6.1: High Level Conceptual view of HITL for DSS

Note:

[1] The founding blocks of the wildfire detection optimizer machinery consists of i) assess current state, ii) evaluate constraints, iii) evaluate objective function and iv) identify a better state

[2] The scenarios and the wildfire DSS provide direct inputs to the decision variables (state) x, the constraint functions $g(x)$ and the objective functions $f(x)$, which are shown on the left side of the figure.

6.3 Introduction

The development of an effective optimization engine requires a holistic consideration of the system, incorporating parameters from the context system, enabling systems, and the system of interest (SOI). This includes environmental, aerodynamic, and operational parameters relevant to the deployment of a fleet of wildfire UAVs. Deployment strategies must be based on understanding historical wildfire data, urban corridors, and lightning information, as well as identifying areas prone to wildfires.

Several deployment scenarios have been developed within the decision-making process, employing decision support systems (DSS) to address real-world complexities. This study further investigates the use of genetic algorithms (GA) as nature-inspired methods to enable rapid and adaptive implementation of this complex problem as an initial approach. Figure 6.1 demonstrates the integration of human-in-the-loop (HITL), which augments the DSS optimization engine by utilizing mobile base stations (MBS) and central base stations (CBS) to systematically dispatch UAVs.

6.3.1 Background

The strategies behind the DSS discussed here cover operational placement of central base stations (CBS) and mobile base stations (MBS) to enhance wildfire detection and effective vehicle dispatch. Continuous monitoring of wildfire risk is also addressed, as it is an essential factor in maintaining robust performance UAV in dynamically changing environments. These findings combine into a comprehensive understanding of the strategies of deployment of the UAV fleet for the detection and communication of wildfires, discovering a systemic approach to solve this complex real-world problem.

1. Performance of optimal MBS dispatch (prior and post)
2. Performance of optimal UAV wildfire points (prior and post)
3. Performance of optimal design of unmanned aerial vehicles (UAV)

The DSS optimization engine interfaces HITL using MBS and CBS to launch UAVs from designated wildfire points (WP). Humans involved in this process can perform scenario selection and make decisions about cost, risk, time, area, and different types of objectives. Also, can make unique decisions, and the fully automatic optimizer engine's decisions can be altered. For example, an optimizer can decide not to use any degraded performance of an UAV, but human operators can decide to do the opposite to maintain the minimum requirements of the mission objective.

6.3.2 Flexibility for level of human involvement

Human involvement in the decision-making process for deployment problems can be categorized into two scenarios: both utilize a Decision Support System (DSS), but decision authority is primarily held by either the optimization engine or the human operators.

- A DSS with a fully automated optimization engine is desirable if it consistently delivers optimal performance. In this configuration, the optimization engine autonomously makes decisions, while human wildfire operators interact with the DSS solely to input relevant data.
- A DSS with semi-automated decision-making incorporates human judgment alongside the optimization engine. This approach is necessary when the optimizer may be insufficient due to poor input data or logistical constraints. Human operators, such as CBS coordinators or MBS vehicle operators, can make and implement decisions, using the DSS to validate their choices and assess performance.

The flexibility of human involvement offers several benefits. First, the ability to identify suboptimal optimizer decisions ensures meaningful human oversight. Second, it establishes trust in the system, as human intervention occurs when necessary. Third, it exposes areas where optimization models require improvement, thereby highlighting opportunities for innovation.

It can be argued that excessive reliance on human detection can slow down suboptimal automation, but that is when HITL must be fully aware of when to step back and let automation execute in full swing. Similarly, it can be said that over dependency on human operators, such as CBS coordinators and MBS vehicle operators, can lead to fatigue. While fatigue is not helpful, focusing on it is not a mission-oriented objective because it can be managed through proper scheduling of human resources.

6.3.3 HITL to Enhance Mission

The human-in-the-loop (HITL) architecture depicted in Figure 6.1 establishes a direct interface, enabling scenarios and wildfire decision support system (DSS) outputs (shown on the right and middle of the figure) to interact with the decision variables (state) x, constraint functions $g(x)$, and objective functions $f(x)$, which are presented on the left side of the figure.

It is not always possible to perfectly specify the true merit, as humans are constrained for several reasons. As a wildfire analyst, CBS coordinator, or MBS operator, it is not always possible to know all the details of local values. There are seasonal fluctuations and daily fluctuations. There are also fluctuations in need (cost, time) driven by man-made factors such as school year, working hours, etc. Therefore, the flexibility for humans to modify or adjust the merit or objective functions, constraints, and solutions at any time, as numerical optimizer iterations support, provides a more useful and practical decision-making system and augments learning about the complex nature of the problem.

Expecting that a set of well-defined merit or objective functions will capture all variations and exceptions is impractical and may significantly increase deployment costs. Even when such details are believed to be incorporated, their effectiveness may be limited. For example, insights from the Colorado Fire Department indicate that local firefighters possess specific knowledge about geographical features, school locations, and session times, which are often not represented in models. This stresses the importance of incorporating human-focused design by supporting effective use of the HITL component within the optimization machinery of the DSS.

6.3.4 Autonomy and Human Focused Design

Thomas B. Sheridan (1978) introduced a ten-level scale of autonomy, ranging from Level 1, where all decisions and actions are performed manually by a human operator, to Level 10, where the system operates entirely autonomously without human involvement [218]. Sheridan's autonomy scale corresponds to Shahroudi's framework for semi-autonomous, human-in-the-loop (HITL) systems as applied in this study [7], [8].

The HITL approach does not impose a strict dichotomy between human involvement and full autonomy. If human operators, such as the CBS coordinator or MBS operators, do not intervene during operations, the system defaults to full automation. Thus, HITL does not require a trade-off or reduction in autonomy. Input from mission stakeholders, including MBS operators, CBS coordinators, and operational analysts, is incorporated throughout the decision-making process of the DSS. This structure enables stakeholders to contribute beyond traditional supervisory roles.

Although some studies demonstrate the feasibility of fully automated algorithmic optimization with minimal human involvement, several key works, including those by Shahroudi [7], [8], explicitly incorporate human in-the-loop interaction. This highlights a gap between algorithmic optimization and real-world decision-making. Shahroudi proposes a semi-automatic optimization framework in which a human designer continuously collaborates with a numerical optimizer [7]. Further research extends this concept to aircraft design, contending that the true merit of design cannot be fully captured by fixed, machine-centric objective and constraint functions alone [8]. Human involvement is therefore essential to achieve the intended optimization outcomes.

Building on this perspective, Langen argues that humans and machines should be regarded as a unified socio-technical system [211]. Thus, optimization processes cannot fully exclude human participation in the-loop, and the optimization engine must incorporate human participation within the loop of the system.

6.3.5 Operators' Involvement With the Optimizing Machinery

MBS operators are able to modify the set of possible site vectors, referred to as X. CBS operators can adjust the constraints represented by $g(x)$ to meet mission objectives. Additionally, CBS operators may refine the objective functions to more closely align deployment strategies with mission requirements at the outset. While the primary goal is to develop an effective optimization engine, certain aspects of the HITL approach require additional refinement to achieve greater maturity within this research project.

6.3.6 Literature Review

Lack of Aerodynamics and Operating Parameters for Wildfire UAV Fleet Deployment

Currently, UAV fleet deployment strategies do not incorporate specific aerodynamic requirements for wildfire applications, particularly with respect to range and altitude. Most strategies in the literature utilize general-purpose, ultra-low-cost small UAVs that fail to meet the demands of

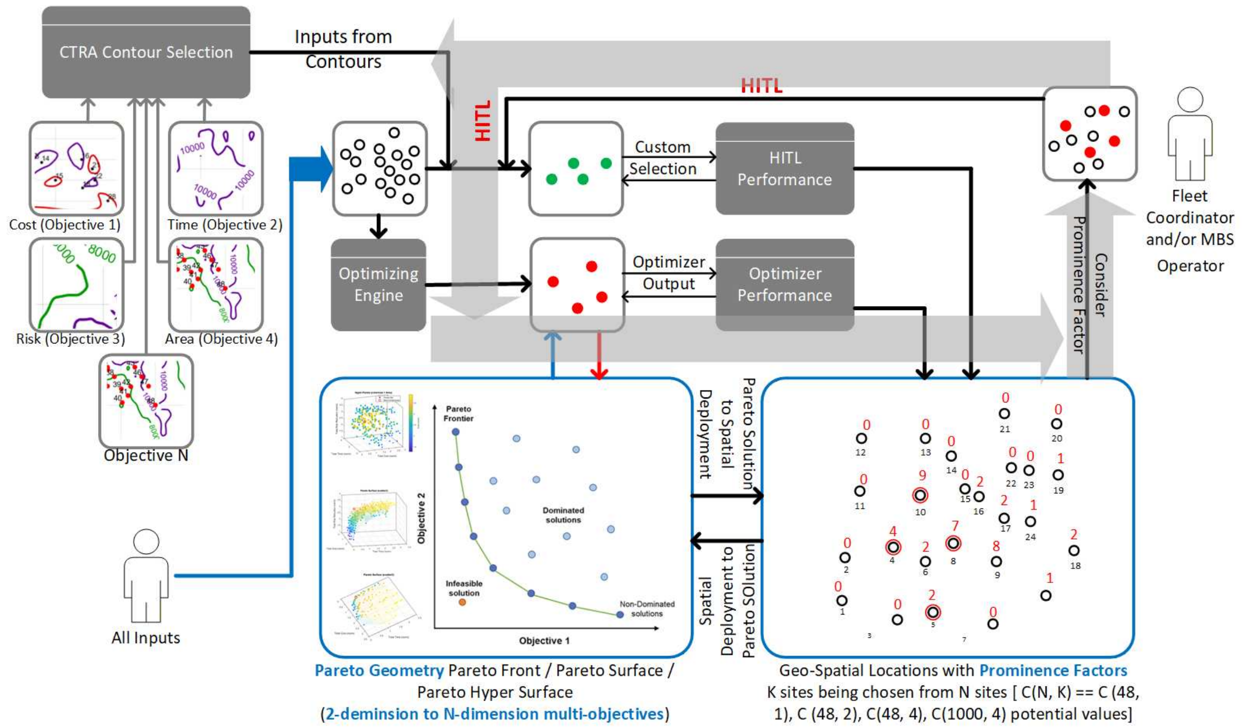


Figure 6.2: HITL Detail Data Flow of the Systems Method for DSS using optimizing engine

Note:

[1] This is the data flow of the conceptual diagram of the HITL of Figure 6.1.

[2] Multi-objective can be extended to N-dimensional objectives.

wildfire terrain. Although several studies have proposed UAV concepts for wildfire applications, these designs remain largely theoretical or insufficiently adapted to the unique aerodynamic and operational challenges of wildfire environments [10], [20], [21], [22], [46], [47], [48]. Some research suggests deployment strategies using UAVs with altitude capabilities between 50 meters and 200 meters, with the best case reaching 1000 m. These altitudes are inadequate for wildfire detection in regions where mountains can exceed 3000 meters. In contrast, the UAVs proposed in this project are typically two to ten times larger and capable of operating at altitudes up to 10,000 feet (3048 meters), with a ceiling of approximately 15,000 feet (4572 meters), enabling effective operation in high mountain environments.

Most existing UAV fleets are made up of short-range, low-altitude vehicles that are not optimized for wildfire operations. An effective response to wildfires requires fleets with UAVs capable of reaching altitudes up to 10,000 feet, operating at higher speeds, and covering geographically inaccessible areas. Research on high-altitude long-range UAV fleets specifically designed for wildfire applications remains limited. Additionally, deployment methods for small, non-wildfire-specific UAVs differ substantially from those for mid- and large-sized UAVs due to logistical, application, and aerodynamic considerations.

In the context of human-in-the-loop (HITL) and decision support system (DSS), current optimization approaches reveal significant gaps. The UAV design parameters are frequently treated as static and lack integration. Hildemann examines data and environmental uncertainty [204], while Pandey addresses design uncertainty [205]. The present research expands this scope considering data, environmental, operational, and HITL uncertainties. Pandey applies Monte Carlo simulation to evaluate expected utility under preference ambiguity [205]. Similarly, this study employs Monte Carlo simulation to model interacting environments, operational autonomy, and human uncertainties.

Current state-of-the-art research primarily addresses generic coverage, agriculture, infrastructure, or communication networks, rather than wildfire detection and suppression. When wildfire is considered, the focus is typically limited to detection or asset placement, rather than adopting a holistic perspective of the system suitable for integration into a decision support system (DSS) [10], [16], [50], [191].

Lack of Multiple UAVs Per Launcher and Multiple Launchers Per Fleet

Although there are numerous tools for optimizing UAV trajectory within the research community, limited research addresses fleet deployment optimization [43], [55], [59], [81], [145]. In particular, there is a lack of research on optimization strategies that involve multiple UAVs per launcher and multiple launchers per fleet for wildfire specific UAVs.

Extensive area coverage during wildfires often requires the deployment of a large number of UAVs. Deploying multiple UAVs from a single launcher is an efficient strategy. The simultaneous use of multiple launchers facilitates a systemic approach to wildfire detection and communication.

Currently, there is no integrated systems design that addresses the deployment of multiple UAVs per launcher and multiple launchers per fleet specifically for wildfire detection. Existing studies typically treat UAV design, detection, and deployment as separate issues. Many assume fixed platforms or focus exclusively on deployment optimization, without co-designing UAV capabilities, payloads, and fleet architecture tailored to wildfire missions [16], [45], [46], [47], [48], [60], [62].

6.3.7 Supported Systems Thinking Principles

The principles of systems thinking are strongly supported in this study for the UAV fleet deployment DSS.

Utilization of Boundary Principle - Knowing the boundaries of the system

The Boundaries Principle identifies, "*Systems boundaries depend on perspectives, purposes, and roles*" [42].

The mission goal of the wildfire detection has been achieved by integrating the MBS operator and fleet coordinator as human elements within the loop. As human elements within the loop, they are able to interact, modify and optimize varying parameters, constraints, and objective functions. They are able to adjust the number of deployment sites, change constraints as needed, and update the objective function. This is illustrated in Figure 6.1. We identified opportunities to utilize different scenarios in which humans can operate under standard operations. However, in situations involving deviations from those scenarios, human operators can interact with the system and significantly enhance system performance from cost, time, risk reduction, and area coverage perspectives. In addition, we further plan to utilize humans more collaboratively as part of future work and expand the current four-dimensional optimization approach to an N-dimensional approach. Human involvement will become even more critical. By utilizing optimization machinery as a rigorous tool, we have shown that including humans within the system boundary in order to support the purpose of the mission. The roles of the MBS coordinator and CBS operator are not only to observe but also to participate as active elements within the system boundary.

Utilization of Human Principle - Why human users?

The Human Principle reflects, "*Humans impact and are impacted by the (wanted / unwanted) emergence of all reachable systems*" [42].

The universal impact of the mission goal is highly dependent on human exposure and welfare. Therefore, interactions involving humans are extremely critical. One example is when humans possess knowledge regarding the safety importance of a school at a certain location. Even though that location may potentially have low risk, the human impact perspective automatically increases the value of protecting that asset.

Often, such considerations may not be captured by an automated optimizer. Thus, the involvement of human operators is critical, and their knowledge serves as essential input to the system. This is why human-in-the-loop systems are very important.

6.4 Systems Methods

The human-in-the-loop (HITL) is the key element in this system method to effectively utilize the optimization machinery of the DSS.

6.4.1 Overall Systems

This systems method uses optimizing engine part of the DSS to find future wildfire utilizing HITL and UAV fleet deployment. The optimization framework addresses multiple objectives. Specifically, four primary objectives are considered: cost, time, risk, and area (CTRA). The optimization process seeks to minimize cost and time while maximizing area coverage and the potential to reduce risk. Human-in-the-loop (HITL) integration is achieved with the multi-objective optimization (MOO) engine via decision support systems (DSS) and scenario-based optimization of operating conditions.

The methodology presented in this chapter integrates human-in-the-loop (HITL) optimization for the engine illustrated in Figure 6.2. The approach, depicted on the left, incorporates human inputs including cost, time, risk, and area contours to facilitate contour-based selections addressing multiple objectives. In addition, manual site selections may be provided as user input.

The method incorporates both generic and user-provided inputs to generate two types of solutions: the optimizer's choice and the human-selected choice, enabling comparison between them. Iteration can occur between Pareto fronts and site selections. The Pareto fronts may represent two-dimensional objectives, three-dimensional objective surfaces, or higher-dimensional hypersurfaces for four objectives.

These solutions can be mapped to different sites to show how specific sites yield particular results. A prominence factor shows how often a site appears across solutions. However, the highest prominence factor does not always indicate the best choice. Final interpretation depends on system interconnectivity and context.

6.4.2 System Inputs

Step 1 - DSS inputs are provided by the fleet coordinator and/ or the MBS operator to "optimize engine" for ODS decisions.

Step 2 - Inputs are provided by the fleet coordinator and/ or the MBS operator using CTRA contours or manual selection of the "custom solution" site based on user decisions.

Step 3 - After inputs are provided, the DSS processes both the human custom solution and the output of the optimizer engine solution.

6.4.3 Methodological Steps and Processes

Step 4 - The DSS generates a PF for 2 objectives tradeoff, Pareto Surface for 3 objectives a Pareto hypersurface for 4 or more objectives.

Step 5 - Thus, the Pareto geometry is formed, and it is possible to go back and forth between the Pareto front to the geospatial location and vise versa.

Step 6 - Next step, the DSS compares the performance of the human-entered site selection vs Optimizing Engine solution.

Step 7 - The geospatial map provides a prominence factor [3]. which can be fed to the input of the fleet coordinator and the MBS operator part of the feedback loop.

6.4.4 System Outputs

Step 8 - The method outputs the following items as listed below,

- optimizer solution one,
- custom human solution, and
- comparison of optimizer vs custom human solutions.

6.5 Simulation Framework

This section details the simulation framework for the Optimal Deployment Strategies (ODS) for wildfire UAV deployment and UAV design.

Figure 6.3 maps potential central base station (CBS) locations for wildfire launching and retrieval in Southwest Colorado. As part of the case study, two candidate CBS locations were identified: one in Cortez, CO, and another in Durango, CO. Cortez vs. Durango are evaluated as CBS options for ODS in Southwest Colorado, District 43 (San Juan River Region).

This section details the simulation framework for the Optimal Deployment Strategies (ODS) for wildfire UAV deployment and UAV design.

6.5.1 Operating Conditions Scenarios

The deployment scenarios of the wildfire UAV fleet are summarized in Figure 6.4. We have considered six different scenarios, and all of these scenarios are affected by HITL [7], [8] [4]. HITL in

[3]The prominence factor of a site is the number of times that site appears in a proposed solution, defined as a set of launch sites for a fleet of wildfire UAV.

[4]Operating conditions scenario-based optimization involves selecting and analyzing specific examples of varying system operating conditions and configurations for the system in question to evaluate its performance under different real-world scenarios.

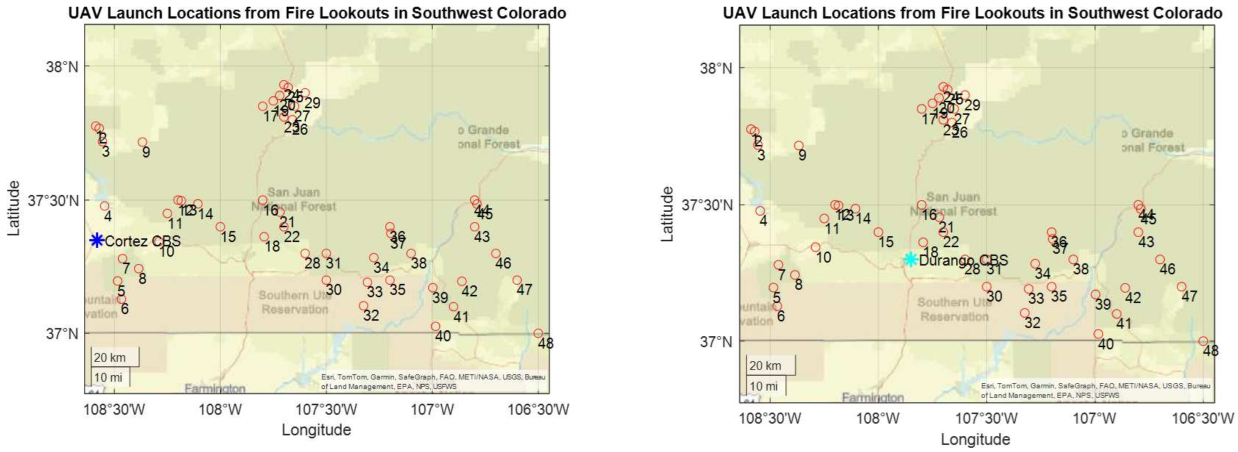


Figure 6.3: CBS Locations options for scenario based optimizations

Note:

[1] Potential CBS locations for wildfire launching and retrieval in Southwest Colorado.

[2] Coretz vs Durango as CBS for ODS at Southwest Colorado, District 43 (San Juan River Region)

these scenarios includes CBS coordinator, MBS vehicle operators, decision makers, and stakeholders in the deployment and design of the Wildfire UAV fleet.

It is important to note that Scenario-based optimization is a method for assessing uncertainty by finding an optimization problem over a finite set of samples. This provides solutions with probabilistic grantees. Campi discuss scenario based optimization, "... a computationally efficient methodology for dealing with uncertainty in optimization based on sampling a finite number of instances (or scenarios) of the uncertainty" [122]. This approach is valuable for chance-constrained programming and robust optimization, as it avoids the needs for exact probability distributions and depends only on sampling. In contrast, in our study, the scenarios in Figure 6.4 represent scenario-based optimization based on operating conditions. This involves selecting and analyzing specific examples of varying system operating conditions and configurations for the system in question to evaluate its performance under different real-world scenarios.

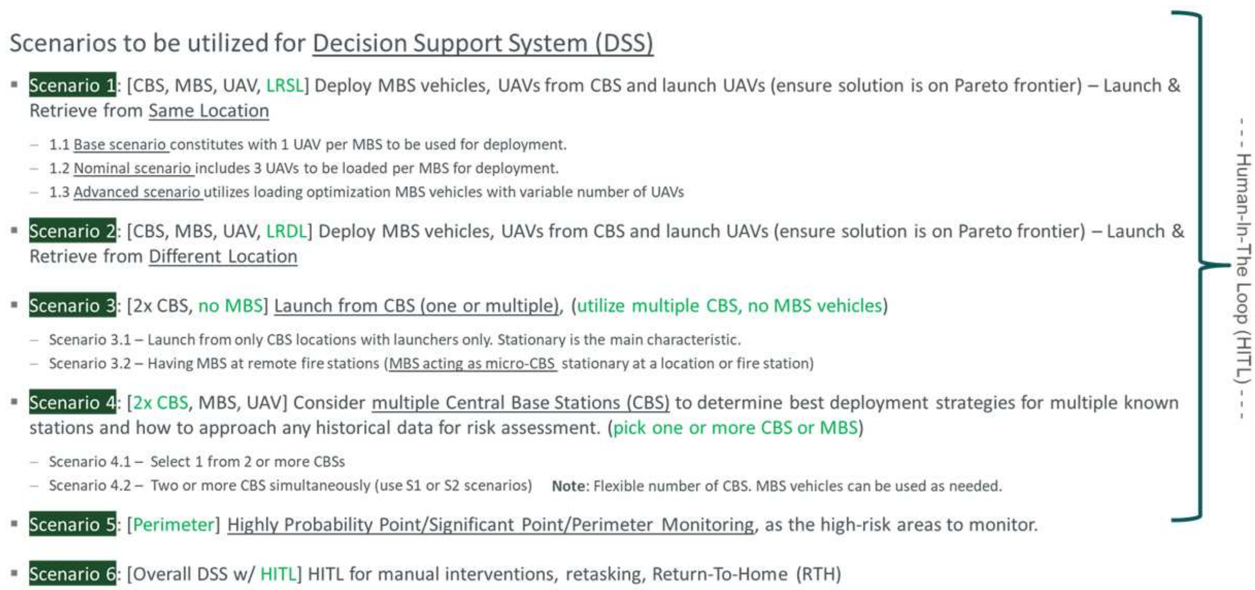


Figure 6.4: Scenarios Selection for Decision Support System (DSS)

Note:

[1] Wildfire UAV fleet deployment scenarios that are operating conditions based.

6.5.2 Two stages optimization approach

An optimization engine is implemented within the decision support system (DSS) to address the problem of UAV fleet deployment. This engine operates in two sequential stages, each feeding into the next to refine the solutions.

- In the first stage, a genetic algorithm (GA) determines the optimal deployment strategy (ODS) based on the locations of the central base station (CBS) and the deployment characteristics of the mobile base station (MBS).

- The second stage utilizes ant colony optimization (ACO) to refine ODS through wildfire points optimization (WPO), emphasizing UAV flight path planning and real-time operational constraints.

The two stages of the optimization methodology are described in Figure 6.5, where the first stage uses the genetic algorithm as part of the optimization machinery.

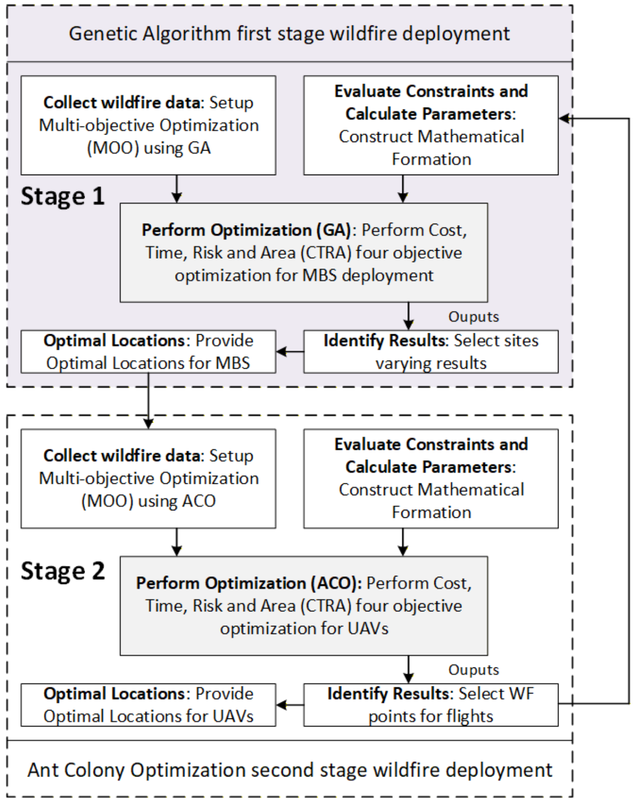


Figure 6.5: Method for two stages of optimization - First stage (GA)

Note:

[1] The genetic algorithm (GA) was applied in the first stage of fleet deployment optimization. This process is illustrated in gray at the top of the figure.

[2] The second stage of optimization, focused on wildfire points (WP), uses ant colony optimization (ACO) as discussed in Chapter 7.

6.5.3 Use of Genetic Algorithm to Solve First Stage Optimization

The first stage addresses wildfire deployment using genetic algorithms, which is the primary focus of this chapter. Chapter 7 will discuss the application of ant colony optimization for the subsequent stage of wildfire deployment.

Solving Complex Problems in Initial Prototypes

Formulating objectives and mapping them to design variables represent one of the most significant challenges in systems engineering, often surpassing the complexity of selecting an optimization algorithm. Optimization of complex real-world problems is computationally intensive, particularly for nonlinear challenges such as wildfire UAV deployment, where there are significant variations in goals, constraints, terrain, fleet configuration and size for different applications. Hence the initial need for a very flexible method of multi-objective constrained optimization that is not sensitive to the change or evolution of deployment strategies and stakeholder needs.

Genetic algorithms enable the optimization machinery to solve complex, nonlinear system problems, as evidenced by previous research [7], [8], [209], [212]. They are an appropriate choice for the initial implementation of our DSS because they can handle highly nonlinear objectives and constraints, are less susceptible to becoming trapped in local optima, and are flexible for general systems engineering applications such as a DSS for wildfire detection. The computational load does not increase as significantly as with some other techniques as the problem dimensions grow. This approach facilitates solving the overall problem.

In this research, the early-stage system prototype employs a genetic algorithm for multi-objective optimization. This approach is appropriate for developing and demonstrating our initial solution to the Wildfire UAV Deployment DSS concept, although eventual productionized versions of our concept for specific wildfire jurisdictions may benefit from highly tuned and tailored optimization methods that do not require as much flexibility.

Commercialization and Alternatives

Genetic algorithms are among the least computationally efficient optimization methods when compared with other constrained optimization techniques, such as numerical optimization algorithms (e.g., *fmincon* in MATLAB), hill-climbing methods, or adaptive meshing.

Shahroudi argues that systematically adapting the search space is more efficient than random sampling and proposes a non-random adaptive grid method for high-speed optimization. This approach enables high-dimensional engineering optimization problems to be solved faster with fewer function evaluations while maintaining a high probability of finding the best solution. It represents a promising approach for commercialization and future time-sensitive iterations of the DSS [88].

The optimization machinery of the DSS includes constraints and objective functions that are highly nonlinear and may exhibit multiple local optima. For the initial implementation of this optimization machinery, a highly generic method was required to accommodate a wide range of fleet operations across multiple scenarios with varying fleet architectures and capabilities. This results in complex, nonlinear, and evolving objective and constraint functions.

While more computationally efficient algorithms may exist for specific applications, production-level implementation and detailed optimization were not prioritized in this study. Instead, the primary objective was to develop a flexible, systems-based method applicable to the widest possible range of scenarios.

6.6 System Model - Wildfire Fleet Deployment and UAV Designs

The optimizer machinery functions as the central engine of the decision support system (DSS), systematically integrating available intelligence such as fire line forecasts, topological data, availability of MBS vehicles and UAVs, and dynamic environmental conditions to generate a logically interconnected and comprehensive deployment plan. This component of the research is developed as a human-centric software tool and implementation (GUI) to accurately represent the concepts underlying the optimization engine.

The DSS incorporates human users to provide detailed UAV operational guidance. Because the architecture accepts incremental data and partial updates, the system remains functional and can enhance its recommendations even when some information is initially unavailable.

6.6.1 Decision Support System (DSS)

The decision support system (DSS) in this research is a key implementation that integrates the optimizer machinery with the graphical user interface (GUI) to make decisions for the deployment of the UAV fleet for the detection and communication of wildfires.

It has different user groups with different perspectives, including wildfire analysts, a UAV fleet coordinator at CBS, and an MBS vehicle operator. The DSS is composed of all these three perspectives, part of the GUI implementation that accounts for both wholistic nature and feedback loops.

Several of the DSS Inputs are the following (not an exhaustive list):

- “Run Deployment” kicks of the optimization algorithm
- “Fleet Deployment Scenarios” can be selected from radio buttons
- “CBS” location can be selected between “Cortez” and “Durango”
- “Max num of MBS vehicles” can be provided as input to the system
- “Max num of available UAVs” also can be provided as input to the system

Several of the DSS Outputs are the following (not an exhaustive list):

- Deployment decisions can be displayed in the form of an array
- GUI displays critical decision support system figures

CBS Coordinator Perspective – DSS CBS View

The coordinator has a perspective of making the best use of the resources provided and addressing the immediate needs of the designated responsibility area, as shown in Figure 6.6. The CBS coordinator can effectively focus on day, week, and fire season goals, and their perspectives are depicted in the CBS Coordinator’s view.

MBS Vehicle Operator Perspective – DSS MBS View

The operators of MBS vehicles have the ability to utilize the specific locations that they are assigned with a number of UAVs that were provided as depicted in Figure 6.7.

MBS operators can effectively focus on the mission of the assigned number of UAVs and specific goals that need to be achieved in the field.

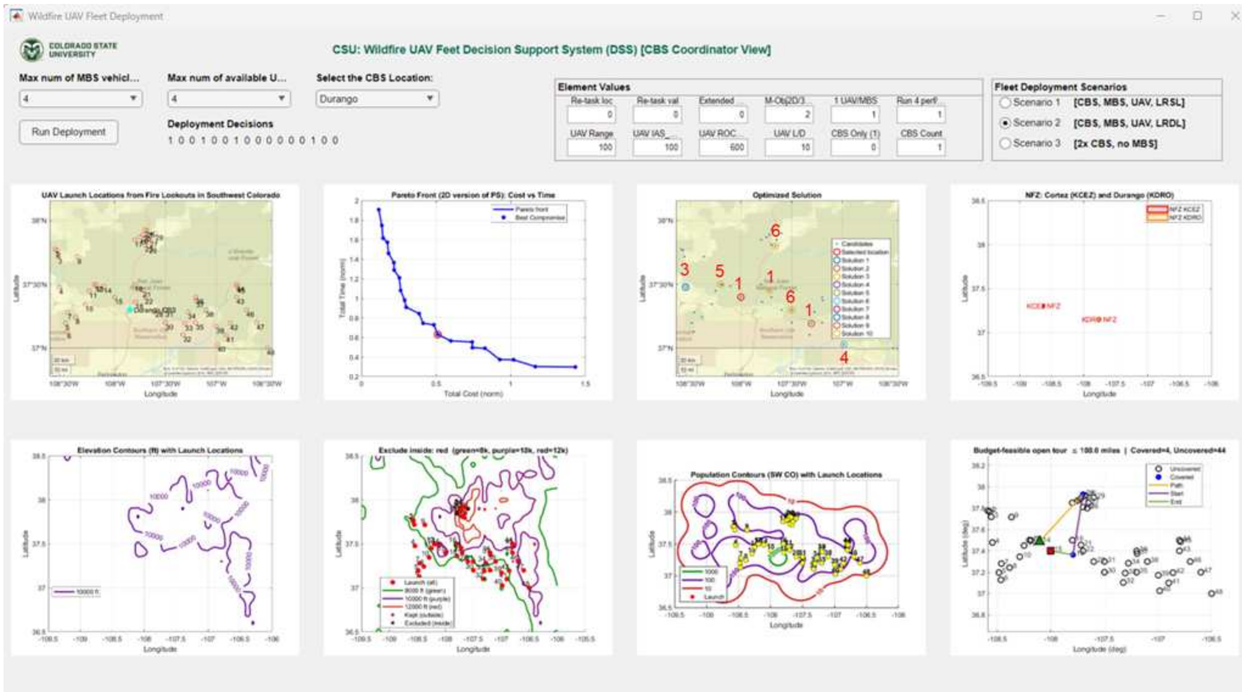


Figure 6.6: CBS Fleet Coordinator View of the DSS GUI

Note:

[1] CBS coordinator view enables to interconnection among wildfire analyst viewpoint and MBS vehicle operator viewpoints.

Wildfire Analyst Perspective – DSS Analyst View

Analysts use the DSS to make sense of the systemic nature of the wildfire problem and how to address it via these specifically designed UAVs [6], [173]. Analysis can recommend changes, updates, and mitigation to flight dynamics issues in UAV design to further enable more effective wildfire detection, as shown in Figure 6.8.

The analysts of the wildfire systemic solution using UAV fleet, also can also gather data and information from DSS to reduce UAV design, reliability, maintainability, and production costs and time. Analysts can focus on a fire season and long-term views, utilizing the information and data logs of the DSS.

Figure 6.7: MBS Operator View of the DSS GUI during pre-flight time and Run-Time

Note:

[1] MBS operators easily and promptly able to view the run-time issues using this view of the DSS GUI.

6.6.2 Enabling Single Digital Thread among users utilizing DSS

Closed loops of communication among MBS vehicle, CBS coordinator, and wildfire analyst enable a single chain of thought process (single digital thread) via these DSS tools, as it uses the same set of data, systemic mission goal.

Integrated simulations typically yield more actionable design insights for complex autonomous systems. Foundational research on human-in-the-loop autonomous systems demonstrates that jointly modeling operator behavior and system dynamics is essential to achieve reliable performance. However, the added complexity may be unnecessary for early-stage abstraction-focused studies in which a coarse uncertainty model is sufficient.

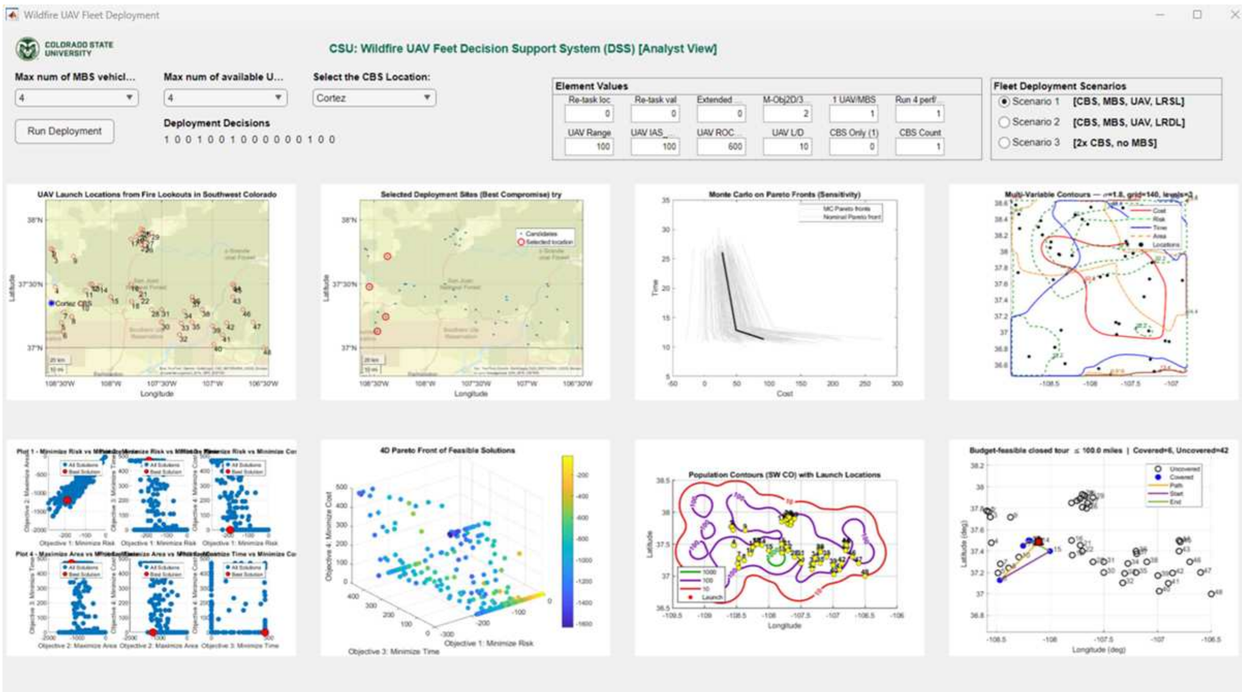


Figure 6.8: Wildfire Analysis View of the DSS GUI

Note:

[1] Wildfire Analysis View of the DSS GUI enables to graphically see and interpret data collected from a single mission to a long period of time.

6.6.3 Human-in-the-loop (HITL) utilizing DSS

The DSS is developed as part of this research work as a human-centric UAV fleet deployment and UAV design tool, and provides a GUI implementation to ensure fidelity to the concepts of the optimizer engine. Essentially, the DSS integrates humans into the optimizer machinery, enabling a human-in-the-loop (HITL) approach with limited or no involvement of the optimization engine, or it can fully depend on the optimization engine. Simulation interfaces within the DSS that jointly model environmental conditions, system autonomy, and human decision-making provide a more accurate representation of real-world operations than approaches that address these uncertainties separately.

Human users, such as CBS coordinators and MBS operators, can provide manual input (e.g., selecting 4 sites of 48 possible sites for launch and retrieval of the UAV), as shown in Figure 6.9.

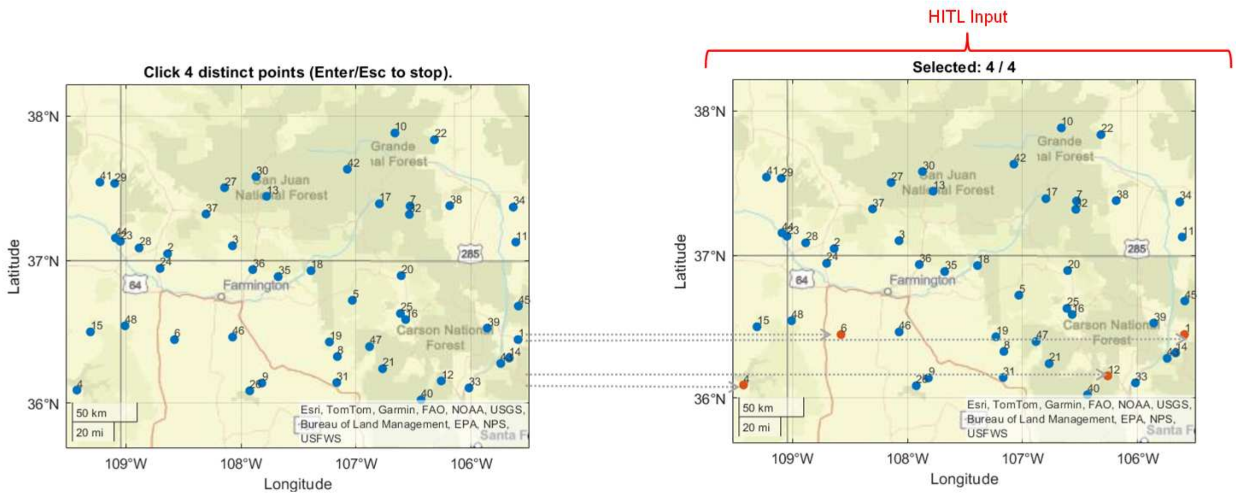


Figure 6.9: HITL manual inputs

Note:

[1] HITL Bi-directionality for solutions and Pareto Fronts (4 picks from 48)

These manual inputs allow the UAV fleet to be deployed based on user choices rather than optimizer decisions. Figure 6.9 presents a simulation in which a user provides input, and Figure 6.11 compares the human decision performance with the optimizer decision performance. Another way to provide input to the optimizer is by selecting contours.

Human input to the optimizer engine may be incorporated through contour selection. Figure 6.10 illustrates the launch sites identified based on these selections. In this approach, humans influence the objective function aspect of the process by selecting options based on criteria such as cost minimization, time minimization, risk-reduction maximization, or area maximization. Green contours typically denote favorable outcomes, purple contours indicate intermediate outcomes, and red contours represent unfavorable outcomes. By evaluating and comparing these contour sets, users can make informed decisions. For example, if cost is not a constraint, a red contour may be selected, whereas prioritizing area maximization would lead to a green contour.

The optimizer can select launch sites autonomously, with human input, or sites can be chosen directly by humans. In both cases, numerical performance comparisons are essential. The figure on the right provides a direct mapping. As shown in Figures 6.9 and 6.10, the decision support system

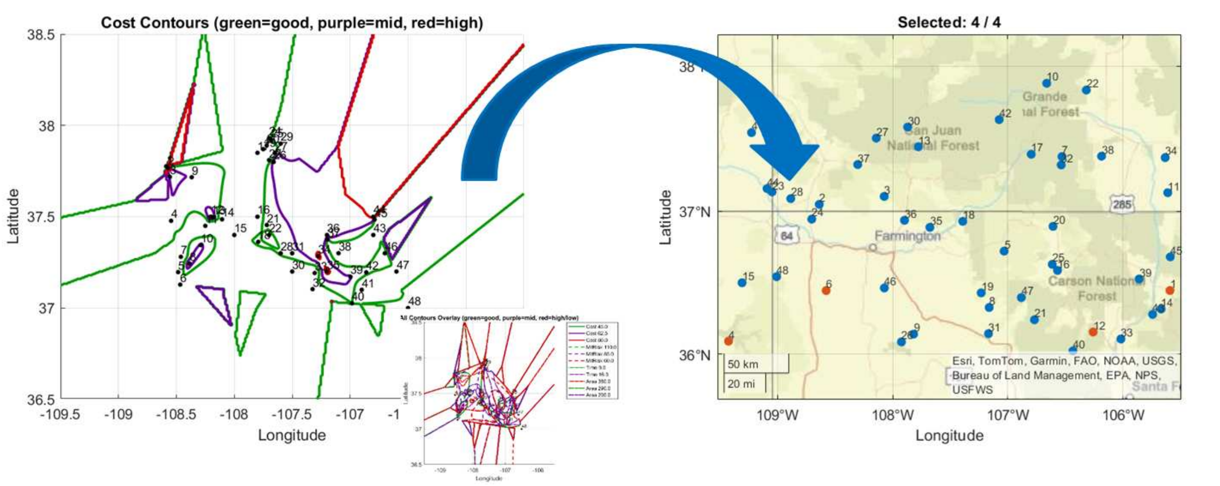


Figure 6.10: Launch sites based on manual contours inputs

Note:

[1] Contour Selection and picking sites based on contours manually as part of the human-centric design

(DSS) presents the human-centric input mechanism, and Figure 6.11 compares the performance of the human vs. the optimizer.

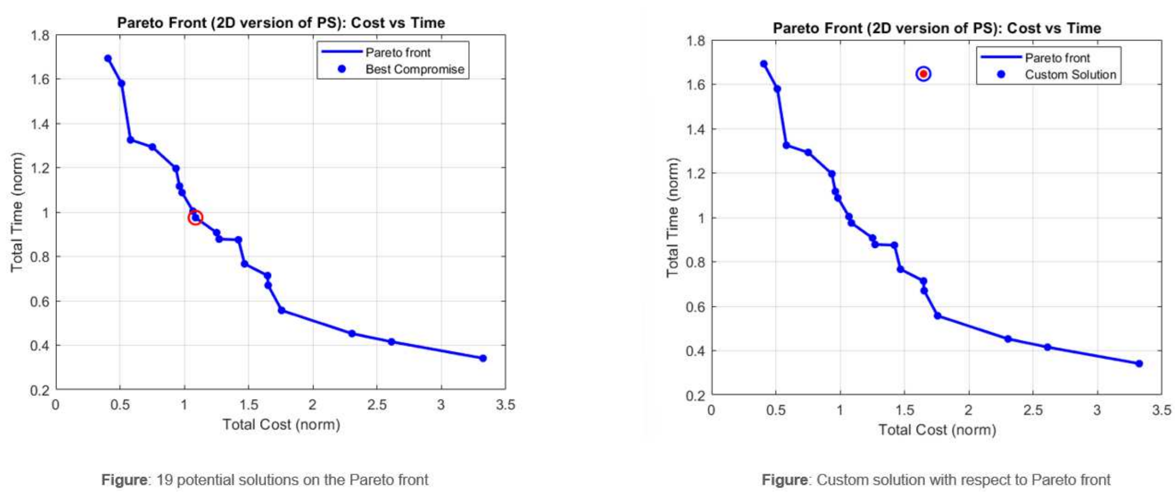


Figure 6.11: Optimizer machinery logistics

The DSS enables comparison with the optimizer's results, shown on the left of Figure 6.11. The left side displays possible solutions along the corridor front; the right shows the custom or human-provided solution. Comparing human input with optimizer input offers clear advantages.

Input to the optimizer machinery can also be provided using contours based on objectives, as shown in Figure 6.12. The green contour is most favorable to the mission goal, the red contour is least favorable, and purple represents intermediate conditions.

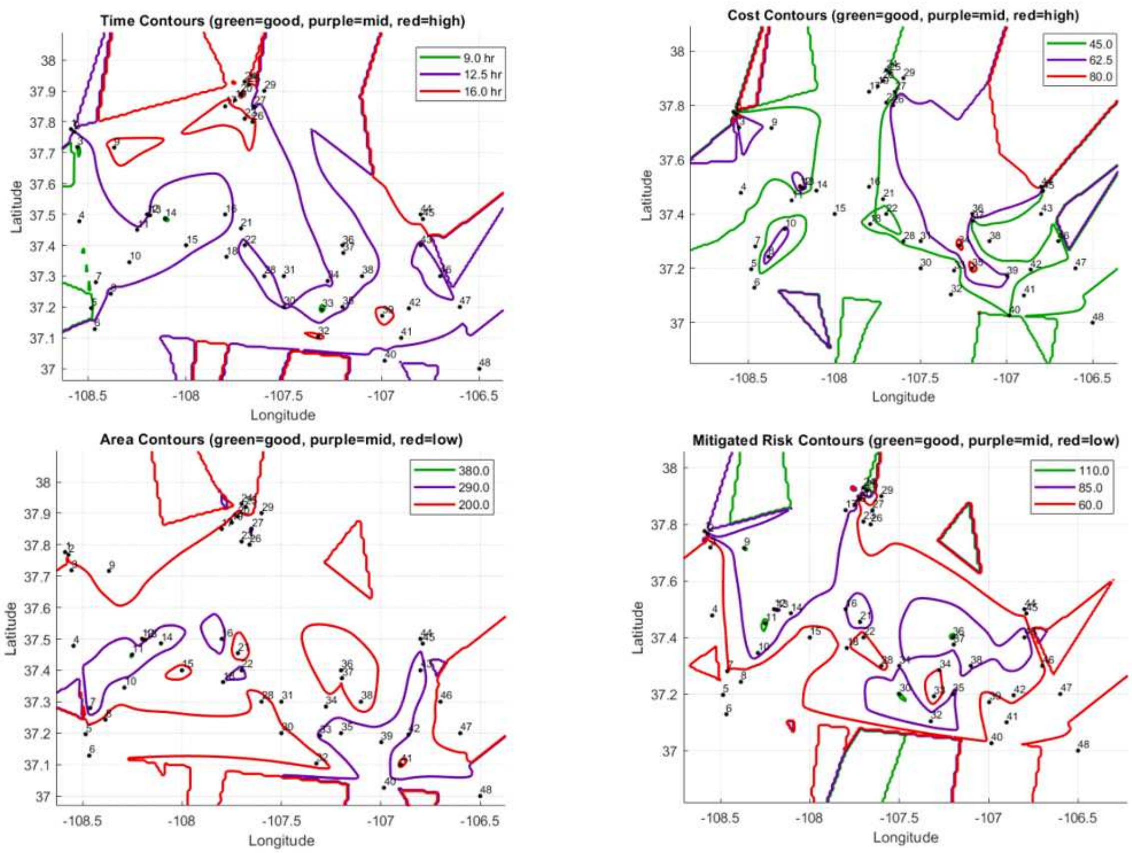


Figure 6.12: Input to optimizer machinery using contours based on objectives

Note:

[1] Select low, mid or high contour lines for each of the objective.

[2] Green contour is the most favorable towards mission goal and red contour is the least favorable towards mission goal.

Figure 6.12 presents all four objectives with contour selection, where green indicates favorable outcomes, red denotes unfavorable outcomes, and purple signifies intermediate conditions. These contours are applied to various objectives, including time (top left), area (bottom left), cost (top right), and risk (top right). The primary objective is to minimize time and cost while maximizing risk reduction and area coverage.

6.7 Problem Formulation of Optimal Deployment Strategies (ODS)

The UAV exhibits nonlinear performance due to its aerodynamic characteristics, fleet deployment dynamics, and the operational constraints summarized in Table 6.1. The table presents the high-level Operational Deployment Strategy (ODS) constraints considered in the formulation of the wildfire deployment and design problem. A detailed decomposition of these constraints, along with their implementation and practical implications, is presented throughout the remainder of this chapter.

Table 6.1: Operational Deployment Strategies (ODS) constraints

Optimization Items	**Complexity Details for Wildfire Items**
Wildfire Topology	1) Historical Wildfire Risk Databases 2) Vegetation fire factors
Geographical Locations	1) Road availability to nearest possible launch location 2) Geographical surface topology 3) UAV Fleet Coordinator input for geographical boundaries
Operational Constraints	1) No Fly Zone (regulatory or safety) 2) Regulatory Control Tower Communication
Communication Requirements	1) Planned coverage of SATCOM 2) Planned coverage of LOS
Atmospheric Constraints	1) Historical atmospheric data for fire conditions
UAV Constraints	1) UAV Device Coverage (LiDAR and/or thermal camera Field of View)
Miscellaneous Constraints	1) UAV Fleet Coordinator Custom Inputs (Pre-plans)

Table 6.2 shows the different types of optimization items that we consider. We start with the ignition map, which accounts for both natural and man-made ignitions. We also consider power line risk, lightning risk, urban corridor overlay risk, historical wildfire maps, and population density, all of which impact risk. Table 6.2 provides a breakdown of the contour selection map, allowing contour selection for each of these objectives.

Table 6.2: Wildfire UAV Fleet Deployment and UAV Design items for MOP Formulation - 1 of 2

No	Optimization Items	Description	Opt. Stages	Additional Notes
[1]	Ignition Map (Natural Ignition) – Lightning Risk: Includes lightning strike probability.	Core Data layers	ODS	Implemented part of the "Risk" objective function and constraints.
[2]	Ignition Map (Manmade Ignition) – Powerline Risk: Separate from ignition, but potentially correlated.	Core Data layers	ODS	Implemented part of the "Risk" objective function and constraints.
[3]	Ignition Map (Manmade Ignition) – Urban Corridor Overlay Risk: Semi-developed areas show higher ignition risk due to human activity.	Core Data layers	ODS	Implemented part of the "Risk" objective function and constraints.
[4]	Historical Wildfire Map: Useful for validating risk trends and identifying fire-prone zones.	Core Data layers	ODS	Implemented part of the "Risk" objective function and constraints.
[5]	Population Density Map: Fires are rare in dense urban centers and uninhabited wilderness but common in lightly populated areas.	Core Data layers	ODS	Urban corridor and "risk" objective addresses population density.

Note:

[1] This is not a comprehensive list but to show the optimization items relevant to risk and ignition parameters.

All of these concerns focus on the ignition or risk factors within the risk objective. The Table 6.3 provides a further breakdown of other optimization items, including the road access map, the no-fly zone map, bingo fuel, the retasking logic and different deployment scenarios. These can be incorporated into the optimization stages, either in optimal deployment (ODS, first-stage optimization) or WPO (second-stage optimization). They are primarily added as constraints and objective functions; however, in some cases, additional logic can also be incorporated into the deployment algorithm.

Table 6.3: Wildfire UAV Fleet Deployment and UAV Design items for MOP Formulation - 2 of 2

No	Optimization Items	Description	Opt. Stages	Additional Notes
[6]	Road Access Map: Needed for deployment feasibility and retrieval logistics.	Core Data layers	ODS	Input was provided from Google selecting the sites for launch and retrieval locations.
[7]	No Fly Zone Map: No fly zones need to be considered.	Core Data layers	ODS, WPO	Implemented part of the constraints logic.
[8]	Bingo Fuel: Ensuring UAVs can return safely.	Operational Constraints & Considerations	WPO	Part of DSS logic and implementation.
[9]	Re-tasking Logic: Ability to shift UAV missions in real time based on detected fires.	Operational Constraints & Considerations	ODS, WPO	Part of DSS logic and implementation.
[10]	Fixed vs. Mobile Deployment (Scenarios): Modeling trade-offs between static and dynamic response strategies.	Operational Constraints & Considerations	ODS, WPO	Six scenarios have been constructed and analyzed to explore fixed vs mobile deployment cases.

All four sets of contours may be integrated into a single figure, as illustrated in Figure 6.13. This configuration can be modified according to specific points and risk levels of interest. Such a representation offers an analytical perspective that enables informed decision-making based on available information, which the optimizer may not fully capture.

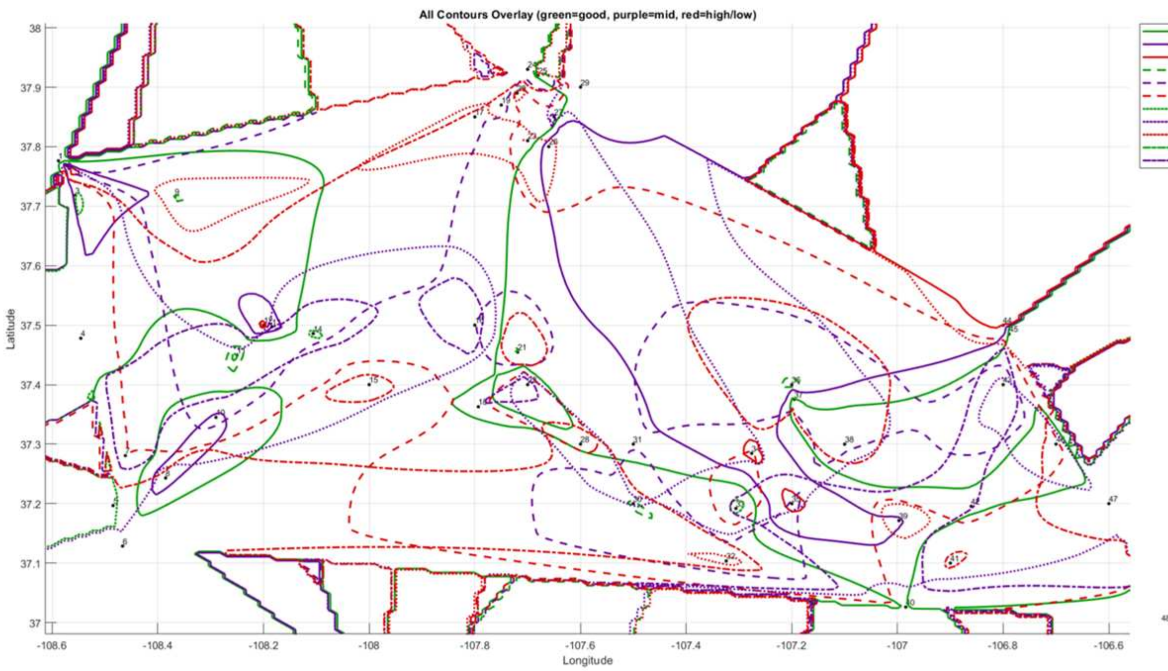


Figure 6.13: All objectives as composite input contours for the DSS

Note:

[1] Composite input contours for all objectives can be provided to the DSS for human decision makers to provide input.

Typically, assets with no value are above 12,000 feet (3700 m), as shown in Figure 6.14 [202]. Thus, when possible, UAVs do not need to be launched near or at 10,000 feet [202]. Altitude contours can be used to exclude certain launch and retrieval sites, thereby improving optimization. This analysis is integrated into the decision support system (DSS) and can be provided to the optimizer to support both automated and human decision-making. Figure 6.14 illustrates the impact of elevation on wildfire risk. At elevations of 10,000 feet or higher, wildfire risk is significantly reduced. Generally, wildfire detection risk begins to diminish above approximately 8,000 feet, and there is minimal value at risk above 12,000 feet.

Additional scenarios consideration involving the CBS exclusively, without any MBS vehicle availability. This requires the UAV to complete approximately the range in which the UAV is in flight loop. Figure 6.15 illustrates the scenario in which only the CBS serves as the launch and retrieval site, assessing whether most areas can be covered. The red circle indicates a 25-mile radius,

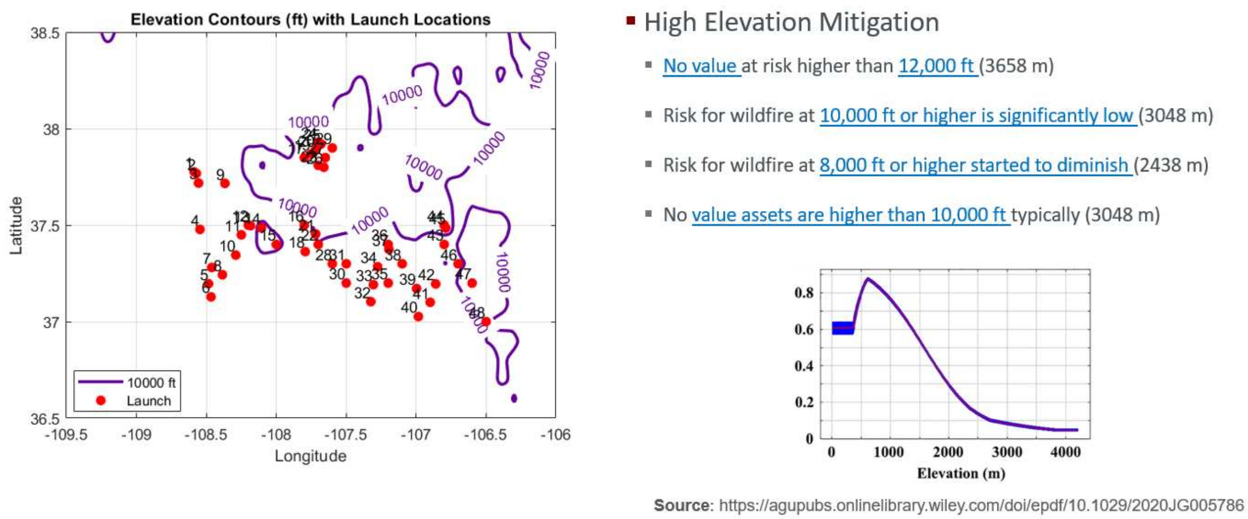


Figure 6.14: High Elevation Mitigation

Note:

[1] Risk for wildfire at 10,000 feet or higher is significantly low (3000 m).

[2] Risk for wildfire detection start to diminish above 8,000 feet (2400 m). [202]

while the green circle indicates a 50-mile radius, encompassing the four counties in the test cases. This method offers an alternative optimization strategy when mobile vehicles are not available. However, this approach may not always be appropriate as it depends solely on the home base. In contrast, it can reduce the costs associated with mobile base stations and can be incorporated numerically into the optimization function.

Figure 6.16 illustrates the two-dimensional optimization process, focusing on cost and time as objectives in a multi-objective optimization (MOO) problem. The selection of a site, depicted in the bottom right, influences the position of the solution on the left side of the figure. The top right demonstrates that a solution may be located on the Pareto front line. However, if a solution is not on the Pareto front, such as a point situated away from it (for example, near point 2), the distance from the Pareto front signifies potential for further improvement in the constraints and objective search. Solutions in this region warrant additional analysis to identify which aspects can be further optimized.

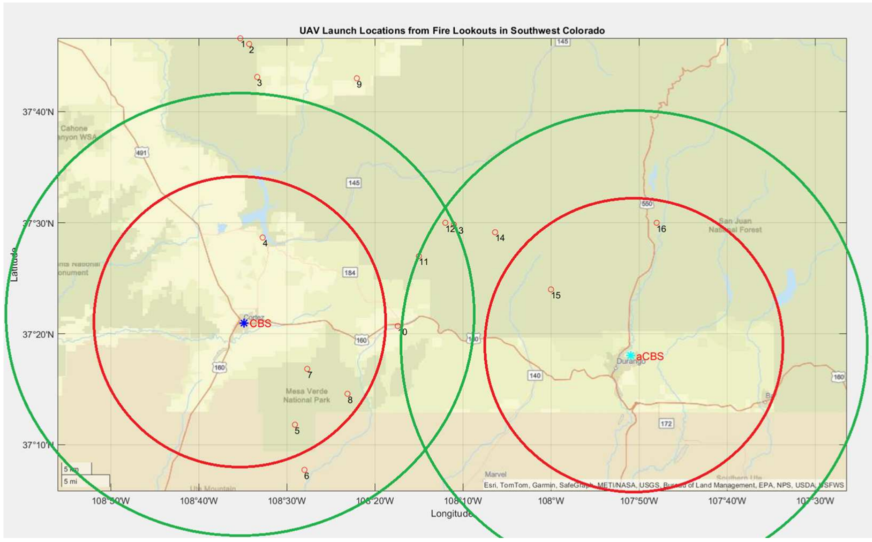


Figure 6.15: CBS only scenario

Note:

[1] An additional scenario where we can use 2 CBS only wihtout using any MBS vehicles for launches.

If human-generated solutions are available, it is necessary to assess whether further optimization is possible. This analysis is extended to three objectives, as illustrated in Figure 6.17. In this scenario, four deployments are selected from 100 potential launch/retrieval sites and evaluated based on cost, time, and risk reduction, with a focus on optimizing these three objectives.

Similarly, we can optimize four objectives, as shown in Figure 6.18, including all mission objectives: cost, time, risk reduction, and area maximization. As a result, the deployment in Figures 6.17 and 6.18 differs when the additional fourth objective is included in the optimization.

Additional variations of the views are presented in Figure 6.18 and illustrated in Figure Figure 6.19. These figures demonstrate that the solution lies on the Pareto front when the curve is manipulated. However, it is not always clear whether the solution lies on the Pareto front, as indicated on the right.

For sixteen different solutions, all available on the left, we use this prominence factor to evaluate them. Figure 6.20 shows the mapping of all solutions on the Pareto front (right) to their geospatial translations. We define the prominence factor as the frequency with which a site is repeated across

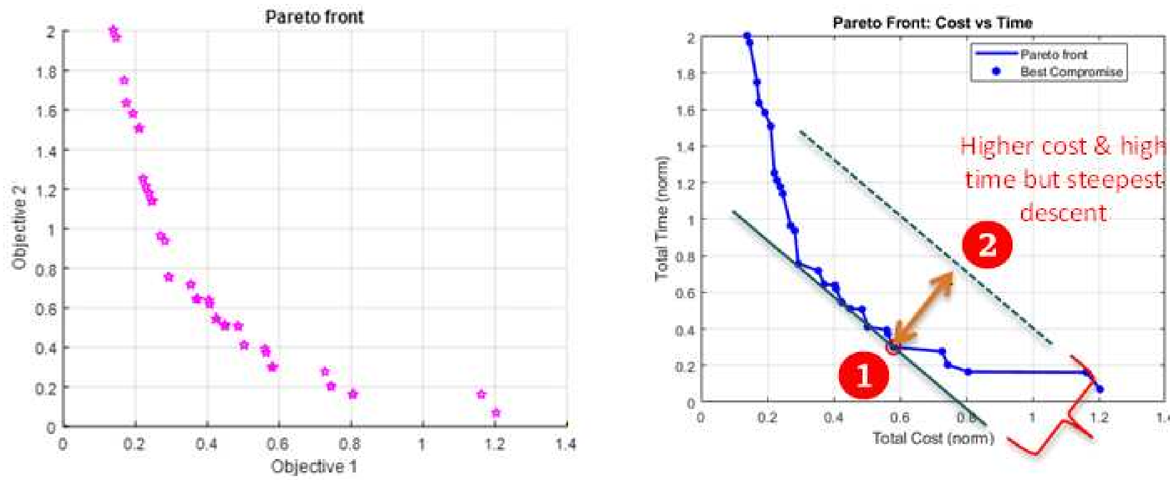


Figure: Pareto Front

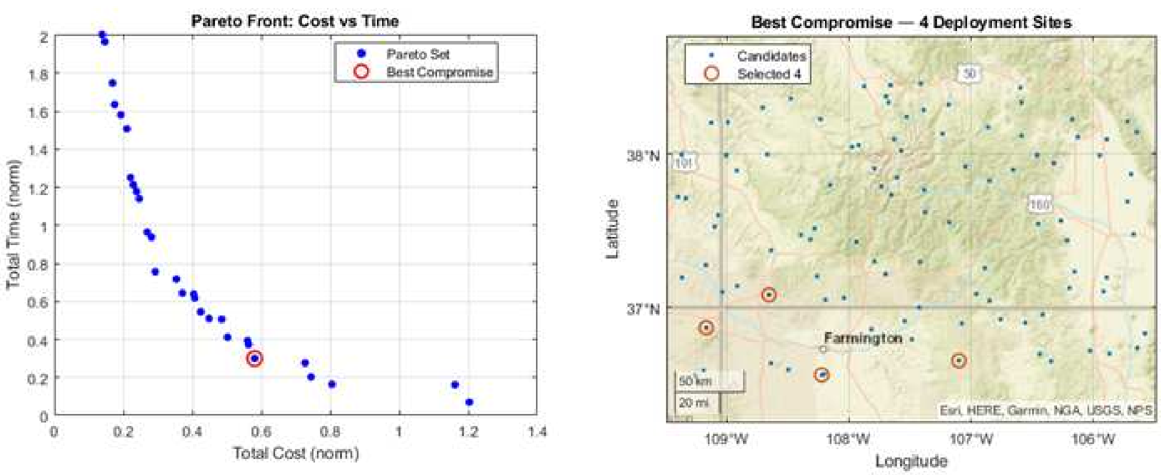


Figure: Four UAVs deployment out of 100 sites (CTR Objectives)

Figure 6.16: Multiobjective Optimization 2D

multiple solutions. In Figure 6.20, each solution includes up to four sites. For example, if Solution 1 provides four sites, we check whether solution 2 repeats any of them. If a site is repeated, its prominence factor increases. This process continues with Solution 3 and so on, tracking how frequently each site appears across all sixteen solutions. As a result, some sites are repeated more frequently - for instance, Site 8 appears 8 times, indicating greater prominence.

This approach enables monitoring of sites that are consistently repeated, a concept referred to as the prominence factor. However, the highest prominence factor does not always yield the optimal solution, as the interconnectivity among different sites can produce more effective outcomes. The

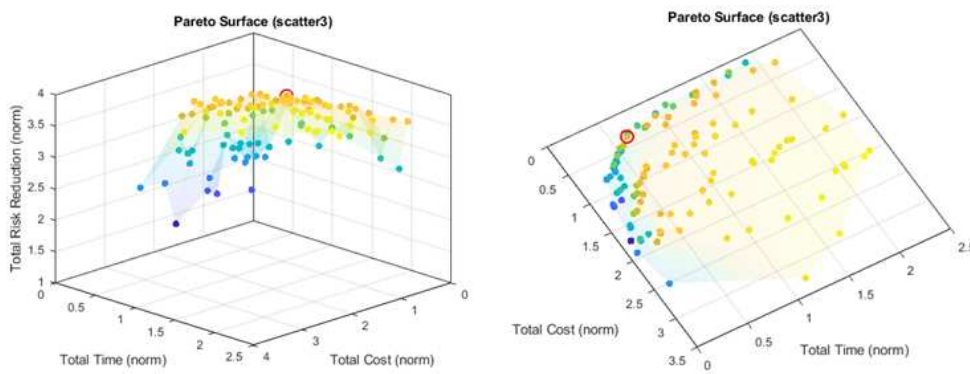


Figure: Pareto Surface

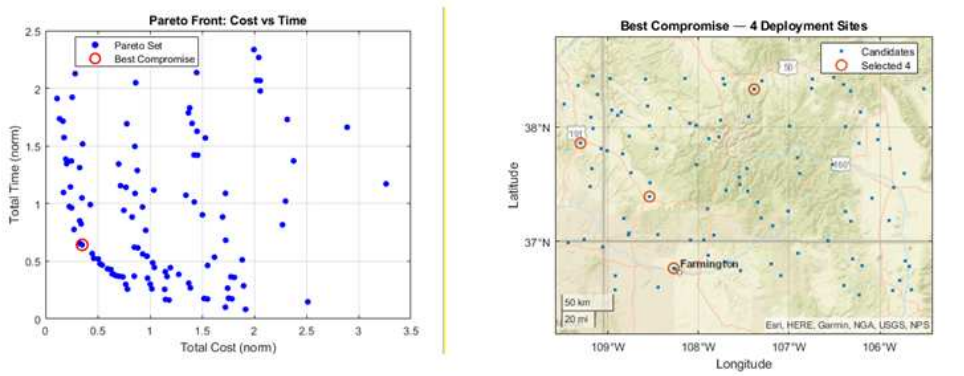


Figure: Four UAVs deployment out of 100 sites (CTR Objectives)

Figure 6.17: Multiobjective Optimization 3D

most effective solution integrates all sites and available resources while considering the specific objective.

6.7.1 Monte Carlo Analysis on the Pareto Front

Monte Carlo analysis of a solution on the Pareto front typically shows a cluster, which may be circular, oval, or linear in shape, and demonstrates how the solution behaves over various scenarios. This method highlights the variations that can shift the Pareto front and indicates the impact of UAV parameters on the solution. Monte Carlo analysis can be represented in a two-dimensional space that considers cost and time, and can be extended to three or four dimensions with the addition of risk and area, so that multiple test cases can be used to understand these variations. This tool helps the analysis drive optimization of aircraft design and deployment.

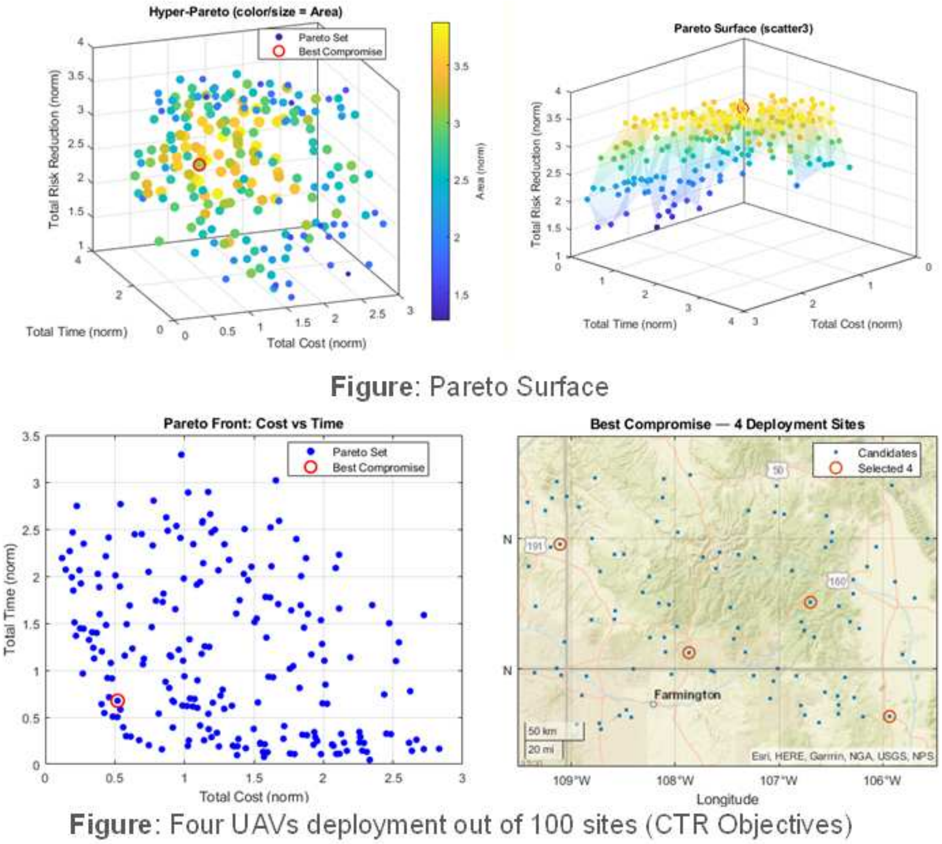


Figure 6.18: Multiobjective Optimization 4D

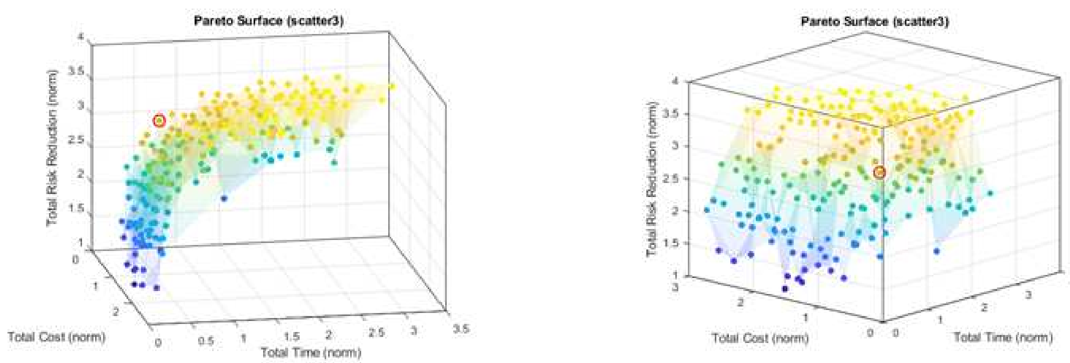


Figure 6.19: Pareto-Optimal Solution in MOO

6.7.2 Pareto Front Selection Using Contours

In scenarios where there is flexibility in picking a solution from the Pareto front, a solution is chosen by finding the closest match to the desired UAV parameters and deployment settings. This approach allows for visual comparison of solutions in terms of cost and time, with the possibility of

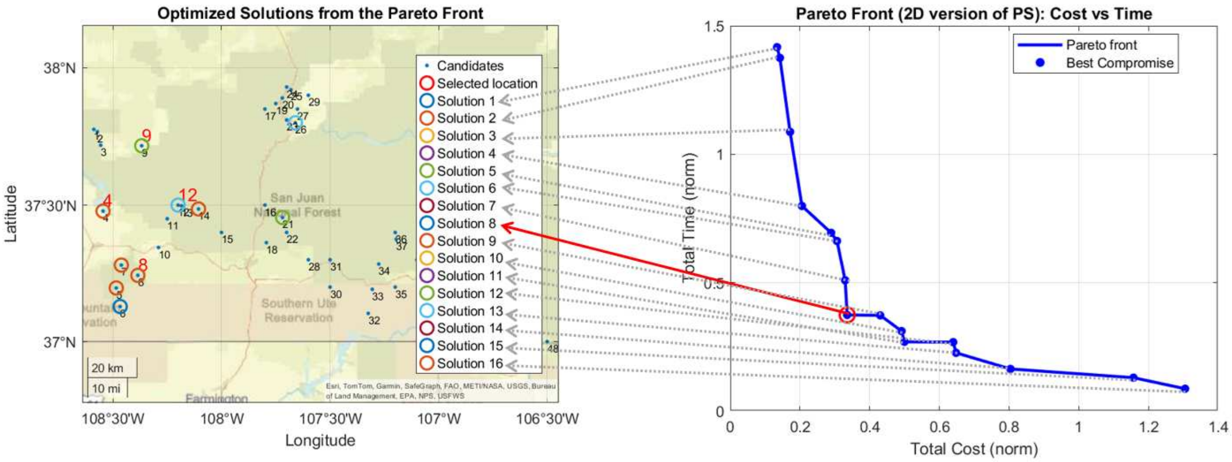


Figure: latitude and longitude of the 4 sites from 16 solutions

Figure: All sites from the pareto front solutions

Figure 6.20: Prominence Factors and Assumptions and Constraints adjustment case

Note:

[1] Prominence Factors are not always the best solutions.

[2] Assumptions and Constraints adjustment case in order to evaluate if we can move the Pareto Front for about 10 GA constraints and 5 ACO constraints.

extending the analysis to include risk and area in three- or four-dimensional spaces. By selecting a contour, such as one based on cost, potential solutions can be identified based on geographic points (latitude and longitude) and then compared to determine how well they fit with the overall Pareto optimization. Although this method may not always yield the maximum benefit from a multi-objective perspective, it provides a systematic way to compare results based on different constraints.

6.7.3 Human in the Loop vs Optimizing Engine - Performance Assessment

The human in the loop capability allows operators to interact with and modify the Pareto front, enabling real-time selection and alteration of deployment scenarios. This interactive process includes varying the Pareto front, selecting specific sites, and assessing how each choice impacts the overall solution with respect to constraints such as cost and time. Graphical representations of key constraints are provided to assist in decision making, thereby ensuring that robust deployment and UAV design strategies are optimized. By integrating human insight into the decision support system, the approach maximizes the robustness of deployment while balancing multiple objectives such as cost, time, area coverage, and risk reduction.

6.7.4 Utilization of Dynamic Pareto Front

The dynamic Pareto Front is a key tool in assessing the run-time wildfire points (RTWP) plan, a critical step in addressing fast-evolving scenarios, even though the preflight wildfire points (PFWP) plan may already offer a robust solution. It is possible to visualize, via Monte Carlo, how RTWP may evolve. This is extremely critical because it can handle a large number of variables that impact decisions, thus reducing the execution time of the optimizer.

6.7.5 Additional DSS characteristics Optimization - Time Management, MBS Vehicle Loading

UAV flight paths are monitored using a wildfire ledger to ensure that any node visited within the previous six hours, as implemented in the current system, is not revisited. This approach optimizes operational coverage.

The loading of MBS vehicles is managed by the decision support system (DSS), which configures each truck or MBS vehicle to carry a specific number of UAVs. Loading may be optimized for maximum wildfire detection capability, resulting in MBS vehicles not being filled to capacity. When a truck is loaded with three UAVs, the UAVs launch from one site and are either retrieved at a different site or returned to the primary site. Further optimization of this process using the particle swarm optimization (PSO) algorithm is identified as a direction for future research.

6.8 Results and Observations from Fleet Deployment Problem

Based on the results of the general study documented in Section second, a specific study was carried out in order to optimize prediction fidelity from wildfire deployment and UAV design co-relations.

6.8.1 Result Summary

We have found a way to incorporate humans in the loop, so that it can take user inputs and provide meaningful feedback to the system, where the analyzer works really well. Some of this input could be provided in the form of contours. Different types of contours are available cost, time, risk, and area (CTRA). Our goal is to maximize the area and the amount of risk reduction achievable by the UAV split.

While we have minimized both costs and time, this is an interesting trade-off in the area. Well, to have significant meaning for UAV split deployment and design, we work with Wildfire Group in the state of Colorado and use the Southwest Colorado case study, looking at data from Montezuma, LA Plata, San Juan, and Archuleta Counties. These four counties comprise the river region and the communication region.

6.9 Discussion

Based on the results of the general study documented in Section second, a specific study was carried out in order to optimize prediction fidelity from wildfire deployment and UAV design correlations.

Testing and Numerical Analysis

The Wildfire UAV fleet deployment comprises varying the deployment variables in hundreds of possible locations with binary decision outcomes for each. The approach compares:

- Enumeration of possible choices (for example, selecting 4 choices out of 6, 100, or 1000 possibilities),
- Versus multi-objective genetic algorithm optimization.

Numerical analysis shows that while full enumeration is computationally expensive and may be infeasible, the genetic algorithm delivers a tractable alternative. Test cases in the wildfire domain demonstrate that, with proper tuning (adjustments to the initial population, maximum generation limits, and visualization techniques), the genetic algorithm reaches near-optimal decisions inside acceptable error limits.

6.9.1 Interpretation of results

The results from the simulation and analysis show that the Optimal Deployment Strategies (ODS) are implemented as part of the optimizer engine and enable the decision support system (DSS) to make critical decisions.

6.9.2 Contribution to the body of knowledge

We provide concrete, implementable knowledge for ODS implementation that makes the DSS significantly more effective. The HITL DSS is a human-centric software tool that integrates the optimizer engine's output with operator input to support critical wildfire-management decisions.

Research Contribution (RC1.1)

This research study developed a set of novel mathematical specifications for an Optimizer Machinery that includes CBS fleet coordinator(s), MBS operator(s), and wildfire systems analysts, enabling a human-in-the-loop (HITL) interface by taking input and comparing with the optimizer solution. Previously, there was no other mathematical specification in which HITL could provide input to a UAV-based wildfire-detection and communication solution.

This research developed a holistic approach to the deployment of the UAV fleet and analyzed the systems architecture for wildfire detection and communication in Chapter 6. The novel optimal deployment strategies (ODS) system utilizes flexible optimization machinery for the wildfire UAV fleet and UAV aerodynamic design. This optimization machine incorporates a human-in-the-loop (HITL) interface, system dynamics analysis using the system dynamics (SD) model and model-based systems thinking (MBST) framework, architecture development with design structure matrix (DSM) or model-based systems engineering (MBSE) models, and computational fluid dynamics (CFD) analysis with an aerodynamic model, and thus contributes to the development of a fleet capable of high-altitude and long-range wildfire operations.

Research Contribution (RC1.2)

The research has developed a novel and quantitative optimization machinery that utilizes a structure consisting of base stations, launchers, and UAVs with an operating conditions scenario-based deployment structure for wildfire detection that utilizes a decision support system (DSS) for wildfire fleet deployment.

The fleet of UAVs we consider is a hybrid aircraft that uses power from both a lithium-ion battery and a fuel cell and is hauled to the launch site on a truck. We integrate knowledge from the research community and develop optimal deployment strategies (ODS) for fleet operations, considering wildfire topology maps, geographic locations, operational constraints, communication requirements, and essential constraints on wildfire mitigation. The proposed systemic approach validates and pre-checks the decision support before launching the UAVs. We also consider where and when to retrieve the UAVs in both normal and abnormal operational cases.

6.9.3 Strengths and limitations

Although the approach is effective for decision making, the study was limited to 48 sites; a commercialized version that incorporates more sites would increase the fidelity of the implementation. In addition, we have not yet fully optimized the algorithm for computational time, which will be addressed in future research.

6.10 Chapter Conclusions

The system methodology involving HITL outlined in this chapter effectively generates models for Operational Deployment Strategies (ODS) and identifies parameters with leverage points for these models. This serves as a valuable step toward extensive prototyping of the optimization problem for fleet deployment. The model identifies opportunities to minimize coverage time by addressing environmental, aerodynamic, and operational constraints (failure rate, maintenance, fleet size, etc.). In the wildfire case study for Colorado, the ODS optimizes timing sufficiently to cover southwest Colorado, the San Juan River region (District 43), for wildfire monitoring and detection.

The operational model also identifies the components necessary to efficiently manage deployment intervals to maximize area coverage and highlights details of fleet size management, noting a range of optimization opportunities.

This model can be enhanced in the future by incorporating additional elements such as fuel efficiency, battery performance, high-risk scenarios, no-fly zones, and access-road availability. Such an enhanced model can yield more refined conclusions on minimizing risk factors and operational costs.

The output of the DSS can be used to develop mathematical expressions for the ODS, enabling evolution toward optimized MBS deployment. The DSS will utilize topographical maps, geographical conditions, varied operational scenarios, and communication and other constraints. Future work will involve developing and applying this wildfire detection and communication optimizer model to achieve additional efficiency in addressing the deployment problem. A mathematical specification or problem construct can be developed that includes MOO with HITL and incorporates two stages of optimization. The first stage focuses on MBS/CBS-based coordination. A novel mathematical specification for an optimizer machinery, including CBS fleet coordinators, MBS operators, and wildfire systems analysts, enables a HITL interface by incorporating input and comparing it with optimizer solutions. Previously, no mathematical specification allowed HITL to provide input to a UAV-based solution for wildfire detection and communication. Combining *Boundaries Principle*, which identifies different parts of the system and who is included within the system, with *Human Principle*, which explains how humans impact and are affected by the system, helps create a more realistic and effective optimization problem.

6.11 Chapter Summary

The output of optimizing machinery is a decision support system (DSS) that can be used to develop mathematical expressions for the ODS to evolve into an optimized MBS deployment. The DSS will utilize topographic maps, geographical conditions, varied operational scenarios, and communication and other constraints. Future work will involve developing and utilizing this wildfire detection and communication optimizer model to find further efficiencies to address the deployment problem.

Chapter 7

Research Question 2: Wildfire UAV wildfire points Optimization (WPO)

7.1 Preface

This chapter addresses research question 2, which examines run-time scenarios involving wildfire points and UAV flight paths. To our knowledge, this chapter constitutes the first comprehensive study to fully address research gap 3.

7.2 Overview

This chapter investigates the absence of joint optimization between launcher and UAV deployment, UAV flight paths, and wildfire points under run-time conditions. It also examines run-time challenges in wildfire UAV fleet deployment and UAV design. Additionally, executing only the necessary components of the second-stage optimization allows the optimization process to operate efficiently as required.

7.3 Introduction

Wildfire operating conditions and scenario-based constraint optimization offer greater flexibility for managing diverse runtime scenarios in UAV wildfire points optimization (WPO). Jointly optimizing launcher deployment and UAV wildfire points or flight paths yields a holistic systemic solution to the overall deployment problem.

We found that coordinated fleet deployment significantly improves WPO planning by facilitating real-time adjustments to runtime issues. Our experiments demonstrated that tuning environmental parameters leads to more accurate WPO. By integrating UAV flight paths with geographic data, environmental characteristics, and wildfire likelihood, we enhanced wildfire detection and communication. The results from this research study give interesting insight into how run-time issues, UAV flight path, and MBS (launcher) and UAV optimization impact overall optimization machinery.

7.3.1 Background

The proposed methodology addresses operational challenges encountered during the deployment of wildfire UAV fleets and the design of unmanned aerial vehicles. The framework employs a two-stage optimization process, where the second stage receives the solution from the first stage and subsequently returns its output. This feedback mechanism allows launcher deployment and UAV optimization to be performed independently, while ensuring integration within a unified wildfire detection system.

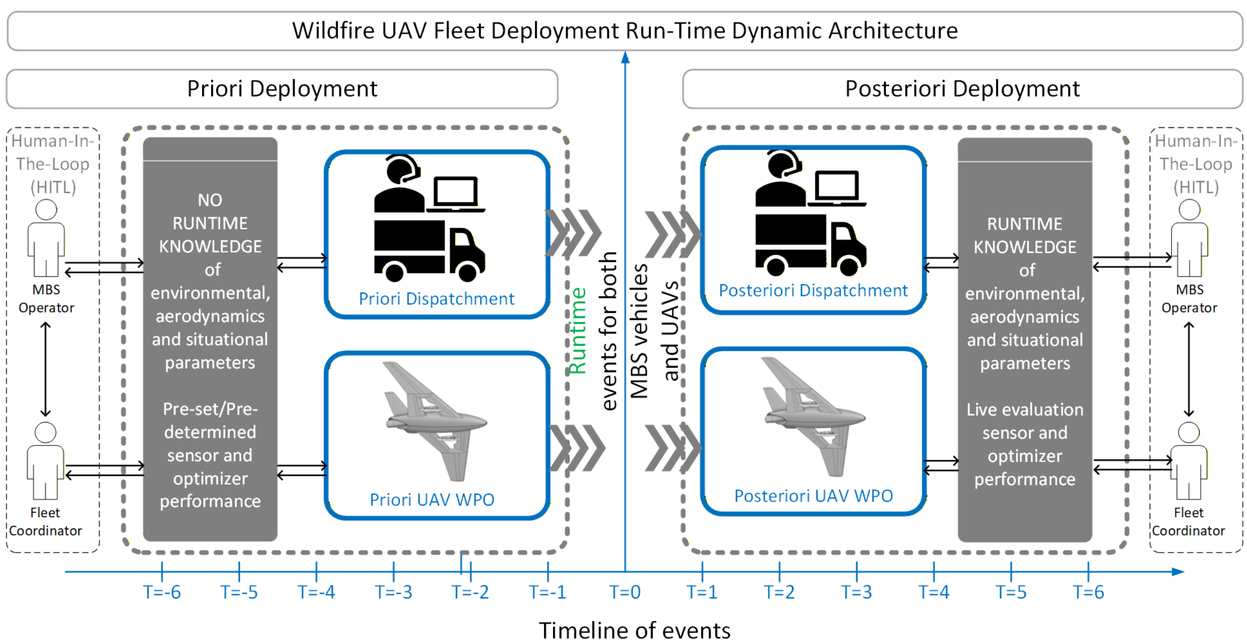


Figure 7.1: Fleet Deployment Run-Time Dynamic Architecture

Note:

[1] The architecture is based on run-time concept at T=0, the execution of the mission starts.

Performance of this fleet deployment architecture is evaluated based on the optimal wildfire points (WP) assigned to MBS vehicles (posteriori deployment shown in Figure 7.1) and the optimal design of UAVs to be able to handle run-time issues [6], [173]. In timeline T=0, immediately after CBS dispatch, both MBS vehicles and UAVs participate in this operational phase. The left side represents priori deployment before runtime, with run-time beginning at T = 0 time frame. The right side depicts the runtime scenario after the T=0 time frame, and it represents posteriori deployment. The posteriori deployment applies to both the MBS vehicle and UAV flight paths. We develop both pre-flight wildfire points (PFWP) plan and run-time wildfire points (RTWP) plan during priority deployment. The primary focus during this stage is optimizing UAV flight paths, for which ant colony optimization (ACO) is employed.

7.3.2 Run-Time Flexibility

It is not feasible to pre-plan all potential run-time events. Therefore, modularized optimization at this stage enables the DSS to generate effective decisions. Operational configuration and design decisions must adapt to run-time variations by distinguishing between issues that impact individual solutions and those that affect the entire set of solutions. This adaptability is achieved through a human-in-the-loop (HITL) framework that operates with a run-time or dynamic Pareto front (dPF). For UAV-based wildfire detection systems, the optimization framework should be modular, supporting complex problem solving while remaining adaptable to mission changes, wildfire events, and varying operating conditions.

7.3.3 Literature search

To date, no studies have addressed the joint optimization of wildfire fleet deployment, UAV flight paths, or wildfire points (run-time) for wildfire detection using a fleet of UAVs. Limited research on joint optimization is available in domains outside of wildfire detection. The most conventional wildfire point planning methods do not account operational condition scenarios and parameter and environmental parameters essential to UAV, including CBS location, elevation of launch sites, air density, temperature, and wind gusts [51], [52], [53], and [145].

Existing disaster-response UAVs are not optimized for the flight control challenges inherent to wildfire scenarios. Previous research demonstrates that UAVs are typically designed for post-event response, rather than predictive deployment, detection, or communication [10], [45], [48]. Among these studies, only one specifically addresses wildfire applications [45]. The present study aims to address this gap by jointly optimizing fleet deployment and flight paths.

There is also a lack of optimization of launchers and UAV Wildfire Points (pre-identified flight paths for wildfire objectives, including risk). Furthermore, several works consider an undesigned UAVs fleet (some cases a single-UAV system) or lack comprehensive fleet-level coordination, multi-objective trade-offs, and scalable task allocation across multiple UAVs in dynamic wildfire environments [45], [47], [48], [49], [61], [62].

The study by Hildemann [204] is static-centric, and Pandey's work [205] is as well; however, our research places greater emphasis on runtime dynamics. The goal of Hildemann's work is decision-making, whereas Pandey's work evaluates incoming decisions, acting almost as an automated decision maker. In our wildfire application, the emphasis is on wildfire point run-time decision-making.

7.3.4 Supported systems thinking principles

The principles of systems thinking significantly impact dynamical runtime situations. Furthermore, having an intelligent architecture that is adaptable and capable of learning from given situations is essential.

Utilization of Emergence Principle - Foreseeing systems behaviors

The Emergence Principle identifies, "*Interactions (including feedback) within and between the three systems cause (sometimes unwanted) emergent behaviors.*" [42].

The mission goal is to develop a comprehensive system that also accounts for runtime conditions, particularly UAV wildfire path simulation and tolerance of any unwanted emergent behavior. Events often occur that can cause emergent behavior. For example, gust winds can alter the impacts of UAV flight paths. To understand runtime situations effectively, it is important to determine whether the gust wind is associated with wildfire conditions. If it is associated with wildfire behavior, continuous evaluation of the situation is necessary. However, if the gust wind is not associated with wildfire conditions, taking advantage of the wind direction may become beneficial. Therefore, the system must recognize unwanted emergent behaviors and monitor them carefully while also identifying beneficial emergent behaviors that can be leveraged, such as taking advantage of a tailwind. By foreseeing system behavior and understanding interactions and feedback between the environment and the UAV system, emergent behaviors can be identified and incorporated into the system. Integrating this approach enhances the overall system performance.

Utilization of Learning Principle - Designing adaptable systems architectures

The Learning Principle identifies, "*(Common) Mental models influencing human decisions about architectures are learnable and adaptable*" [42].

It is critical for UAV systems to adapt during runtime situations. Having a mental model in place allows the system architecture to adjust, adapt, and learn from runtime conditions. Our goal is not only to operate in predetermined situations but also to adapt, learn, and take advantage of dynamic conditions. As illustrated in Figure 7.2, we identified opportunities to eliminate unnecessary portions of the optimization process and execute only the portions required during runtime situations.

Furthermore, we utilized an architecture that includes not only the UAV architecture itself but also the deployment system architecture. This architecture adapts through a decision support system that provides feedback from operators and wildfire fleet architects or designers to UAV architects.

7.4 Methodology

7.4.1 Overall System

In this methodology we emphasize on runtime wildfire points (RTWP) planning on operational decision-making during mission execution. The influence of varying environmental conditions on UAV performance and the potential for performance-related issues are also examined.

Optimization Problem Formulation based on Run-Time

The first step in the development of practical and high-fidelity real world optimization problem formulation.

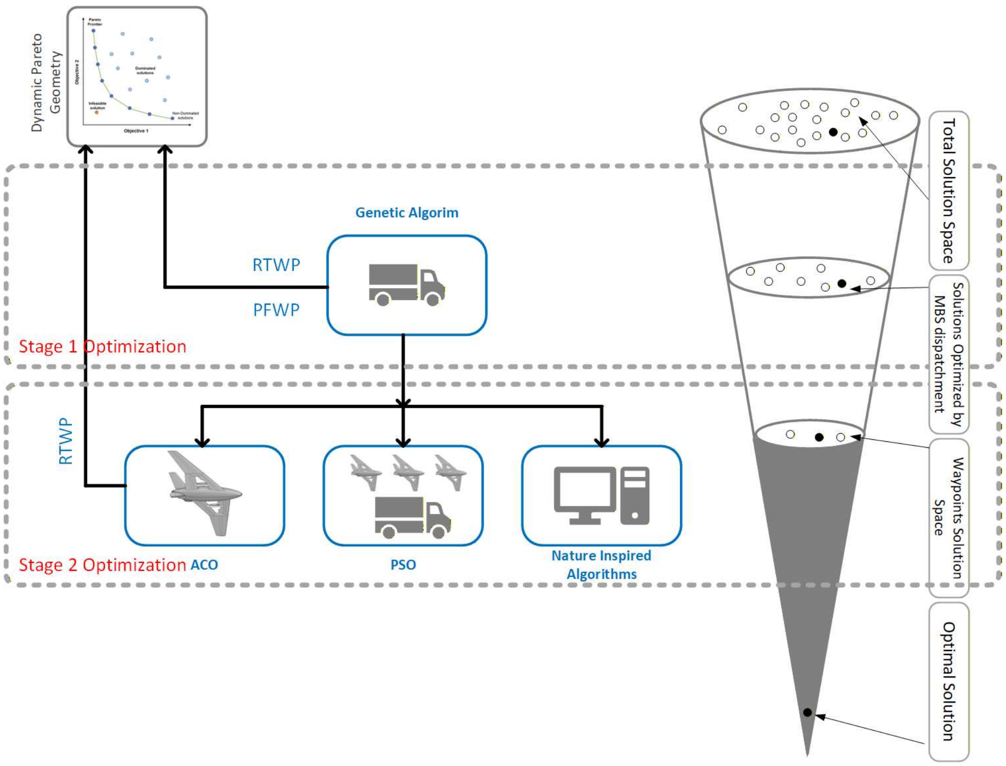


Figure 7.2: Method for Two stages of Optimization

Note:

[1] This uses ACO as needed part of the second stage optimization.

Systems Pre-flight Wildfire Points (PFWP) plan before Run-Time (Priori Deployment)

The Preflight wildfire points plan (PFWP) prepares the optimizer to run before deployment for the MBS vehicle deployment and the UAV flight paths. The case of PFWP solutions is based on the inputs and variables that were provided straightforwardly prior to deployment. The primary benefit of PFWP is that the optimizer can run longer. The Preflight Wildfire Points (PFWP) plan includes a no fly zone (NFZ), altitude impacts, and parameters that do not change much. It also includes all the dynamic variables as a starting point.

7.4.2 Systems Run-Time Wildfire Points RTWP plan during Run-Time (Posteriori Deployment)

In the run-time wildfire point (RTWP) plan, the DSS's primary construct is to utilize a dynamic Pareto front and proactively pick the most relevant, better-adapted solution. MBS can run the optimizer and investigate potential environmental and artificial conditions, especially as they change.

The run-time wildfire points (RTWP) plan includes a calculation of dynamic Monte Carlo as simulation conditions appear. The RTWP can be visualized via MBS vehicle operator perspective GUI.

Two stages of the optimization methodology have been described in 7.3 where the second stage uses the ACO algorithm as part of the optimization machinery.

Overall System Method Description Method two employs the second stage of the two-stage ODS optimization strategy, a practical mechanism for addressing a complex, real-world problem. The second stage primarily emphasizes run-time wildfire points (RTWP) plans, UAV re-tasking and run-time issues for operating conditions scenario-based optimization as shown in Figure 7.3.

The goal of the optimizer machinery is to optimize multiple objectives. For this research study, we consider four major objectives for the optimization problem: cost, time, risk, and area (CTRA). The optimization goal is to minimize cost and time and maximize area coverage and the opportunity to reduce risk.

7.4.3 System Inputs

The systems method for WPO requires the following inputs:

Step 1 - Collect wildfire points (WP) data for each site.

Step 2 - After data collection, ensure that input from stage 1 optimization is received on MBS locations before proceeding.

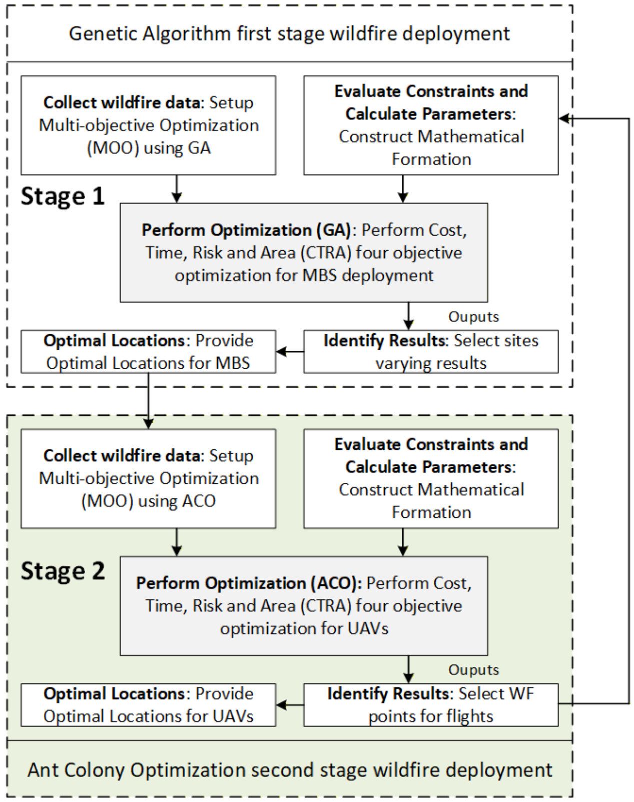


Figure 7.3: Method for two stages of optimization - Second stage (ACO)

Note:

[1] The genetic algorithm (GA) was applied in the first stage of fleet deployment optimization, as discussed in Chapter 6.

[2] The second stage of optimization, focused on wildfire points (WP), uses ACO algorithm. This process is illustrated in green at the bottom of the figure.

7.4.4 Methodological Steps and Processes

Step 3 - Once all inputs are gathered, evaluate constraints and calculate parameters, using this information to construct the mathematical formulation for stage 2.

Step 4 - After constraints and parameters are established, perform optimization using ACO for cost, time, risk, and area (CTRA) as objectives for UAV flight paths.

Step 5 - Generates effective paths for UAVs to fly to and return from the launch location, or land at a new location, while accounting for re-tasking and runtime constraints.

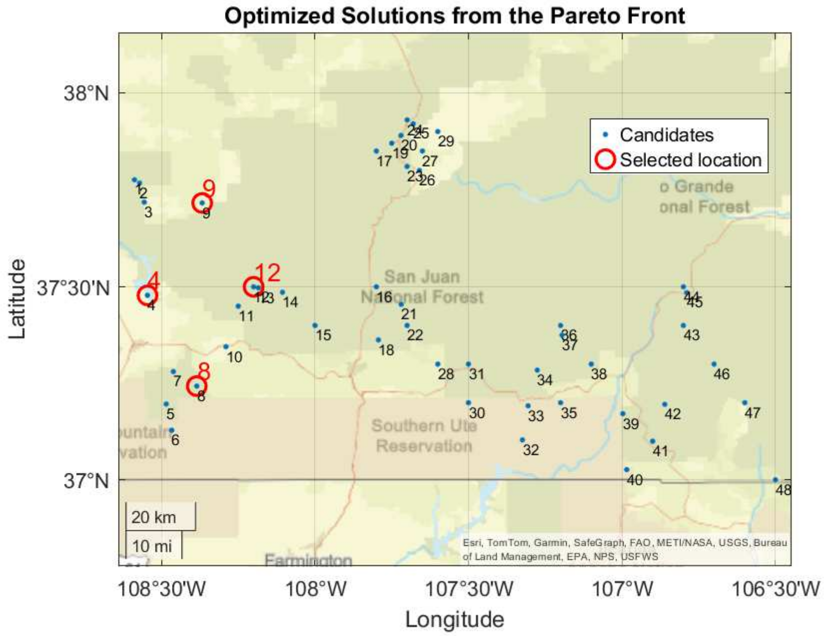


Figure 7.4: Selected Locations - Optimized Solutions from the Pareto Front

Note:

[1] Four launch locations, selected out of 48 WP sites considering both stages of optimization.

Step 6 - Next, feed the generated flight path and landing location outputs from stage 2 back to stage 1 optimization, enabling further refinement.

7.4.5 System Outputs

The systems method for WPO provides the following outputs:

Step 7 - Once updated outputs are received from stage 1, incorporate feedback and repeat the iterative feedback loop as necessary.

Step 8 - As each round of feedback is integrated, update the Pareto front dynamically with new information from each iteration.

Step 9 - At the end of each iteration, check and record the updated dynamic Pareto front as the algorithm's result for that cycle.

Step 10 - The method outputs the following items as listed below,

- The output of this is the fast calculated solution,
- Optimized flight path and
- Landing locations

Step 11 - (Optional and Productionization) The Second-stage optimization can be run to optimize the loading of the MBS vehicle with 1, 2, or 3 UAVs (up to the maximum capacity). The recommended algorithm is Particle Swarm Optimization (PSO).

Step 12 - (Optional and Productionization) Additional second-stage optimization can be run as needed with recommended nature-inspired algorithms.

7.5 Utilization of Dynamic Pareto Front

The concept of the dynamic Pareto front is a key component of RTWP, helping with fast-evolving scenarios and serving as a key element in optimizing computation time, even though we have a robust solution at the PFWP. It is possible to visualize, via Monte Carlo, how RTWP may turn out. This is extremely critical because it can save time or reduce the optimizer's execution time, and it can help handle a large number of variables, as they can impact decisions. Here is an example of a scenario with four selected locations with the prominence factor indicated in Figure 7.4. The (DSS) does not always pick the sites with the highest prominence factor. It takes into consideration the interconnection and feedback loops among the drop-off and pick-up choices of the MBS vehicles, etc.

The impacts of the wind direction for the UAV are shown in Figure 7.5. No fly zone (NFZ) for the wildfire UAV fleet can be for regulatory or safety reasons. Also, ODS may choose to self-imposed NFZ if a certain area is not supportive of the mission goals (ie. flying over areas higher elevation than 10,000 ft). NFZ on airports in Southwest Colorado is shown in Figure 7.6.

The launch and retrieval same location (LRSL) strategy enables the MBS vehicle to deploy and recover the UAV at the same site, as illustrated in Figure 7.7. In contrast, the launch and retrieval

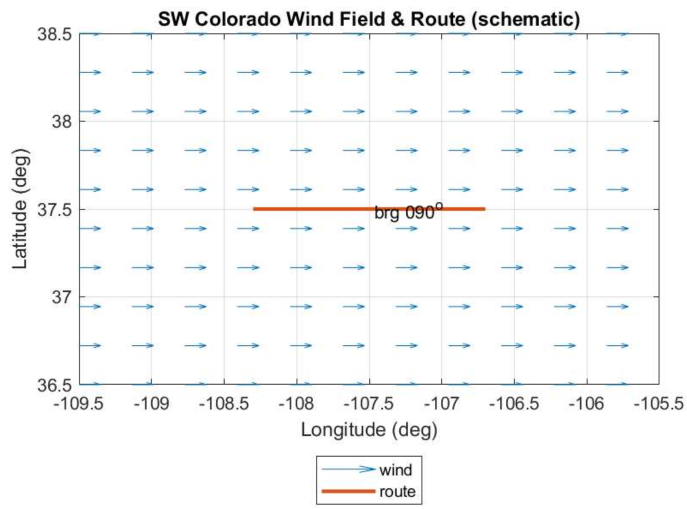


Figure 7.5: Wind direction impacts for UAV

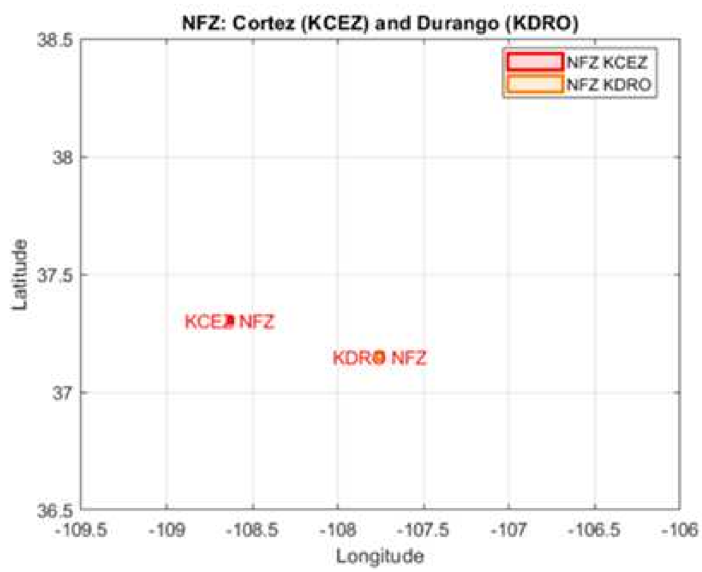


Figure 7.6: NFZ over airports in Southwest Colorado

Note:

[1] NFX over airports in Southwest Colorado shown here.

[2] NFZ are part of PFWP planning but executed during run-time.

different location (LRDL) strategy permits the UAV to be deployed and recovered at different sites by the MBS vehicle.

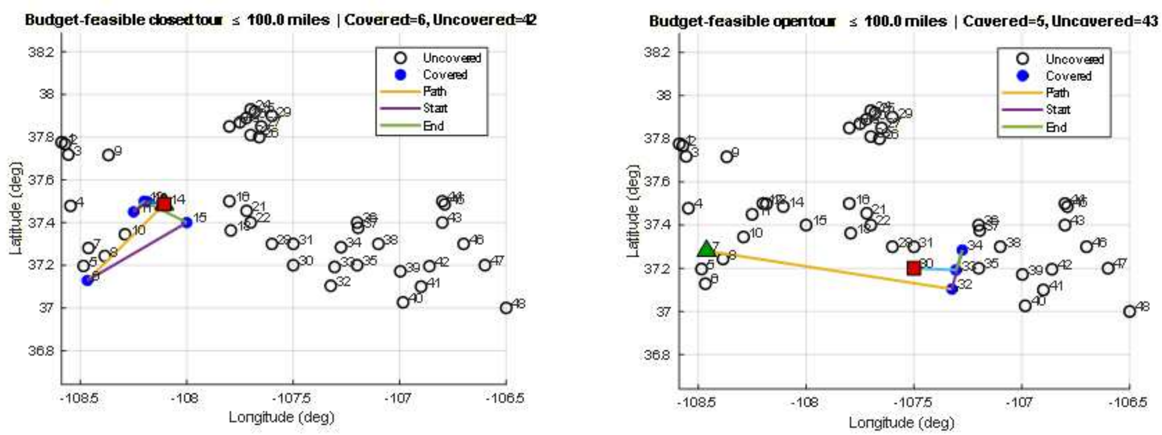


Figure 7.7: Wildfire UAV Launch/Retrieval Optimization (Scenario variation HITL)

Note:

[1] Launch and Retrieval Same Location (LRSL) for wildfire UAV

[2] Launch and Retrieval Different Location (LRDL) for wildfire UAV

7.6 Results and Observations for WPO & UAV Flight Paths

Based on the results of the general study documented in Section second, specific, study was carried out in order to optimize prediction fidelity from wildfire deployment and UAV design co-relations.

7.6.1 Dynamics Factors

UAV aerodynamics (such as L/D, Rate of Climb, etc.) can, due to its design and architecture, contribute to the objectives of the deployment. Essentially, the goal is to reduce the deployment time and the overall flight time show in Figure 7.8. The results shown in 7.8 demonstrate that varying the lift-to-drag ratio (L/D) and the rate of climb (ROC) produces climb times ranging from 4 to 24 minutes. This represents a significant variation within the anticipated total flight time of 70 to 90 minutes, accounting for approximately 5% to 30% of the mission duration. In our testing, we considered two locations, Cortez and Durango. Achieving a very high L/D or a high rate of climb

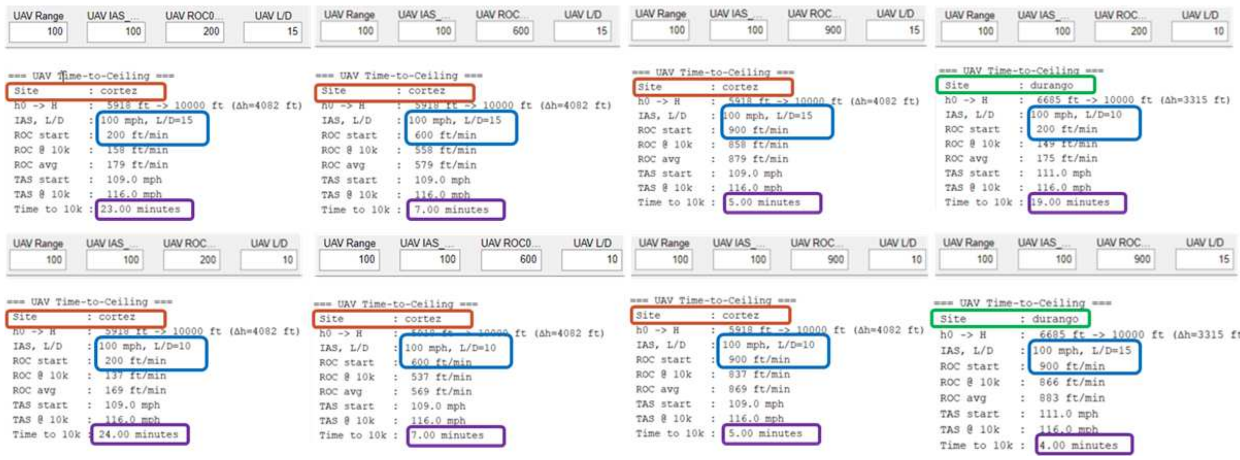


Figure 7.8: UAV Aerodynamics and impacts on total flight time for Wildfire mission

Note:

[1] Varying L/D and rate of climb, we have a climb time of the flight profile to be anywhere between 4 minutes and 24 minutes.

can increase aircraft design complexity and cost. For the Hybrid UAV (H-UAV) considered in this study, both parameters are also directly related to fuel consumption and battery usage.

Although parameters such as the lift-to-drag ratio (L/D) are fixed for a given UAV design, evaluating different L/D values illustrates how design decisions influence deployment scenarios. The objective is not to alter an existing design, but to establish a feedback mechanism through which field operators can inform designers that a particular L/D may increase mission response time from four to twenty-four minutes.

A similar principle applies to the rate of climb. Although these parameters remain fixed, they influence site selection and operational elevation, which in turn affect deployment. This closes the often-missing feedback loop between field operations and design by demonstrating how deployment outcomes can directly inform future UAV designs.

The elevation of the launch site significantly affects the runtime performance of unmanned aerial vehicles (UAVs), particularly during launch, since it determines the time required to reach the operational ceiling. Launch sites at specific elevations may be excluded based on operator decisions. Wildfire points (WP) located at elevations above 8,000 feet are excluded, as illustrated in Figure 7.9.

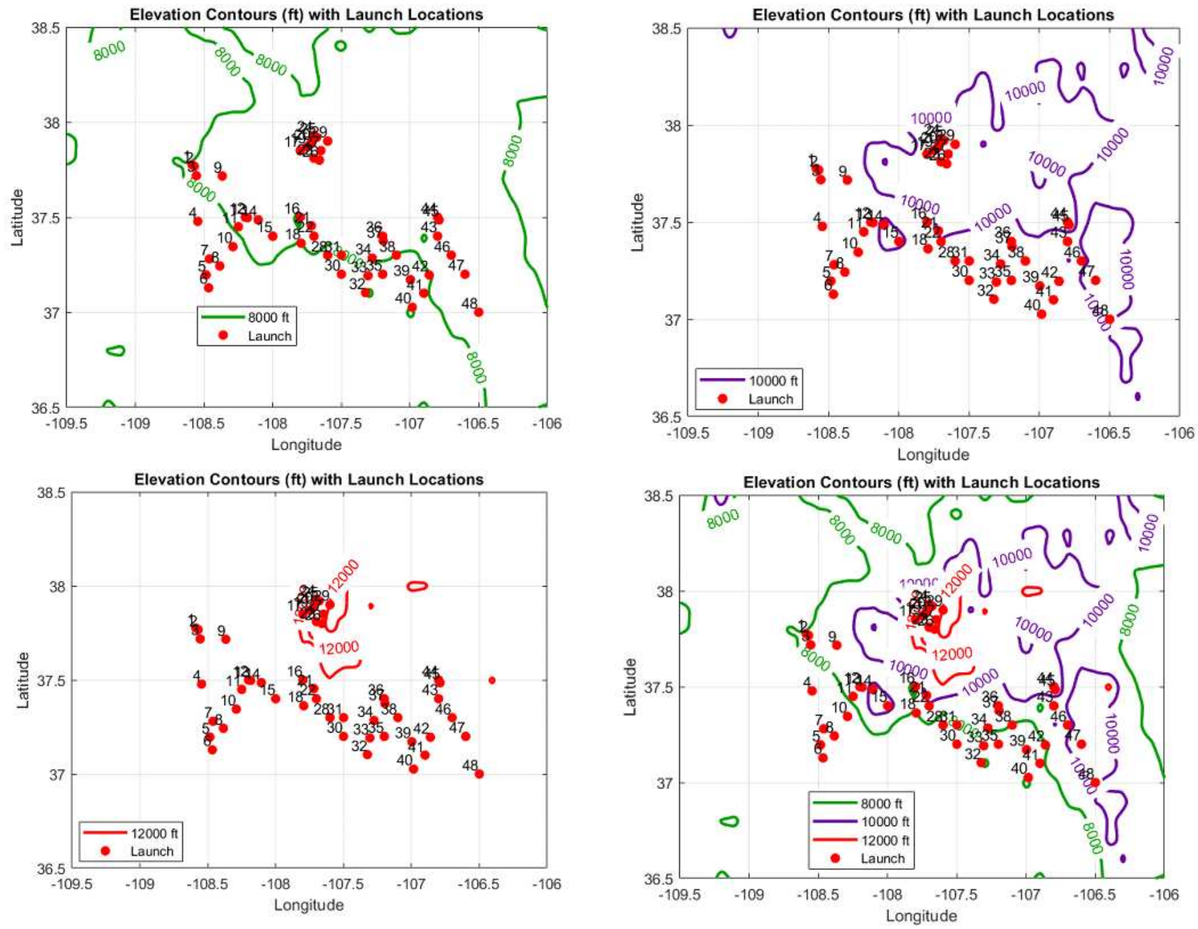


Figure 7.9: Elevation of the Launch Sites fro Exclusion

Note:

[1] UAV has full performance up to 10,000 feet. UAV with degraded performance between 10,000 ft to 12,000 feet.

[3] No wildfire risk above 12,000 ft for the UAVs.

This presents various elevation contours, beginning with the top-left contour at 8,000 feet. The top-right contour represents 10,000 feet, while the bottom-right contour corresponds to 12,000 feet. The bottom-right section displays all elevations of the bottom-right for comparison.

Points may be excluded, as necessary, at the operator’s discretion for specific sites. The impact of wildfire decreases substantially below 8,000 feet. Points within the top-left contour, as well as those above 10,000 feet, may be excluded, except for areas with legacy funding within the park.

Similarly, all points within the red contour can be excluded for operational reasons. Identifying these excluded points is important for confirming effective launch elevation effectiveness and optimal site selection. Exclusion of points is determined by operator decisions at specific sites. Identifying these excluded points is essential to ensuring effective launch procedures and the most efficient flight paths.

7.6.2 Impacts on Dynamic Factors - Altitude Analysis for Deployment and UAV Design

Evaluation of performance based on different launch and retrieval strategies. Empirical data supporting the integration of environmental factors into the operational model of the UAV. In

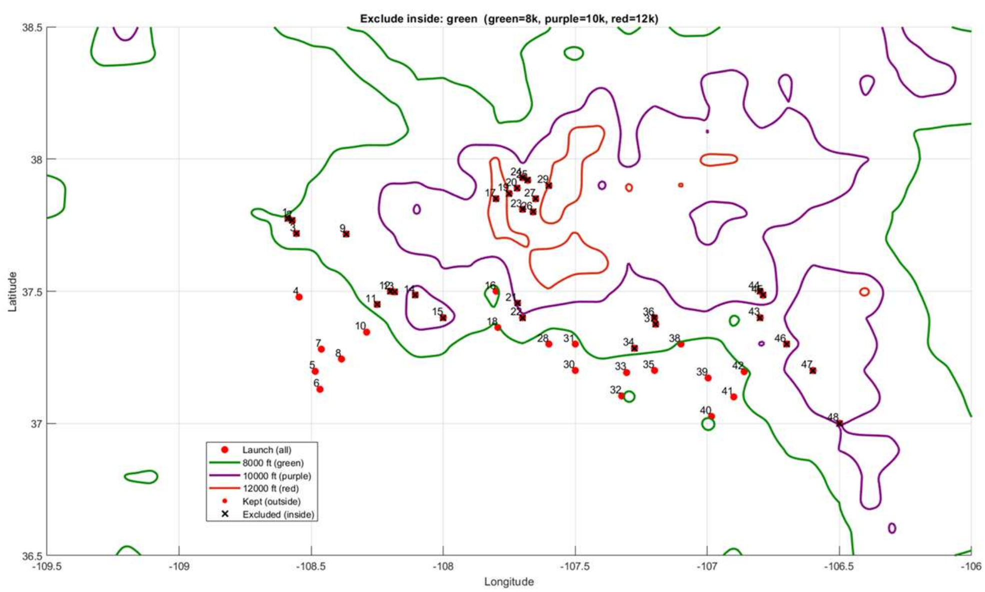


Figure 7.10: High Altitude Excluded Points

Note:

[1] Degraded performance (or less than optimal performance) can be available at higher than 10,000 ft

Southwest Colorado, the probability of wildfires decreases with increasing elevation [201] above 8,000 feet. In other words, the areas most prone to wildfires are predominantly at low to mid elevations for two distinct reasons. The first reason is that higher elevation regions, such as subalpine and alpine areas, rarely experience hot, dry weather conditions conducive to fire.

The second reason is that while human impacts (such as population density) play a significant role at lower elevations, their influence is much weaker at higher elevations. Thus, we consider the urban corridor to be part of our DSS optimizer machinery. The excluded points for high altitude are shown in Figure 7.10.

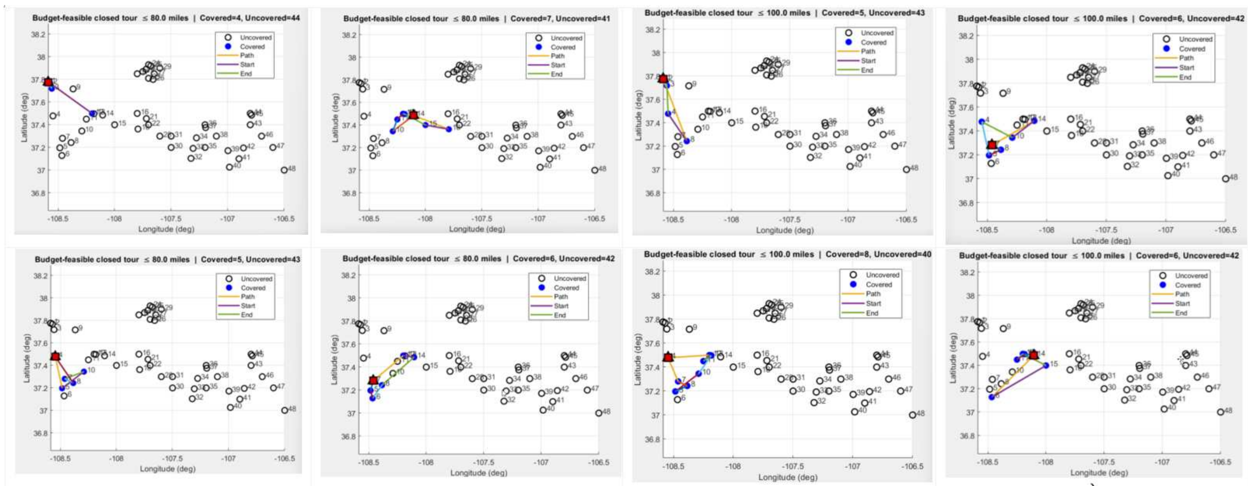
Figure 7.11: True Airspeed vs Altitude

Note:

[1] Hybrid UAV Range variation based on battery and fuel capacity and fuel usages which impact the wildfire fleet deployment performance.

Anticipated airspeed variation based on the altitude which impacts the wildfire UAV performance as shown in Figure 7.11. The impacts of UAV range can be simulated using the DSS as shown in Figure 7.12. We have simulated a scenario where we launched 4 UAVs from 4 different locations with LRSL mechanism to be returned to the same location for landing. We varied the range to be 80 miles and 100 miles.

The test result clearly shows the flight path differences and reduction in meaning objective optimization. Thus, we clearly can see the impacts of range and flight path pattern for launched UAVs. Similarly, the UAV design/characteristics parameters like UAV speed, L/D, ROC, etc. can impact the flight paths and the four objectives of the deployment.



UAV Range (battery / fuel usages) 80 miles max capacity for each of 4 launched UAVs

UAV Range (battery / fuel usages) 100 miles max capacity for each of 4 launched UAVs

Figure 7.12: Impacts of UAV Range Capacity

Note:

[1] Anticipated airspeed variation based on the altitude which impacts the wildfire UAV performance.

7.6.3 Second stage for flight path optimization

We perform two stages of optimization, the second focusing on runtime issues. This is part of the second-stage optimization; it has a feedback loop with the first-stage optimization, and, by doing so, we have a robust, first- and second-stage optimization that can be dynamically run on demand as runtime issues arise. Thus, we do not need to run both the first- and second-stage optimizations.

7.6.4 Interpretation of Result

The results from the simulation and analysis show that the Wildfire points optimization (WPO), the second stage optimization are implemented as part of the optimizer engine and enable the decision support system (DSS) to make critical decisions.

Impacts of Environmental Parameters During Run-Time

The environmental parameters which are often stochastic and can have unpredictable fluctuations and changes in wind, temperature, air pressure, air density, and all those can impact ROC, UAV speed, L/D of the etc. With better understanding of wind speed and wind directions, we can calculate the impacts of wind on the UAV speed and take advantage of a UAV's tailwind rather than fly against it. When possible the DSS adapt to those stochastic parameters during run-time.

MBS Vehicle Run-Time issues

We can also add delay parameters for simulating traffic delays that can impact the MBS vehicles to be late at the launch and retrieval locations.

Additionally, often these runtime issues are captured in part of the operating conditions scenarios. The operating conditions scenario-based optimization is different from scenario-based optimization that uses distribution uncertainties. In our research, scenarios refer to operating conditions such as deployment parameters (number of CBS, number of MBS vehicles, etc.).

Often, a single parameter can be either a run-time issue or a systemic issue. An example of such a parameter is the cost of fuel. If there is an issue with the fuel supply at a particular location, a solution would incur a cost impact. This is an example of a run-time issue. Compared to this, if there is a nationwide increase in fuel prices, then all possible solutions are impacted. Thus, it will not be a run-time issue, but a systemic one that affects all possible solutions.

Result Summary

Human-in-the-loop has been a critical part of the concepts. We have found a way to incorporate humans in the loop, so that it can take user inputs and provide meaningful feedback to the system, where the analyzer works really well. Some of this input could be provided in the form of contours. Different types of contour are available cost, time, risk and area (CTRA). Our goal is to maximize the area and the amount of risk reduction achievable by the UAV split. While we have minimized both costs and time, this is an interesting trade-off in the area. Well, to have significant meaning for UAV split deployment and design, we collaborate with Colorado Division of Fire Prevention and Control, District 4 (San Juan River Region) in the state of Colorado and use the Southwest Colorado case study, looking at data from Montezuma, La Plata, San Juan, and Archuleta Counties. These four counties comprise the river region and the communication region.

Based on the results of the general study documented in the chapter, we can decide that the operational configuration and design decisions can adapt to runtime issues when human-in-the-loop (HITL) is in place.

7.6.5 Contribution to the body of knowledge

We present proven methodologies for implementing WPO, thus enhancing the effectiveness of the DSS. The DSS is designed as a human-centric software tool that integrates outputs from the optimization engine with operator input to support critical decision-making in wildfire detection and communication. The primary contributions to the body of knowledge are as follows:

Research Contribution (RC2.1)

Modularized / dynamic Pareto Front Framework: Operating Conditions Scenario-Based Optimization of the at Run-Time: This research has developed scenario-based optimization (operating conditions) and separated the optimization of the CBS & MBS vehicle and the flight path of the UAV within a continuous optimization loop with HITL, followed by their integration into a unified system to accomplish holistic wildfire detection tasks.

We have developed a set of mathematical expressions for fleet deployment and fleet paths/Wildfire Points Optimization. This research has developed an optimization engine with two stages that enables a wildfire-detection system based on UAVs.

We analyzed the impacts of fleet deployment on the planning of wildfire points and run-time issues in Chapter 7. We have experimented with environmental parameters for wildfire points optimization (WPO) efficiency. In addition to UAV flight paths and WPO efficiency, we also focus on a geographic map, environmental parameter characteristics, and wildfire likelihood to detect and communicate wildfires.

Research Contribution (RC2.2)

We provide a novel framework and data-based modularized model to address complex problem-solving and provide a comprehensive solution for wildfire detection while maintaining

adaptability to run-time scenarios. This approach uses a dynamic Pareto front, where only the affected portion of the optimization is re-executed at runtime rather than recomputing the entire solution.

This system method integrates fleet path or wildfire points optimization, WPO strategies, PFWP, RTWP, and runtime decisions.

- Develop a prototype model for wildfire points optimization (WPO) strategies based on UAV fleet deployment.
- Develop strategies to perform the PFWP plan and RTWP (different strategies) and run in WPO.
- Run the strategies in the context of changes in field effects, mission goal, mission risk, and performance.

7.6.6 Strengths and limitations

Although the approach is effective for decision making, the study was limited to 48 sites; a commercial version that incorporates more sites would increase the fidelity of the implementation. In addition, we have not yet fully optimized the algorithm for computational time, which will be addressed in future research.

7.7 Chapter Conclusions

Wildfire operating conditions and scenario-based constraint optimization improve flexibility in managing diverse run-time scenarios within UAV wildfire points optimization (WPO). Simultaneous optimization of launcher deployment and UAV wildfire points or flight paths offers a comprehensive solution to the deployment problem.

The proposed methodology addresses run-time challenges in wildfire UAV fleet deployment and UAV design through a two-stage optimization process. In this framework, the second stage receives the first stage solution as input and subsequently returns its output to the first stage. This iterative feedback mechanism allows launcher deployment and UAV optimization to be performed independently while maintaining integration as a unified system for wildfire detection. System performance is assessed using optimal UAV wildfire points.

Operational configurations and design decisions must adapt to run-time challenges by distinguishing between issues that impact individual solutions and those that influence the entire solution set. The resulting improvements are substantial, and the technology is feasible with current capabilities. Thus, the findings of this study represent progress towards real-world implementation and commercialization. Experiments from these chapters demonstrated that applying system thinking principles, such as *Emergence Principle* and *Learning Principle*, allows mental models to integrate runtime and dynamic systems into effective optimization models. As a result, the system can not only operate effectively, but also take advantage of favorable emergent behavior, learn from runtime situations, and adapt accordingly.

7.8 Chapter Summary

This chapter addresses research question 2, which pertains to run-time scenarios. Examines strategies for managing run-time challenges in wildfire UAV fleet deployment and UAV design. Executing a portion of the second-stage optimization ensures that only the necessary optimization components are utilized, thus addressing research gap 3.

Chapter 8

Research Question 3: Robust Deployment and UAV Design / Flight Controls

8.1 Preface

To address the research question 3 (RQ3) and bridge research gap 4, we have designed a step-by-step methodology to determine trade-offs in wildfire unmanned aerial vehicle (UAV) fleet deployment and UAV design. This chapter ties together materials from Chapter 6 and Chapter 7 to identify where and how emphasis could be placed, if there is an opportunity to focus on deployment or design parameters, and what the impacts would be, keeping the ultimate mission goal of wildfire detection given objective functions.

8.2 Overview

This chapter examines the decision parameters for both the wildfire deployment of the UAV fleet and the design of the UAV, with the aim of determining how these factors can be adjusted to achieve mission objectives. In the context of wildfire UAV deployment, it is essential to focus on the parameters that directly influence the decisions made by the central base station (CBS) fleet coordinator and mobile base station (MBS) vehicle operators. The CBS fleet coordinator and MBS vehicle operators jointly make fleet decisions to maximize operational impact. For the objective of deploying the wildfire UAVs fleet, the MBS operator is responsible for the UAVs assigned to the MBS vehicle and for ensuring optimal performance. The purpose of this chapter is to evaluate opportunities to maximize UAV deployment capacity. In some cases, unused capability may exist depending on the decisions made, and it has been identified that the deployment and design parameters are directly interdependent.

8.3 Introduction

In this chapter, we investigate the dependencies and correlations between fleet deployment decisions and UAV design parameters. The results of the deployment are shaped by operational factors such as the location and elevation of the launch-site, environmental conditions including temperature and weather, geographic characteristics, regions prone to wildfires, and proximity to urban corridors. Among these factors, launch-site location and elevation are particularly influential because they directly affect mission feasibility and operational performance. The significance of these deployment parameters depends on the UAV's capabilities. For instance, a UAV's ability to perform reliable vertical takeoff and landing at high elevations determines which deployment locations are viable.

An integrated framework is introduced to simultaneously evaluate deployment and design, rather than treating them as independent concerns. The framework incorporates a human-in-the-loop (HITL) sensitivity-tuning process, which facilitates iterative feedback between UAV design and deployment decisions to identify the most significant opportunities for enhancing overall mission performance. This feedback mechanism enables both design and deployment processes to evolve concurrently as operational knowledge increases.

The framework further ranks the deployment and UAV design parameters through trade-off analysis and tornado chart sensitivity analysis as shown in Figure 8.1. This ranking clarifies which parameters deserve the most sensitivity tuning throughout the system life cycle, from UAV design and development to fleet deployment and operational planning. By identifying the most influential parameters, CBS coordinators or MBS operators can allocate MBS vehicle or UAV to the regions that offer the greatest potential to positively impact the effectiveness of wildfire detection.

8.3.1 Background

The architectural trade studies discussed in Chapter 3 (UAV MBSE Architecture Analysis) and Chapter 4 (UAV CFD Analysis) demonstrate the value of this integrated methodology. Several variants of the surface-less flight controls (SFC) architecture were systematically evaluated

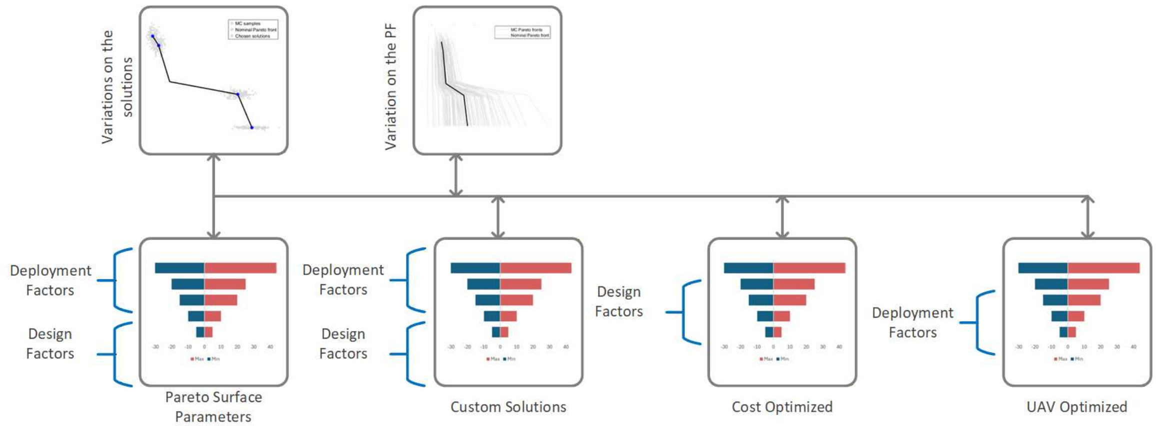


Figure 8.1: Method for selecting wildfire leverage point between deployment and design

Note:

[1] Utilizing this method, a greater range of surface parameters can be evaluated for deployment and design.

[2] Custom solutions can be assessed for both deployment and design factors.

[3] Cost, time, risk factors and area can be optimized.

[4] Either the UAV design (configuration) or the deployment scheme can be optimized.

alongside conventional flight-control architectures. The results showed that while the baseline UAV architecture remains feasible, the integrated design-deployment analysis identified a novel architecture capable of significantly improving mission range, survey time, vehicle weight, and specific cost under representative deployment scenarios.

The simulation results indicate that the ranking of the deployment parameters and the UAV design parameters influences the site selection outcomes. Altering a single deployment parameter also affects the design parameters. Additionally, tornado charts generated from the parameter list and deployment decisions exhibit variability. Varying these parameters leads to different decisions, which in turn affect objectives such as cost, time, risk, and area. The proposed methodology follows a forward process: the parameters are listed, ranked, the Pareto front is identified, and the deployment to the site is executed.

8.3.2 Literature Search

Joint design and deployment, together with human-in-the-loop (HITL) integration, are essential components of any decision support system (DSS). However, most existing approaches lack genuine joint design and deployment, and even when both are mentioned in research, they are often excluded from a comprehensive feedback loop that incorporates HITL. Many state-of-the-art methods rely on offline optimization or planning frameworks without real-time execution, HITL, or decision-support capabilities. These approaches do not address operational deployment in dynamic and uncertain wildfire scenarios [10], [16], [46], [48], [50], [60], [61], [62], [191].

Hildemann studies spatial allocation, which is consistent with the deployment approach presented in this study [204], whereas Pandey's research focuses exclusively on the design space [205]. In contrast, our research addresses both design and deployment, facilitating tradeoffs between these domains to optimize mission objectives. UAV design parameters are typically static and require integration. With respect to uncertainty, Hildemann [204] examines data and environmental uncertainty, whereas Pandey [205] addresses design uncertainty. Our study considers data, environmental, operational, and human-in-the-loop (HITL) uncertainties. Hildemann [204] aims to support decision-making, while Pandey [205] analyzes incoming decisions and functions as an automated decision-maker. Within wildfire research, particular emphasis is placed on HITL, which is essential to the wildfire fleet deployment DSS.

8.3.3 Supported Systems Thinking Principles

While integrating and exploring the trade space between fleet deployment and UAV design, systems thinking principles become even more critical.

Utilization of Learning Principle - Learning from deployment to influence design

The Learning Principle identifies, "*(Common) Mental models influencing human decisions about architectures are learnable and adaptable*" [42].

Our goal is not only to utilize UAV to their full potential, but also to provide effective feedback to UAV designers and architects. The system must adapt and learn from operational scenarios and provide input to the design process accordingly. Custom or human-generated solutions may not always represent the most optimal solution. However, if we can validate that a human-generated solution strongly supports the objective solution, we can optimize the Pareto front to align with the human solution as an optimal solution and adjust the parameters accordingly.

In addition, we can optimize both deployment and design through a feedback loop, making the architectures learnable and adaptable.

Utilization of Human Principle - HITL

The Human Principle depicts, "*Humans impact and are impacted by the (wanted / unwanted) emergence of all reachable systems*" [42].

Because our mission goal is to achieve the mission objective, both fleet deployment and UAV design are considered reachable systems within this research study. We explore how humans can affect both deployment and design. As illustrated in Figure 8.1, we identified situations in which deployment factors should receive higher priority, situations in which design factors should receive higher priority, and situations in which only deployment or only design factors are emphasized. Human involvement can influence all of these aspects. In addition, by understanding what matters most through the human principle, we can improve system performance by trading between design and deployment factors.

8.4 Systems Methods

The method of selecting the wildfire leverage point between deployment and design is summarized in Figure 8.1 along with Table 8.3.

8.4.1 Overall System

Optimizing wildfire detection and communication using unmanned aerial vehicles (UAVs) requires flexibility in adjusting deployment and design parameters. This flexibility is achieved through sensitivity analysis and the incorporation of parametric data within the optimization process. Identifying the sensitivity of solutions to specific objectives provides essential information for parametrizing the Pareto front. This approach clarifies the influence of deployment and design factors on system outcomes and supports informed trade-offs. The present study simulates a framework to guide the application of this method.

The process for selecting the leverage point between deployment and design in wildfire detection is illustrated in Figure 8.1. As depicted, a range of possible solutions is generated, represented by the top-left and top-right blocks. This solution space, referred to as the variation corridor, is explored according to performance metrics, logical constraints, and alternative solution strategies.

The generated solutions are parameterized using deployment setup parameters and design factors. These solutions may be ranked according to Pareto-optimality criteria or by comparing customized solutions with optimized alternatives. Evaluation can be based on various objective functions, such as minimizing cost, deployment time, and risk, or maximizing coverage area, availability, or other relevant performance metrics, depending on the design objectives. The following section presents the detailed steps of this method, including the role of human involvement in identifying the leverage point between deployment and design.

8.4.2 Method Details

This method of trading between deployment and design utilizes an integrated deployment and design methodology to identify the optimal leverage point through a sensitivity analysis tuning process, with a focus on human-in-the-loop (HITL) considerations.

The objective is to perform a sensitivity analysis to visualize the Pareto front and assess the impact of deployment and design factors. Our study considers four main objectives: cost, time, risk, and area (CTRA). For demonstration, we focus on cost and time, with method three providing a detailed examination of the time objective. In some cases, cost details are limited for clarity.

8.4.3 System Inputs

This method requires a Pareto front generated by the optimizer engine from stage 1 and stage 2 optimizations. Inputs should include deployment parameters, design parameters, or both. Additional

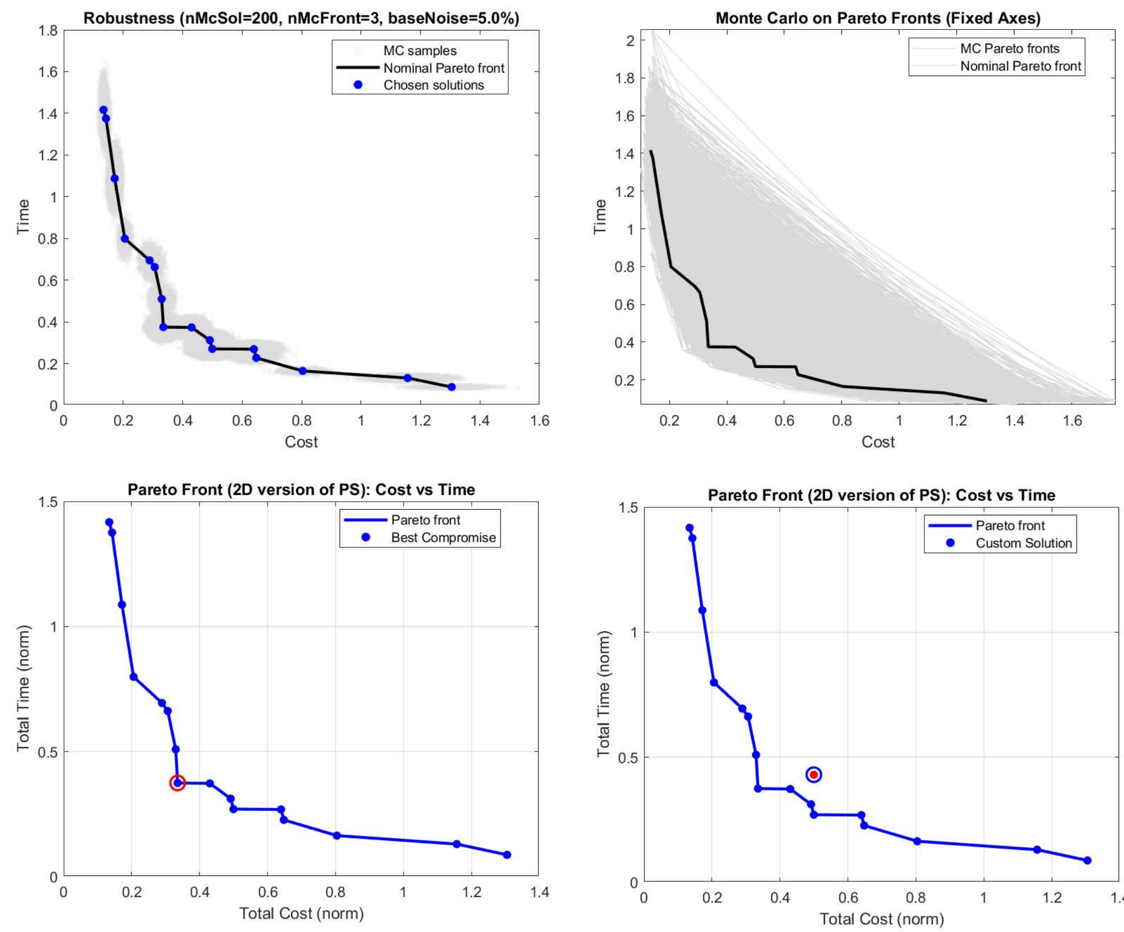


Figure 8.2: Envelope of Wildfire Deployment and Design Parameters Using Monte Carlo Simulation

Note:

[1] First figure on the top-left shows localized impacts on a specific solution (a set of sites). This could be planned (PFWP) or run-time (RTWP). Second figure on the top-right is systemic impacts for all possible solutions, larger impacts on all solutions. By definition this is not run-time (PFWP only).

[2] The bottom-left figure shows the Pareto front with a selected deployment solution by the DSS. For reference, the bottom-right figure shows the Pareto front with a custom solution picked by HITL.

input may cover parameter ranges not directly optimized, as well as nominal and critical parameter ranges.

8.4.4 Methodological Steps

The method performs Monte Carlo on each of the solutions on a Pareto front and provides uncertainty and how parameters and constraints can influence the solutions. Additionally, the

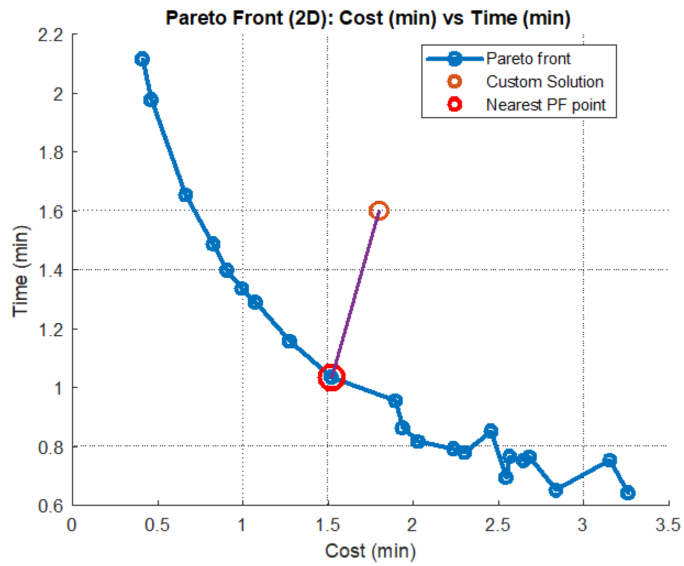


Figure 8.3: Exploring Pareto Geometry

Note:

[1] The shortest Euclidean distance to a solution on the Pareto front is used to provide a geometric evaluation of numerical performance.

[2] Similar analysis can be extended from 2 objectives to 3 objectives or more.

method performs Monte Carlo on the entire Pareto front, including all the solutions, and provides uncertainty and how parameters and constraints can influence the solutions.

[Step 1] Pareto and parametric distributions - Envelope of Pareto front movement vs. parametric distributions.

[Step 2] Tornado charts for points on Pareto front - Analyzing movement along the Pareto front and visualizing using tornado charts.

[Step 3] Critical parameters- Identifying key parameters for operators' decision changes.

[Step 4] Fully integrated parameters and constraints - Using tornado Charts, going from wildfire parameters to deployment site selection, and vise versa (examples are forward process, reverse process, etc.).

[Step 5] Wildfire human decision makers- CBS Coordinators and MBS vehicle operators as human decision makers (min risk to be taken, max time, field feedback, etc.).

It utilizes additional processes, forward process and reverse process, and both processes can be run.

The details of the forward process (pipeline) are as follows:

– Generate integration list deployment and design critical parameters

– Perform parametric ranking of integrated deployment and design parameters using one-factor-at-a-time (OFAT) method or Monte Carlo (MC) method.

– Adjust and shift the key parameters as per the influences

– Generate a new Pareto front with updated parameters

– Pick a solution from the Pareto front and gather the site locations (assignments)

(Optional and commercialization) - The details of the forward process (pipeline) are as follows:

– Pick a solution from the Pareto front and gather the site locations (assignments)

– Generate a new Pareto front with updated parameters

– Adjust the key parameters according to the influences

– Perform parametric ranking of integrated deployment and design parameters using one-factor-at-a-time (OFAT) method or Monte Carlo (MC) method.

– Generate integration list deployment and design critical parameters

(Future growth for commercialization) - Run both processes.

8.4.5 System Outputs

The method yields a parameterization of the Pareto front and ranks the critical parameters. The sensitivity analysis process also provides the following outputs:

- Guidance on prioritizing deployment parameters versus design parameters.
- Identification of constraints suitable for potential revision.
- Recommendations for updating the requirements and refining the formulation of optimization problems.

8.5 Simulation Framework: Methodology for Sensitivity Analysis

We develop a robust systemic way to perform sensitivity analysis for wildfire UAV Fleet deployment and design considering key parameters. This is a framework to implement the final goal of an optimizing engine that operational decisions for deployment and design parameter sensitivity checks.

8.5.1 [Step 1] Pareto and Parametric Distributions - Envelope of Pareto Front movement vs. parametric distributions

As the first step, we characterize the Pareto front that envelopes the Multi-Objective Optimization (MOO) problem for the Decision Support System (DSS). Envelope of Pareto front movement versus parametric distributions (10 points) : For a 10-item list of parameters (5 deployment, 5 design). We characterize how to evaluate the design and deployment parameter envelope in Table 8.1.

Details of Step 1

Once we have the optimization results and form a Pareto front, we perform a Monte Carlo analysis of the Pareto front to understand how it varies with respect to the objectives of cost and time. We also performed Monte Carlo simulations on solutions on the Pareto front to understand how they can vary.

From any point on Pareto geometry to Pareto front

Each outcome can be measured by its distance from the Pareto curve in the normal (perpendicular) direction to the curve. This normal distance serves as a multidimensional metric that can be calculated in a two - dimensional space (2D) or three - dimensional space (3D) by projecting each simulated point onto the normal vector of the curve.

Table 8.1: Robustness and sensitivities of the solution envelopes (Monte Carlo)

Param Type	Localized Impacts (PFWP or RTWP) - uncertainty of a solution (planned/Run-Time)	Systemic Impacts (PFWP) - changes in all solutions (not Run-Time)	Comments
Fleet Deployment	1. Launch Delay (traffic) (RT) 2. Wind direction (RT) 3. Team/crew late (RT) 4. known refueling stop (P) 5. planned maintenance (P)	1. Number of UAVs 2. Min distance between two launch sites 3. Min risk threshold change 4. New NFZ regulatory 5. Environment/weather pattern change (long term, i.e. avg. temp)	MBS vehicles are dispatched from CBS location(s)
UAV Design	1. Battery drain (unexp) (RT) 2. Comms loss / latency (RT) 3. Weight (reconfigurable) (RT) 4. Another UAV visited (RT) 5. Sensor Performance (RT)	1. ROC (aerodynamics) 2. Battery endurance /Range 3. Weight (fixed) 4. Supply chain change 5. L/D (aerodynamics)	Weight can be fixed or re-configurable (modular-ized)

Note:

[1] (RT) refers to Run-Time and (P) refers to pre-planned.

[2] PFWP plans are pre-planned parameters. RTWP plans are pre-planned and run-time parameters.

[3] Additional parameters to consider are Battery/fuel cost inc/dec inc/dec (dep & systemic), supply chain cost inc/dec (dep & systemic), UAV Speed regulatory policy (fly slow/fast) (dep & systemic), Propulsion efficiency (design & systemic), road infrastructure (dep & systemic), payload mounting issue (design & localized).

These list of parameters contribute significantly while developing the optimizer and running the optimization algorithm. We identify the critical ranges of these parameters with respective wildfire deployment and design.

Selected list of critical parameters for simulation model

1. Battery / endurance factor
2. Site Elevation
3. Lift-over-Drag (L/D)
4. Weight
5. Rate of climb (ROC)

6. Minimum risk threshold
7. UAV speed
8. Temperature
9. Launch delay
10. Comms loss / latency

Additional wildfire deployment parameters that we have used throughout this research are

1. Number of MBS
2. Min distance between launch sites
3. CBS Location
4. Number of CBS
5. No fly zone (NFZ)

Additional wildfire UAV design parameters that we have used throughout this research are

1. Surface-less Flight Control (SFC) weight
2. UAV Range

Monte Carlo - a) on a solution in a PF vs b) on the entire PF (set of solutions)

When a point is chosen along the Pareto front, a fixed solution already exists for that point. By conducting a Monte Carlo (MC) study around any point on the Pareto front, a cloud of simulated results is produced.

We used Monte Carlo shown in Figure 8.2 to analyze the Pareto front envelope to analyze the impacts of the deployment and design parameters. The second column of Table 8.1, lists the fleet deployment and UAV design parameters that can be characterized by the first figure in Figure 8.2. This set of parameters characterizes the uncertainty in a specific solution. This can happen either in Run-time or preplanned (PFWP plan or RTWP plan).

The third column of Table 8.1, lists the fleet deployment and UAV design parameters that can be characterized by the second figure in Figure 8.2. This set of parameters drives systemic changes to all possible solutions. This is considered during the PFWP plan only (not run-time).

Parameters impacting the Pareto front

The key parameters for wildfire UAV fleet deployment and UAV design include (but are not limited to the following items.

1) Deployment Parameter - the distance between the deployment sites: We must ensure that a specific separation exists between these sites.

2) Deployment Parameter - minimum risk reduction: A certain minimum level of risk that must be mitigated, which requires an understanding of the composite wildfire risk involved.

3) Design Parameter - UAV L/D: UAV L/D ratio, which identifies the flight control capabilities that are sufficient to meet the mission goal of wildfire detection.

4) Design Parameter - UAV Range: UAV range is critical to know how the UAV should go to have the optimal benefit of the mission.

5) Design Parameter - UAV vertical speed and true airspeed: UAV vertical speed and true airspeed can impact the launch and retrieval locations.

5) Design Parameter - UAV weight: UAV weight essentially impacts the efficiency of the UAV flight dynamics.

6) Design Parameter - Altitude for UAV: Altitude is a critical performance parameter for a UAV for its performance reasons.

7) Deployment Parameter - Elevation for wildfire risk: Elevation is also an operational deployment factor because it is critical to know that above a certain altitude, fire impact is low and may not need to deploy an MBS vehicle to a high elevation deployment sites.

Assumptions that Impact Decisions

The following assumptions influence key decision-making processes.

1) Number of UAVs per MBS Vehicle: The assumption is that each MBS vehicle can load up to 3 UAVs. In our initial base case, we assume that each MBS vehicle transports 1 UAV. Our additional cases assume that each MBS can nominally transport 3 UAVs.

2) Number of Launch and Retrieval sites: The assumption is that 48 sites are reasonable for the initial prototype implementation of ODS in DSS. This is due to practical limitations and this assumptions may have to be changed during commercialization effeort.

Varying Parameters to Observe Pareto Front Impact

The first flow of activity employs a tornado chart to rank deployment and design parameters. These ranked values are then used to run the optimization problem, which identifies the resulting sites and Pareto front or surfaces. Additionally, by adjusting each parameter, the effects of variations on the tornado analysis results can be observed.

The second flow of activity, which proceeds largely in reverse order to the first, involves selecting a Pareto front and choosing a solution from it. This solution is then mapped to the corresponding geographic locations or sites. The allowable range for constraints, as well as which constraints may be modified, can also be determined.

Observation from Step 1

We discovered that several parameters shift the Pareto front more than others, as we observed during the Monte Carlo analysis. We also analyzed the variation in solutions resulting from parameter changes. Some parameter variations result in solutions that remain clustered, while others cause greater dispersion. These findings enhance our understanding of the uncertainty associated with the Pareto front and its solutions, accounting for parameters from both the UAVs and the deployment context.

We pinpointed a set of critical deployment parameters and a separate set of critical UAV design parameters. For the initial study, we limited the analysis to approximately five deployment parameters and five UAV design parameters to evaluate their impact on performance.

Pareto Geometry - comparing custom solution to optimal solution

The method progresses from parameter ranking to optimization, followed by analysis of the resulting product to identify the most effective solutions. In addition, the influence of different parameter choices on cost, execution time, risk reduction, and area coverage is examined. This approach provides insight into the trade-offs among objectives and informs both parameter selection and constraint definition.

A thorough understanding of solutions on the Pareto front, as well as the information provided by any point within the Pareto geometry, is essential. Each point characterizes the optimization landscape and indicates how close a candidate solution is to the optimal trade-off surface. The shortest Euclidean distance from a candidate solution to the Pareto front serves as a valuable metric for evaluating solution quality, as shown in Figure 8.3. The direction and magnitude between points within the Pareto geometry, including the Pareto front, Pareto surface, and Pareto hypersurface, demonstrate how objectives can be traded. The Pareto front enables trade-offs between cost and time; the Pareto surface extends these trade-offs to cost, time, and area; and the Pareto hypersurface further incorporates wildfire risk and area coverage.

8.5.2 [Step 2] Tornado Charts for Points on the Pareto Front: Analyzing Movement Along the Pareto Front and Visualizing It Using Tornado Charts

Three points along the Pareto front of time versus cost are selected to illustrate how tornado charts vary with respect to the objectives of fleet deployment and UAV design. Three representative solutions on the Pareto front are evaluated, each corresponding to a distinct deployment configuration. The first solution represents the low cost, high mission time extreme. The second solution is the DSS-optimal configuration, which achieves a balance between cost and mission time. The third solution represents the high cost, low mission time extreme. These three points are selected to facilitate analysis of variations in deployment and design parameters across the Pareto front, as shown in Figure 8.4.

The figure presents tornado charts illustrating the mission time objective (top row) and the cost objective (bottom row) at three representative points on the Pareto front. These points represent the

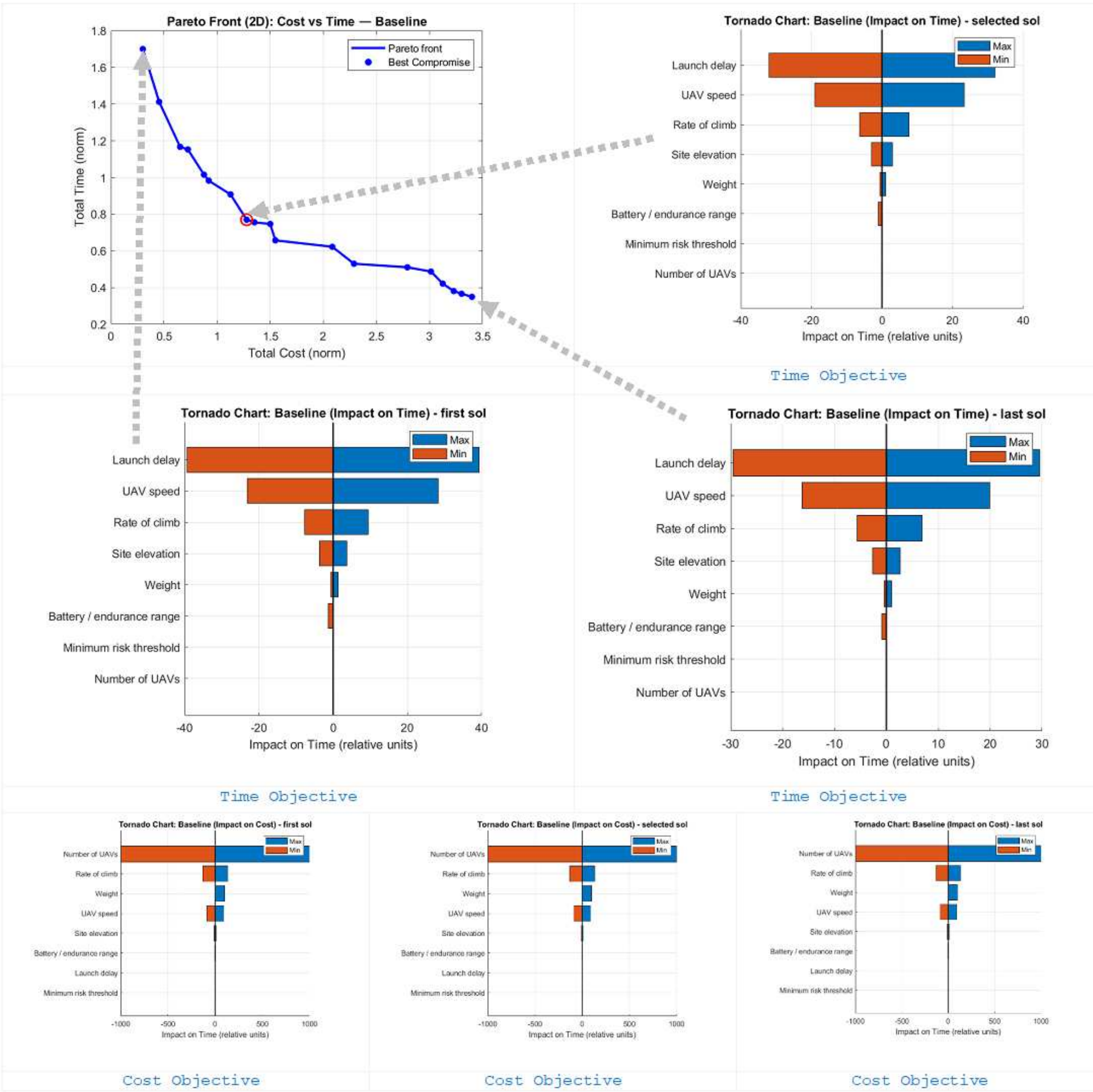


Figure 8.4: Tornado charts illustrating the mission time objective (top row) and cost objective (bottom row) at three representative points along the Pareto front

Note:

[1] Tornado charts for time objective for three points on the Pareto front top right and middle two figures

[2] Tornado charts for cost objective for three points on the Pareto front are the bottom three figures

low-cost, high-mission-time solution, the DSS-optimal solution, and the high-cost, low-mission-time solution.

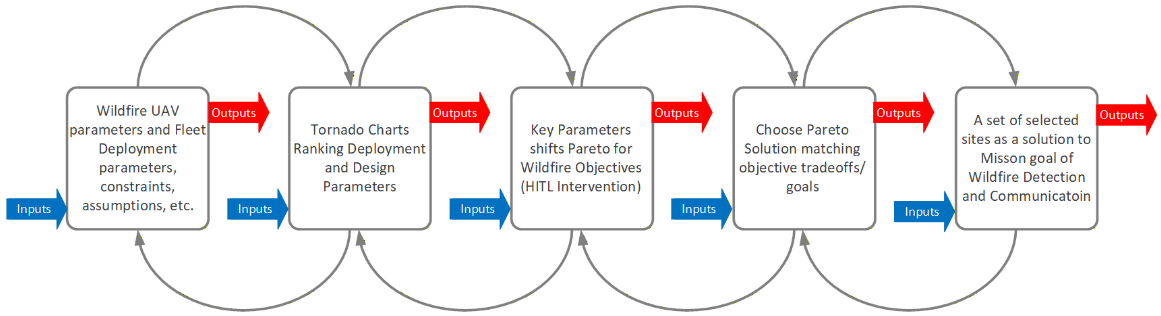


Figure 8.5: Method for Selecting the Wildfire Leverage Point Between Deployment and Design

Note:

[1] Forward process (pipe line) goes from left to right

[2] Reverse process (pipe line) goes from right to left.

Figure 8.5 illustrates the forward and reverse processes used for sensitivity tuning of deployment and design parameters.

Details of Step 2

We construct a Pareto front and analyze the variation among its solutions. These variations are often subtle and may result from underlying assumptions. Three representative solutions are selected from the Pareto front for performance evaluation. The test results identify the most effective solution, which serves as the basis for our definition of optimality.

Observation from Step 2

When cost is the primary objective, solutions on the left side of the Pareto front are preferred (e.g., point cost .3). Conversely, when time is the major concern, solutions on the right side of the front are prioritized (e.g., point time .3). Selecting three Pareto-optimal solutions and determining their parameter values provides a comprehensive understanding of Step 3, facilitating navigation of the Pareto front and evaluation of each solution using tornado charts and analysis of critical parameters from both deployment and design perspectives.

8.5.3 [Step 3] Critical Parameters - Identifying Key parameters for operators' decision changes

Determine 2 major parameters that might change the operators' decisions:

- Equality Constraint parameter (pick the most important equality constraint: identify the parameter)
- Inequality Constraints (pick the most important inequality constraint)
- Select a point on the Pareto front and then show two tornadoes

Scenarios-Based Optimization - Impacting Decisions

Here are three different types of solution set focusing on three sets of issues:

- The speed-focused solution
- The endurance-focused solution
- The wind-gust solution

Further analysis of the wind-gust solution is conducted. Scenario-based optimization is considered, including various operational scenarios and their respective sub-cases. For instance, the impacts of wind scenarios are examined. Table 8.2 presents a comparison of factors influencing UAV performance under different operational and environmental conditions.

Wind Scenarios impacting fleet deployment and UAV design parameters

Scenario A: Wind-sensitive and less weight scenario - High-impact parameters are Rate of climb, Battery/endurance factor, and L/D

Scenario B: Wind-robust and heavyweight scenario - High-impact parameters are L/D, Weight, and Rate of climb

Scenario C: Mid Wind and high Endurance scenario - High-impact parameters are Battery/endurance factor, Rate of climb and L/D.

Table 8.2: Ranking of Operational Parameters for Wind Test Case

Rank	**Scenario A: Wind-sensitive, high speed**	**Scenario B: Wind-robust, heavier**	**Scenario C: Mid-wind, high endurance**
1	Rate of climb	L/D	Battery / endurance factor
2	Battery / endurance factor	Weight	Rate of climb
3	L/D	Rate of climb	L/D
4	Weight	Battery / endurance factor	Weight
5	Max altitude factor	Max altitude factor	Max altitude factor
6	Comms/latency factor	Comms/latency factor	Comms/latency factor
7	Sensor noise variation	Sensor noise variation	Sensor noise variation
8	Site elevation	Site elevation	Site elevation

Note:

[1] Comparison of factors affecting UAV performance under different operational and environmental conditions.

[2] UAV design characteristics C under mid-wind and high endurance mission goal in the middle column (first item to compare).

[3] UAV design characteristics A under high wind-sensitive/gust wind mission goal in the last column (second item to compare).

These parameters form the basis of our deployment and design plan. We incorporate them into a step-by-step process.

Details of Step 3

The critical inequality constraints that we have identified are the following:

1. UAV rate of climb (ROC)

2. UAV lift-to-drag ratio (L/D).

3. Elevation of deployment sites.

4. Minimum risk to mitigate.

The critical equality constraints that we have identified are the following.

- Minimum distance between two launch sites: at least one mile.

- Number of UAVs available for deployment: four UAVs. (In this case, we consider one UAV per MBS vehicle, with a detailed allowance of up to 3 UAVs per MBS vehicle.)
- Ideal loitering altitude: 10000 ft.
- Sensor width limit: four miles.

Observation from Step 3

In this third step, we examine several key constraints. We identify the critical and/or "leveraging" parameters: two equality constraints and two inequality constraints

8.5.4 [Step 4] Fully Integrated Parameters and Constraints: Using Tornado Charts to Relate Wildfire Parameters to Deployment Site Selection and Vice Versa

The goal of the fourth step is to build a realistic plan that primarily respects inequality constraints while avoiding excessive restriction of the solution space.

Details of Step 4

This analysis highlights the significance of specific constraints. The fourth step involves formulating a realistic plan that meets the inequality constraints while preserving flexibility within the solution space.

The forward process is represented from left to right, whereas the reverse process is shown from right to left. During the forward sensitivity analysis, a defined set of deployment and design parameters identifies the optimal locations for MBS vehicle deployment and UAV launch, as elaborated in Figure 8.10.

Forward and reverse sensitivity analysis with HITL

Forward and reverse sensitivity analyzes are developed for UAV fleet deployment and UAV design parameters, as summarized in Table 8.3.

Table 8.3: Wildfire UAV fleet and design forward and reverse sensitivity analysis

Sensitivity	Analysis Activity		
Forward Analysis	1) parameter list	→	2) tornado ranking
	2) tornado ranking	→	3) key parameter shifts Pareto
	3) key parameter shifts Pareto	→	4) choose Pareto solution
	4) choose Pareto solution	→	5) site locations (map + assignments)
reverse Analysis	5) site locations	→	4) recover Pareto solution
	4) recover Pareto solution	→	3) parameter that moves front
	3) parameter that moves front	→	2) tornado check
	2) tornado check	→	1) refined parameter list (ranking param)

Forward sensitivity analysis uses a set of deployment and design parameters to determine optimal locations for MBS vehicle deployment and UAV launch. Conversely, reverse sensitivity analysis employs specified deployment allocations to identify the corresponding parameter values and their allowable tolerances, which are analogous to binding or active constraints in optimization. Table 8.3 provides an overview of the forward and reverse sensitivity analysis workflows.

The design parameters and the operational deployment parameters (and their sensitivities) influence the deployment site as shown in Figure 8.6.

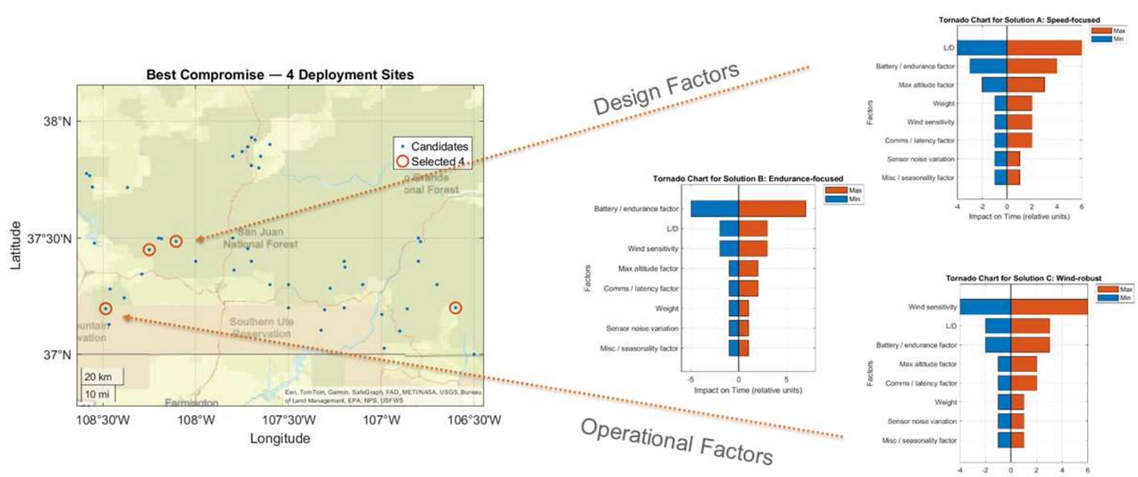


Figure 8.6: Design Factors and Operational deployment factors

Note:

[1] Changes in design parameters and deployment parameters influence the deployment site.

The elevation analysis of the launch site for deployment is depicted in Figure 8.7.

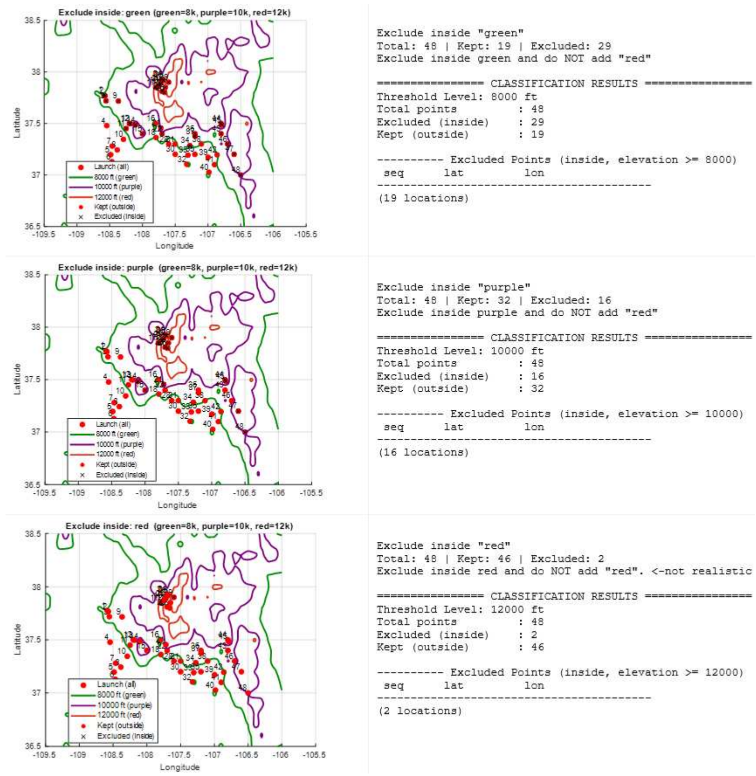


Figure 8.7: Launch Site Elevation analysis for deployment

Note:

[1] Launch site elevation 8000 ft or below is good option for deployment

[2] HITL can exclude high elevation points launch sites

Figure 8.8 shows the test results for the scenario based sensitivity analysis where we consider wind scenarios for fleet deployment and impacts on UAV design. These scenario based analysis can also be extended to general scenarios from Chapter 6.

It is effective to launch UAVs from 8000 ft or below and we can select those location. Figure 8.9 shows the Elevation contours to identify suitable launch locations.

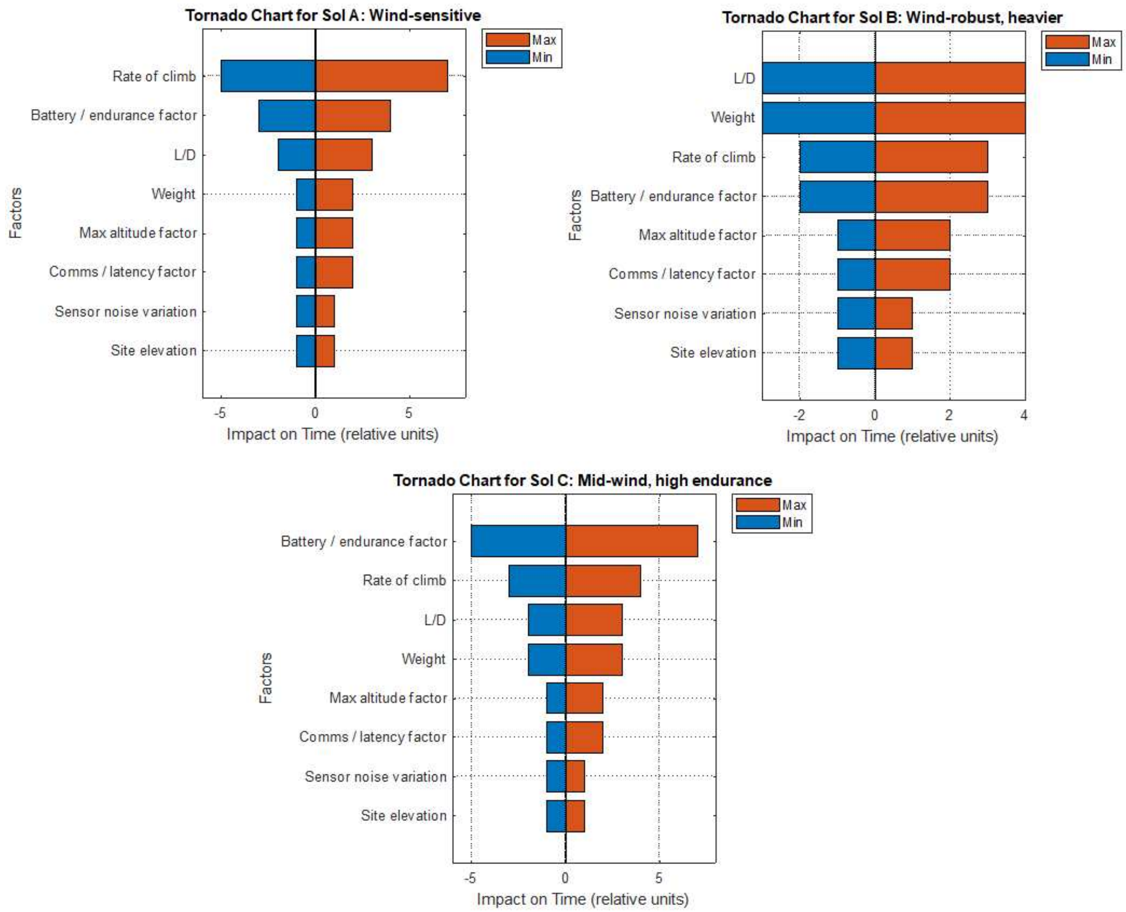


Figure 8.8: Parameters for wind operating conditions sensitivity analysis

Note:

[1] Table 8.2 shows the comparison of factors affecting UAV performance under different operational and environmental conditions.

Observation from Step 4

The sensitivity analysis assessed the effects of varying wind scenarios on fleet deployment and the corresponding impacts on UAV design. The findings demonstrate that launching UAVs from elevations below or below 8,000 feet is the most effective strategy. Appropriate launch locations can be determined using elevation contour maps, as demonstrated.

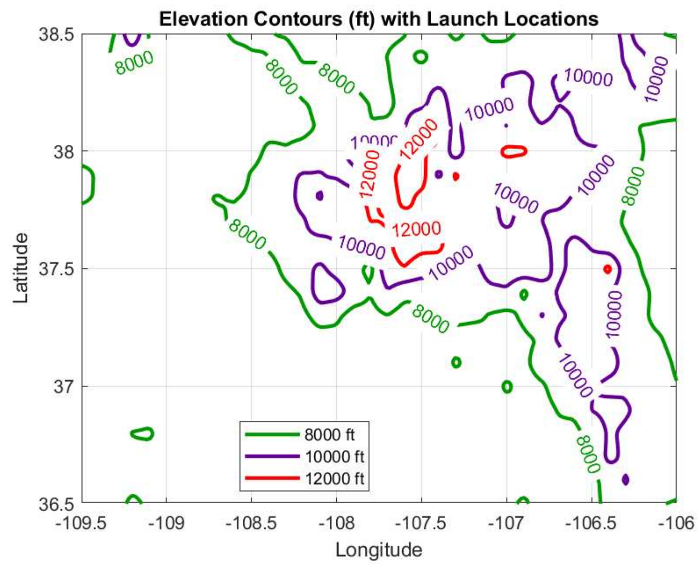


Figure 8.9: Elevation contours to identify suitable launch locations

Note:

[1] It is effective to launch UAVs from 8000 ft or below and we can select those location.

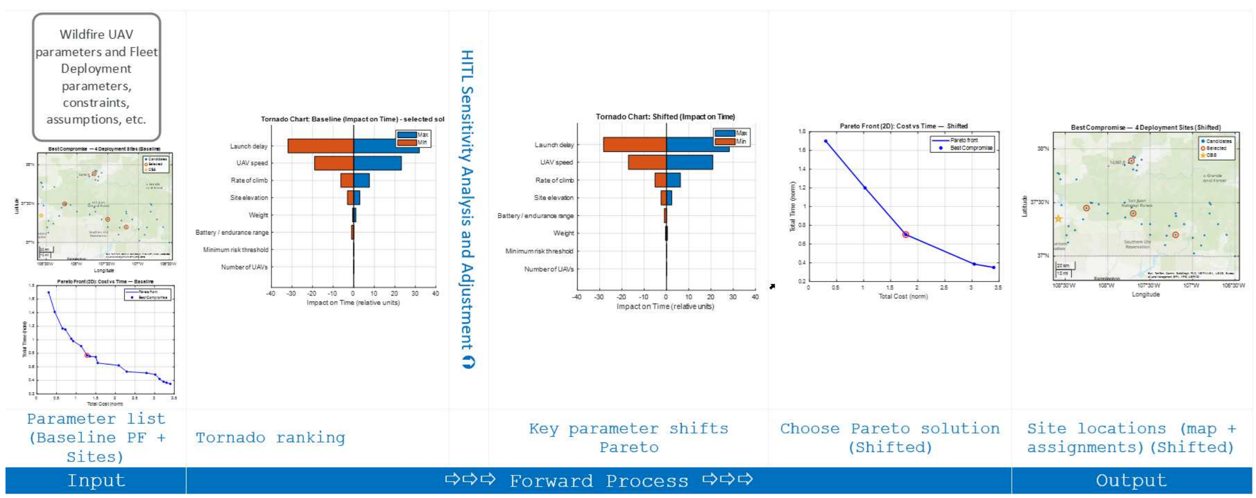


Figure 8.10: Adjusted deployment by changing parameter ranking

Note:

[1] Forward sensitivity analysis activities allow to take a list of deployment and design parameters and ultimately determine the sites where to deploy MBS vehicles and launch UAVs from.

8.5.5 [Step 5] Wildfire Human Decision Makers - CBS Coordinators and MBS Vehicle Operators

In this fifth and final step, we account for human decision-making to vary the parameters identified in the previous steps

Details of Step 5

Human interventions modify the output of the decision support system (DSS). For example:

- Changing the maximum allowable time (e.g., setting a ten-hour firefighter shift) alters the deployment solution.
- Adding asset values, such as protecting a school, increases the cost value and changes the optimal solution.
- Adjusting the minimum deployment distance (e.g., from 5 to 2 miles) affects the layout.
- The preservation of battery endurance by 50% influences the parameter choices

Observation from Step 5

Observations show that reducing the climb rate by an UAV dramatically changes the solution, illustrating how human decisions affect the outcome. By demonstrating these impacts with the DSS, we show that human input significantly affects trading between deployment and design for wildfire detection and a UAV-based solution.

8.6 Systems Model: Fully Integrated Deployment and Design

Now we have a more predictive tool with numerical analysis using Pareto geometry in order to optimize overall mission performance and mission goals for wildfire detection and communication by UAV fleet deployment strategies and UAV design.

The method for selecting the point of leverage of the wildfire between the deployment and the design is shown in the Algorithm 1. This algorithm has two processes, 1) the forward process and 2) the reverse process.

Algorithm 1 Forward Process Wildfire UAV Deployment & Design Parameter Sensitivity Analysis

begin INITIALIZATION

BEGIN PROCESS

  Initialize Parameters and Constraints

    Initialize for parameters, constraints range

    return PARAMETER LIST

  Ranking of Deployment and Design Parameter

    Input parameters changes during runtime

    Update Model (ODS Decisions)

    return RANKED PARAMETERS

HITL INTERVENTION

  User Decisions or Choices

    Input shift parameters

    Input shift Pareto fronts

END PROCESS

  Shifting of Parameters and Pareto Front

    Update Parameters, Constraints & Assumptions

    return NEW SET

  Choose Pareto Matching Objectives

    Update Model (Based on new Pareto)

    Evaluate Model (Based on new solution)

  Choose Pareto Matching Objectives

    return SOLUTION SET OF SITES

return FINAL RESULT

Note:

[1] Method for selecting wildfire leverage point between deployment and design Forward Process for Wildfire UAV Deployment and Design

[2] Reverse Process sensitivity starts from the bottom and ends at the top of this algorithmic flow.

High-elevation launch sites may require improved UAV performance characteristics, such as lift-to-drag ratio (L/D), rate of climb (ROC), fuel consumption, and operational time. Launch sites at high altitudes can be excluded, as illustrated in Figure 8.11.

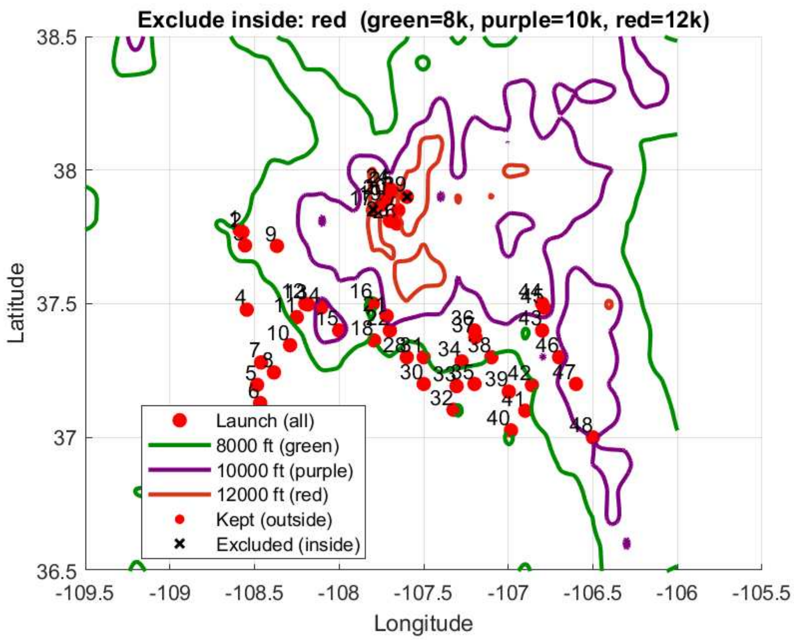


Figure 8.11: Elevation Considerations for UAV Launch Sites

Note:

[1] High-elevation launch sites may necessitate enhanced UAV performance characteristics, including lift-to-drag ratio (L/D), rate of climb (ROC), fuel consumption, and operational time.

High elevation is frequently associated with a lower risk of wildfire [201]. High-value assets that require protection are generally scarce at higher elevations. The associated risk decreases above 8,000 feet (2,438 meters) and becomes substantially lower above 10,000 feet (3,048 meters) [201]. Additionally, high-value assets are rarely located above 10,000 feet and there is effectively no asset risk above 12,000 feet (3,658 meters). These elevation-dependent factors should be integrated into the assessments of launcher deployment locations and the corresponding UAV design trade-offs.

High-elevation launch sites often require enhanced UAVs performance characteristics, including lift-to-drag ratio (L/D), rate of climb (ROC), fuel consumption, and operating time, while potentially exposing UAVs to reduced wildfire impact. Therefore, these factors should be systematically evaluated within the trade space defined by deployment parameters (elevation, location, historical fire risk) and UAV design attributes (L/D, ROC, and related metrics).

8.6.1 Navigating Pareto Geometry (Pareto Front, Pareto Surface, Pareto Hypersurface) using Forward-Reverse Process

The sensitivity analysis consists of two processes: a forward process and a reverse process. These processes proceed from a defined set of parameters and constraints, allowing a ranking through tornado charts and facilitating the analysis of their respective influences.

Sensitivity Analysis Forward Process

Sensitivity analysis involves a forward process, whereas the reverse process begins with a set of parameters and constraints. These parameters are ranked using tornado charts to analyze their influence on the solution. This approach facilitates the development of a front setup solution for a parade front, allowing adjustments by selecting different points along the front or shifting its position. The results are presented in Figure 8.10.

Sensitivity Analysis Reverse Process

For a given set of deployment sites, the corresponding solution is identified, and its position relative to the Pareto front is determined. Trade-offs among solutions are then analyzed to assess the impact of parameter choices on system performance. This approach facilitates the refinement of parameter ranges as necessary.

Sensitivity analysis, employing both forward and reverse processes, supports systematic exploration of Pareto geometry. While implementations of the forward process exist, Chapter 6 and Chapter 7 provide the foundation for defining optimality, establishing mission priorities, and navigating the Pareto geometry. This framework addresses scenarios with two objectives on a Pareto front, three on a Pareto surface, or four on a Pareto hypersurface (Pareto manifold), and supports human-in-the-loop decision-making, parameter adjustment, and identification of optimal solutions.

The objective is to operate within specified parameter constraints and assumptions, while also evaluating whether these limits should be reconsidered and, where appropriate, expanded or optimized to enhance overall system performance. The deployment may be adjusted by adjusting the ranking of the parameters to optimize the objectives illustrated in Figure 8.10. Reverse sensitivity analysis enables the determination, for a given allocation, of the required parameter values and their available tolerances, analogous to binding or active constraints. Further experiments in this area represent opportunities for commercialization and future research.

This approach offers a clear, quantitative understanding of how various factors influence performance, thereby supporting informed decisions regarding deployment and design trade-offs.

8.6.2 The Workflow of the Decision Support System (DSS) Implementing LV Architecture

The workflow of the Decision Support System (DSS) is a critical component that illustrates the logical viewpoint (LV) architecture of the overall implementation of the system shown in Figure 8.12. The DSS graphical user interface (GUI) is designed to support multiple human users, including wildfire analysts, CBS coordinators, and MBS operators. This workflow addresses diverse user perspectives and facilitates human-in-the-loop decision-making through manual inputs, customized operational contours, and objective-specific constraints.

The GUI features three distinct user interfaces, each tailored to the specific requirements of its respective user group. These interfaces supply the necessary input for the initial stage of the optimization process. The first-stage optimization addresses four primary objectives: minimizing operational cost, minimizing response time, reducing risk, and maximizing area coverage. A genetic algorithm is employed to perform this multi-objective optimization. The first-stage optimization uses case-specific data collected for the Southwest Colorado, including wildfire risk metrics, weather information, distance calculations, travel-time estimates, and other operational parameters. The system generates various plots and visualizations to assist users in interpreting the optimization

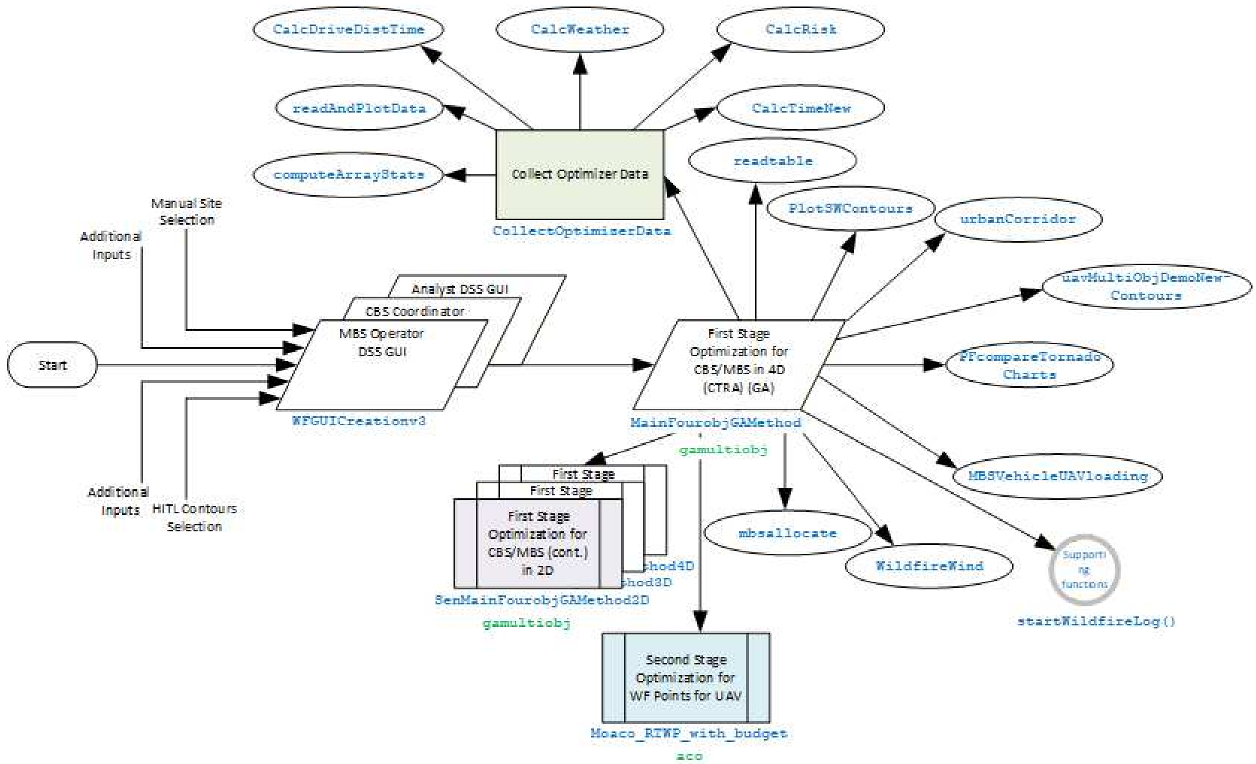


Figure 8.12: Workflow for comparison

Note:

[1] The DSS GUI interface has been developed for the human users using this workflow reflecting logical viewpoint (LV) architecture implementation.

results. Each GUI perspective offers eight custom visualizations to support the decision-making needs of its designated user role.

The first-stage optimization is directly related to the second-stage optimization, which focuses on planning wildfire points (WP) for unmanned aerial vehicles (UAV). This stage considers operational factors affecting UAV performance, including wind direction and environmental conditions. It incorporates parameter ranking methods and evaluates loading configurations for MBS vehicles and UAVs. Sensitivity analysis is conducted by varying optimization objectives and comparing system performance across multiple operational scenarios.

In summary, the DSS GUI has been implemented to support multiple human users through a structured workflow that reflects the logical viewpoint architecture of the Decision Support

System. The integration of user-specific interfaces, multi-objective optimization, visualization tools, UAV mission planning, and sensitivity analysis provides a comprehensive framework for informed wildfire response planning and operational decision support.

8.6.3 Direct Analysis of Varying Ranking of Parameters based on deployment, design, and operational scenarios

The capacity of unmanned aerial vehicles (UAVs) to achieve rapid vertical lift significantly affects overall mission performance. Environmental conditions further influence UAV performance by altering vertical climb rate and loiter capability, which in turn affect flight speed, operational range, fuel consumption, and mission effectiveness. The combined impact of these factors determines the efficiency of the deployment strategy.

The results offer new insights into optimizing UAV design parameters to maximize the advantages of Optimal Deployment Strategies (ODS). Additionally, the findings identify deployment parameters that most significantly influence mission performance, thereby facilitating the design and deployment of UAVs for enhanced operational effectiveness.

Observations and results analysis

The simulation and testing results indicate that optimizing the lift-to-drag ratio (L/D) significantly affects both horizontal and vertical lift, which in turn reduces the operational time required for deployment.

The results also show that specific deployment decisions can substantially increase UAV costs without yielding significant improvements in mission performance. For instance, designing UAVs for deployment from altitudes above 12,000 ft provides minimal benefit toward achieving mission objectives. Overdesign of UAVs similarly leads to considerable increases in system costs. These trade-offs are depicted in the tornado charts. Sensitivity analysis and parameter ranking further reveal that the relative importance of deployment parameters varies. In certain scenarios, UAV design parameters exert a greater influence on mission performance, while in others deployment decisions are the primary determinants.

Wind conditions significantly affect UAV performance. Simulations were conducted under various operating conditions, including calm, moderate, and gusty winds, to assess the behavior of the system. The findings suggest that it is not always necessary to design all UAVs to withstand extreme wind conditions. For example, regions such as Southern California require UAVs capable of operating in strong Santa Ana winds, while other regions experience much milder conditions during the wildfire season. In the Southwest Colorado, wind speeds are generally lower during the primary wildfire season, from June through October. Therefore, developing and deploying UAV variants tailored to specific regional and seasonal wind conditions can improve both cost-effectiveness and overall mission performance.

8.6.4 Direct Analysis of the Configuration of UAV pre-deployment

Flexibility for both the CBS coordinator and the MBS vehicle operator offers significant advantages in this operational context. To further investigate this capability, an additional scenario was analyzed in which the configuration of the UAV sensor was adjusted according to the specific requirements of the mission.

Thermal sensors are typically more effective during nighttime operations, whereas conventional cameras yield better results in daylight. The performance of thermal sensors may decline under hot daytime conditions due to reduced thermal contrast. Adjusting the sensor payload to match operating conditions ensures that only necessary sensors are carried, which reduces the overall weight of the UAV's.

A lower payload weight increases the UAV's carrying capacity and extends its operational range, thereby improving the overall mission goal of wildfire detection and communication.

8.7 Results and Observations for Leverage Point Between Deployment & Design

The methodology consists of several key steps: characterizing the human-in-the-loop envelope, analyzing Pareto front movement, identifying constraints, utilizing tornado charts, and integrating human-in-the-loop (HITL) processes. Together, these steps facilitate systematic navigation of the framework to achieve the mission objective of wildfire detection and communication through a UAV-based solution. Based on the findings of the general study discussed in previous sections, a targeted investigation was conducted to optimize overall mission performance for detection and communication. This investigation focused on UAV fleet deployment strategies and UAV design.

Based on the results of the general study documented in this chapter, we can conclude that identify the best points of leverage for deployment-strategy outcomes at runtime by considering both the UAV design and the deployment problem together. UAV deployment and UAV design are very closely correlated, especially when a good feedback loop is available.

8.7.1 Sensitivities between fleet deployment and UAV design

This research demonstrates the ability to identify key leverage points to improve the outcomes of the deployment strategy at runtime.

1. Maximum benefit is achieved when unmanned aerial vehicle (UAV) design and deployment processes are connected through a feedback loop that incorporates human-in-the-loop (HITL) decision-making.

2. The proposed framework integrates operating conditions with parameters from both deployment and UAV design, enabling users to determine whether to prioritize deployment decisions, design and development, or a combination of both.

3. The framework enables users to trace the entire decision-making process, from analysis through design, deployment, site selection, and related processes, and to work backward to understand how each stage influences deployment outcomes and design decisions.

4. For a fixed UAV design, the framework incorporates realistic feedback from deployment scenarios, allowing users to evaluate trade-offs and identify operating conditions and deployment strategies that optimize overall performance.

5. This approach allows UAVs to operate as cyber-physical systems that can be architecturally reconfigured in response to changing field conditions.

6. Joint consideration of deployment and design addresses scenarios in which operators seek to understand the limitations of current fleet architectures or designs and wish to initiate or request changes to UAV configurations.

7. Integration of deployment and design supports scenarios in which designers seek to assess the validity of UAV architecture or design in operational contexts. Rather than relying solely on mission assumptions, this approach incorporates fleet operators' concerns into the design process.

Direct Analysis / Strengths and Limitations

Although the approach is effective for decision making, the study was limited to 48 sites; a commercial version that incorporates more sites would increase the fidelity of the implementation. In addition, we have not yet fully optimized the algorithm for computational time, which will be addressed in future research.

8.7.2 Contribution to the Body of Knowledge

We provide actionable knowledge to improve wildfire decision support systems (DSS) by systematically identifying leverage points between deployment strategies and UAV design. We introduce a framework that integrates operating conditions with deployment and UAV design parameters, enabling prioritization of deployment or design and development according to specific operational requirements.

Research Contribution (RC3.1)

This research provides a novel systems method where we can integrate operating conditions with parameters from deployment and UAV design, so that priority and emphasis can be given to deployment or design/development.

We developed systemic methods in Chapter 8 for wildfire UAV Fleet deployment and UAV design. The identification of the leverage point between the deployment and the UAV design (SFC of the UAV) and the FIW (MBSE, Trade Study, CFD) is critical to finding a meaningful solution for detection and communication. An emergent, comprehensive understanding of the usage of MBSE, CFD analysis, systems dynamics modeling, and optimization problem-solving addresses the need for wildfire detection and communication.

- Contribution would be developing a method to identify the leverage point between "fleet deployment" and "UAV design".
- We develop a SFC architecture to reduce weight to increase L/D, and increase the range. We perform an architecture trade study of different flight control options.
- Development of MBSAP for SFC utilizing MBSE. Also, review the MBSAP architecture for wildfire UAV.
- We develop a model for the UAV that uses the fan-in-wings (FIW) concept, SFC, and understand the benefits of flight controls utilizing a CFD model.

Research Contribution (RC3.2)

This research has applied a set of Systems Thinking principles [42] that allow a human user to walk through the entire process from analysis to decisions, to design, to deployment, to site selection, and similar processes, but in reverse order, to understand the impact of each step for either deployment or design, or both.

We used case study data for the state of Colorado for wildfire scenarios for UAV fleet deployment, wildfire points planning, and advanced flight control architecture.

Research Contribution (RC3.3)

This research provides a novel and simulation-based decision support system (DSS) model where a fixed design can have realistic feedback and input from deployment scenarios, and understand the best trade-off points.

We used case study data for the state of Colorado for wildfire scenarios for UAV fleet deployment, wildfire points planning, and advanced flight control architecture. By contributing these items to the research community, we are planning to bridge the gaps in the current state-of-the-art of fleet deployment body of knowledge.

8.8 Chapter Conclusions

The research presented in this chapter demonstrates that UAV design is integral to maximizing the effectiveness of wildfire detection missions. Specifically, effective design enables rapid, cost-efficient, and accurate coverage of extensive areas, as exemplified by the Southwest Colorado test case. Recognizing the flexibility and modularity of UAV design, as well as the capability for straightforward deployment, allows adjustments to deployment strategies or UAV configurations in alignment with mission objectives. This methodology establishes a trade space that facilitates implementation by CBS fleet coordinators or MBS vehicle operators. Multiple system methods were employed to illustrate this capability during wildfire modeling and simulation.

This chapter demonstrates that applying systems thinking principles, such as *Learning Principle* and *Human Principle*, enables the development of solutions that effectively balance the deployment and design factors. Facilitating these trade-offs optimizes mission objectives. Thus, human operators are able to provide more comprehensive solutions for wildfire fleet deployment operations. The chapter examines the potential commercialization of this concept, which would allow deployment decisions to be translated into design decisions more rapidly and support the availability of additional modular options.

8.9 Chapter Summary

This chapter synthesizes materials from Chapter 6 and Chapter 7 to identify optimal areas for emphasis, specifically with respect to opportunities to focus on deployment or design parameters and their respective impacts. The objective is to establish a method to determine the highest-leverage point between the deployment of the wildfire UAV fleet and the UAV design and thus address research question 3 (RQ3) and bridge research gap 4.

Chapter 9

Future Work and Reflection

9.1 Preface

This chapter outlines potential directions for future research on wildfire detection and communication using UAV design and UAV fleet deployment. The author of this dissertation also offers reflections pertinent to the present study, demonstrating its contribution to ongoing, broader research initiatives outside the scope of wildfire detection and communication.

9.2 Overview

Future work will help to commercialize the UAV design and the fleet deployment optimization engine of the decision support system (DSS) for the detection and commination of wildfires. However, reflections establish a wider context and facilitate knowledge exchange within research communities. Although not directly related to primary research, the reflections indicate parallels and connections that reinforce the overarching research objectives.

To facilitate commercialization, the adoption of more efficient and potentially modified system methodologies and algorithms is recommended. Future research should focus on improving the scalability of the optimization framework to support additional objectives or higher-dimensional Pareto fronts. The observations beyond wildfire detection and communication discussed in this chapter do not constitute direct research findings; however, they may provide valuable insights for related fields of study.

9.3 Introduction

Future research should examine the *execution time* of the optimization framework. genetic algorithms offer a flexible and effective solution to the problem of wildfire deployment of the UAV fleet. For commercial applications, it may be necessary to develop a more efficient or modified version of these optimization algorithms.

It is also important to investigate how the optimization objective scales with more objectives or a higher-dimensional Pareto front. The present study considers four objectives, which consist of cost, time, risk, and area. The research does provide additional sensitivity analysis of the trade-offs between time and cost objectives. However, the system methods described are adaptable and can handle more objectives. This scalable approach may enable further development, collaboration with experts, and future commercialization with detailed specifications and a better graphical user interface.

Further research could also explore the integration of *large language models (LLMs)*, autonomous or semi-autonomous interaction with existing air traffic control *(ATC) systems* via text-based communication, and the mitigation of *Satellite Communication (SATCOM)* / data link latency challenges.

The reflections discussed in this chapter will provide valuable insights for related fields. For example, *defense-aerospace threat mitigation* challenges could be addressed using a layered defense framework similar to the approach outlined in this study.

Similarly, *large-scale commercial aircraft design, global deployment, and landing requirements* planning can benefit from analogous design and deployment methodologies. The proposed methodologies could be applied to scenarios that require layered air defense systems or large aircraft for global transportation, while adjusting for geographic, weather, and command-in-the-loop variability.

Nature-inspired algorithms also show considerable promise as an initial strategy for solving complex real-world problems that are not easily addressed by manual methods. These insights are based on the conclusions of the current research.

9.4 Future Work - Continuation of Wildfire Detection and Communication Using UAV Fleets

Insights gained from the analysis relate to how integrated design and deployment strategies contribute to improved UAV effectiveness and guide future work. Future commercialization considerations are discussed in this section.

9.4.1 Scalability of the number of objectives

A further direction for future work concerns the scalability of the number of objectives or dimensions in the Pareto front of the optimization framework. Our research initially considers four objectives and subsequently focuses on two. Based on our results, we are confident that the insights gained from the sensitivity analysis and the detailed investigation of these two objectives are applicable to optimization problems involving all four objectives, as well as to cases with additional objectives and higher-dimensional design spaces.

We propose two primary techniques to enhance scalability: Pareto geometry exploration and analysis, and Principal Component Analysis (PCA). Initial scalability analyses have been conducted using these methods. However, further work is required to strengthen and robustly adapt the optimization engine for higher-dimensional optimization problems.

Figure 9.1 illustrates the distance between a selected solution and the optimal solution on the Pareto front. This concept forms the basis for evaluating additional objectives. In the present example, the Pareto front is defined by two objectives: time and cost. Introducing a third objective transforms the Pareto front into a Pareto surface. In this scenario, it becomes necessary to determine the shortest distance from a selected solution, such as the custom solution shown, to the Pareto surface. This approach naturally extends the methodology from two-dimensional to three-dimensional optimization.

Figure 9.2 depicts the normal line to the tangent of the Pareto front. Since the Pareto front may exhibit varying degrees of smoothness, it can first be approximated by a smooth curve. The tangent and corresponding normal vector can then be computed at any point along the front. This

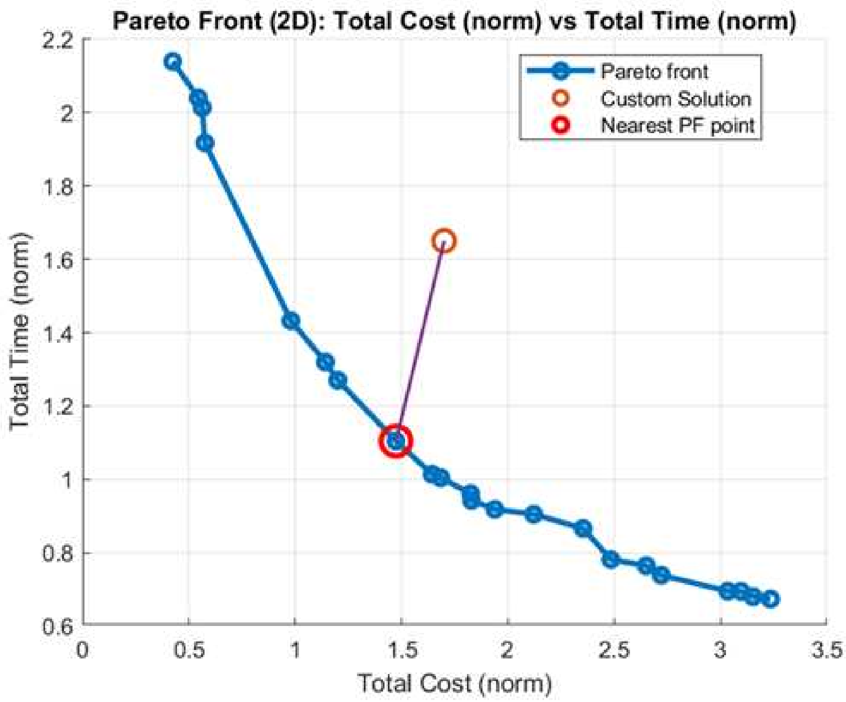


Figure 9.1: Distance between selected point and the optimal solution on the PF

Note:

[1] Distance between selected point and the optimal solution on the PF in order to understand the steepest path.

geometric representation offers further insight into how Pareto geometry can be utilized to analyze and navigate higher-dimensional optimization problems.

Our long-term objective is to extend these techniques to optimization problems involving four, five, or more objective functions, thereby enabling efficient exploration and analysis in increasingly higher-dimensional design spaces.

9.4.2 Principal Component Analysis (PCA) for Reducing the Complexity of the Multi-Objective Problem (MOP)

We examine whether PCA and related dimensionality reduction techniques can effectively reduce problem complexity, thereby facilitating the identification of a more tractable set of objectives. The PCA shown in Figure 9.3 [203].

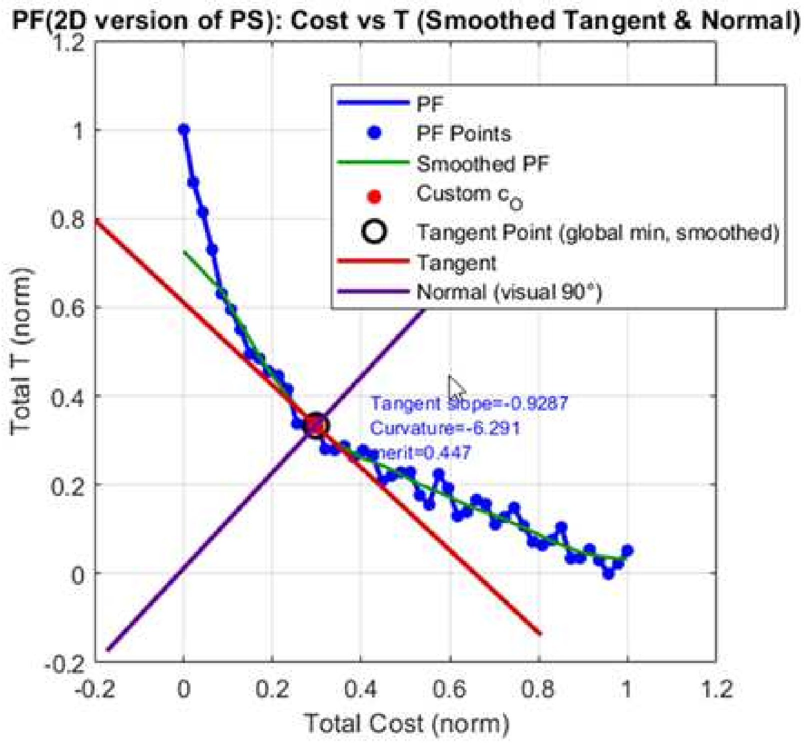


Figure 9.2: The normal line to the tangent line of the Pareto front

Note:

[1] The normal line to the tangent line of the Pareto front

In our wildfire case study conducted in Southwest Colorado, we address four objectives: time, cost, risk, and area coverage. The objectives of time, cost, and risk are minimized, while area coverage is maximized.

One approach is to use PCA to aggregate objectives into broader categories, such as minimizing expenditure (cost and time) and maximizing performance (risk reduction). This methodology enables transforming a four-objective optimization problem into a two-objective formulation, thereby reducing a complex four-dimensional trade space to a more manageable two-dimensional representation. However, the performance objective requires careful definition and evaluation, which constitutes an area for future research. This approach offers a promising direction for addressing complex problems characterized by competing objectives.

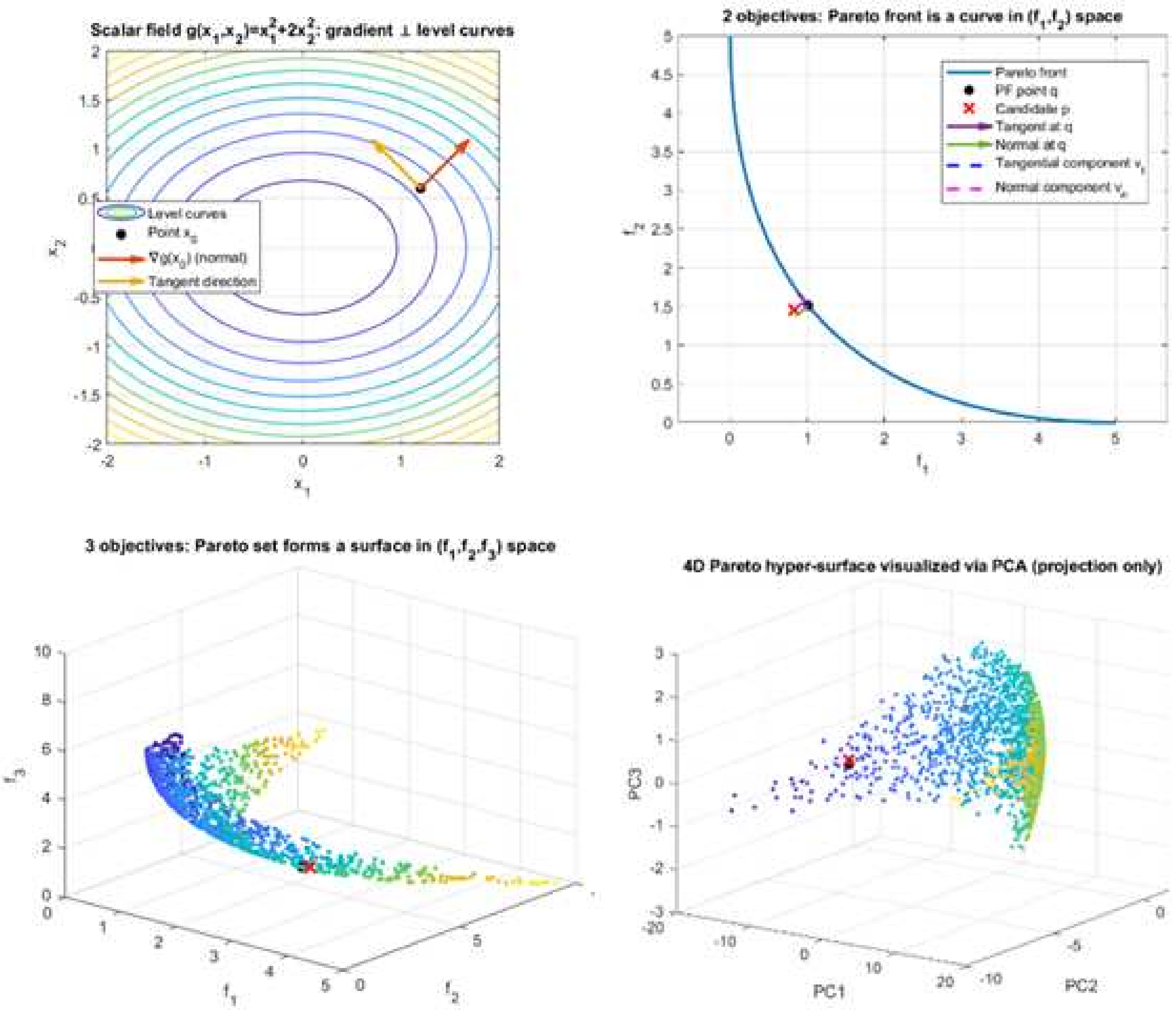


Figure 9.3: Principal Component Analysis

Note:

[1] Principal component analysis (PCA) help reduce 4 dimension and/or 3 dimension to manageable 2 dimension [203].

It is important to acknowledge that PCA alone may not always yield effective simplification. The utility of PCA depends on the manner in which objectives are grouped and represented. We have identified a direction for further investigation and validation of this approach.

In general, PCA facilitates reducing higher-dimensional objective spaces, such as those with 3 or 4 dimensions, into more manageable 2-dimensional representations while preserving much of the underlying information and structure.

Principal Component Analysis (PCA) - Balancing Dimensionality Reduction and Information Preservation

An important consideration is whether reducing the number of objectives results in the loss of essential technical details embedded within those objectives.

For example, combining objectives into a broader category, such as expenditure, can obscure important distinctions. In certain scenarios, cost may serve as the primary constraint, whereas in others, time may be the dominant factor. Aggregating these objectives can diminish the influence of each individual constraint. In addition, some costs may represent the value of asset protection rather than solely minimizing expenditures, and these nuances may be overlooked.

Therefore, although principal component analysis (PCA) and similar techniques can simplify problem-solving and facilitate the navigation of complex trade spaces, they may also obscure important details. The potential benefits of objective reduction are considerable; however, the approach must be carefully designed and rigorously evaluated. When applied appropriately, objective reduction can simplify multi-objective wildfire detection and response problems while preserving the most critical decision-making factors.

Losing details example - elevation When the objective is to maximize performance, it is often defined in terms of risk reduction and area coverage. However, these broad objectives may obscure critical distinctions. For example, maximizing area coverage does not necessarily differentiate between high-risk and low-risk regions.

Elevation is a key factor in the deployment of U. Research indicates that the risk of wildfires decreases substantially at elevations above 8,000 feet. Thus, aggregating performance objectives, such as risk reduction and area coverage, can overlook critical elevation-related effects.

Losing details example - lightning orientation Similarly, in wildfire risk reduction, lightning risks are a significant consideration. Notably, specific aspects of lightning risk, such as the distinction between positive and negative lightning strikes, have been discussed and considered. Although these factors have been briefly discussed and considered, they may be overlooked when risk is aggregated into a broader objective. Thus, critical characteristics that influence decision-making may not be fully represented in the optimization process.

Therefore, a potential approach is to expand the number of objectives considered for wildfire detection and communication. This expansion would enable the decision support system (DSS) to better represent critical factors, manage competing firefighting objectives more effectively, and identify more meaningful optimal solutions.

9.4.3 Optimization Algorithm for Reduced Execution Time

The execution time of the optimization machinery is an interesting area for future work. Genetic algorithms are a powerful research approach for the wildfire UAV fleet deployment problem due to their flexibility. For commercialization, other algorithms besides GA may be needed to achieve execution-time efficiency.

9.4.4 Utilization of HITL with LLM and AI

Although human-in-the-loop (HITL) approaches are essential, integrating artificial intelligence (AI) and large language models (LLMs) offers an exciting area for advancing wildfire detection and UAV fleet design.

Integration with Large Language Models (LLM)

Integration of large language models (LLM) can improve wildfire detection and communication by establishing a comprehensive knowledge base and enabling efficient data sharing for predictive analysis. Training and deploying LLMs with DSS data is expected to improve wildfire identification by optimizing unmanned aerial vehicle (UAV) control logic and facilitating coordinated fleet deployment. The HITL approaches can specify when, where, and how to refine the LLM based on insights from the optimizer and the implementation of deployment algorithms.

AI as Part of X-ILT

Human-in-the-loop (HITL) integration is implemented using a multi-objective optimization (MOO) engine, supported by decision support systems (DSS) and scenario-based optimization of operating conditions. Currently, only HITL is within the research scope of this dissertation; however, for commercialization, AI will be considered in the future (AI-in-the-loop), thereby enabling Human/AI-in-the-loop (X-ITL).

The methodology described in this chapter incorporates HITL optimization within the engine. Both the HITL and AI-in-the-loop (AI-ITL) approaches can be categorized as human or AI-in-the-loop (X-ILT) methods, allowing comparison of their output with that of the optimizer. The X-ILT framework details the data flow of the system method for decision support systems (DSS) that utilize the optimization engine and HITL.

9.4.5 Integration with Existing Air Traffic Controls (ATC)

Integration with air traffic controls (ATC) will allow safe flights at high altitudes and allow close proximity to a dense population. wildfire points optimization (WPO) methods add an additional layer of efficiency to an UAV to reduce energy consumption and extend range. UAVs that are specifically designed for this application, with custom flight controls, are an essential component of this fleet deployment, as we have seen in our preliminary results.

9.4.6 Challenges of SATCOM for UAV Communication

Effective SATCOM communication is essential to transmit wildfire data - from UAVs to orbiting satellites. The main challenges of this link have been examined by several researchers; Wang, Speece, and Bokhtier discuss in [215]. Our research team has collaborated with several universities to address these issues.

9.5 Reflection on Various Applied Systems

The knowledge from this research study can be applied to large scale commercial aircraft design for global utilization. Also, similar optimization methods are applicable to the air defense system.

9.5.1 Large-Scale Commercial Aircraft Design and Global Operations

The deployment model may offer advantages for large-scale commercial aircraft design and global operations. The Tribhuvan International Airport (KTM) in Kathmandu, Nepal, exemplifies an environment where the landing and takeoff of large commercial aircraft pose challenges due to environmental and geographical constraints that aircraft manufacturers should consider.

Large passenger aircraft designed to optimize for landing approaches like KTM can significantly improve safety records while keeping costs low. Optimizing passenger aircraft design for operations at airports such as KTM could enhance safety and reduce costs.

9.5.2 Air Defense System

The expertise gained from research on wildfire UAV systems engineering and distributed fleet management is transferable to integrated air defense applications. The methodologies established for wildfire operations can be adapted to the development of multi-layered air defense architectures.

9.5.3 Nature-Inspired Algorithms for Solving Complex Real-World Nonlinear Problems

Nature-inspired algorithms have demonstrated effectiveness in solving complex, real-world, non-linear problems. While such problems are often initially formulated as linear models for simplicity, these algorithms are capable of addressing underlying non-linear characteristics and facilitating significant advancements. As most real-world problems are inherently non-linear, nature-inspired algorithms offer a robust approach for tackling both linear and non-linear formulations and for generating effective critical knowledge.

1. Genetic Algorithm (GA)

2. Ant Colony Optimization (ACO)

3. Particle Swarm Optimization (PSO)

4. Whale Optimization Algorithm (WOA)

Genetic Algorithm setup in MATLAB that is highly configurable and suitable for prototyping. Table 9.1 captures Genetic Algorithm Setup. As a reflection, it can be stated that future work can be easily prototyped if other algorithms, such as ACO, WOA, and PSO, can be configured similarly.

Table 9.1: Genetic Algorithm Setup in MATLAB

Feature/ Input	gamultiobj() (Built-in GA)
Population Size	PopulationSize
Num of Generations/Iterations	MaxGenerations
Bounds	lb, ub
Fitness/objective function	Built into function
Multi-objective handling	Pareto ranking/ NSGA-II (Non-dominated Sorting Genetic Algorithm II)
Crossover Operator	CrossoverFcn
Mutation Operator	MutationFcn
Selection Operator	SelectionFcn
Problem Encoding	Vector of real and integer values
Elitism or archive of solutions	ParetoFraction, internal
Constraint handling	ConstraintTolerance
Parallel support	UseParallel, automatic
Plot functions	PlotFcn, built-in options

We adapt the ant colony optimization (ACO) algorithm to find effective wildfire points as shown in Figure 9.4. We found ACO, another example, a nature-inspired algorithm, to be very suitable for the purpose of identifying wildfire points, which we can utilize for our research study.

GA Application in Wildfire UAV Fleet Deployment and Design

Genetic algorithm is a great research approach for the wildfire UAV fleet deployment problem (discrete optimization with binary values) for is flexibility purposes.

- Wildfire UAV fleet deployment involves discrete decisions with binary values determining whether to select certain deployment options where the combinatorial possibilities can be extremely large.
- Genetic algorithms are well-suited to these challenges because they use mechanisms such as crossover, mutation, and elitism to explore large search spaces without resorting to exhaustive enumeration.
- They are designed to find high quality, near-optimal solutions swiftly, even when the full enumeration of possibilities (for example, choosing among hundreds or thousands of binary combinations) would be computationally infeasible.
- Comparative studies showing that the results of the genetic algorithm are within 1% of the optimal values (obtained using slower brute-force methods) further support their use in this context, as they balance accuracy with computational speed.

Ant Colony Optimization (ACO)

Application of ant colony optimization (ACO) in Wildfire UAV fleet deployment and design for wildfire point optimization (WPO). Within the wildfire points optimization (WPO) component of the decision support system (DSS), the ant colony optimization (ACO) algorithm determines efficient navigation paths for unmanned aerial vehicles (UAVs) through wildfire points. Table 9.2 presents a comparison between the genetic algorithm (GA) and ant colony optimization (ACO).

Particle Swarm Optimization (PSO) for MBS Vehicle Loading Optimization

Particle Swarm Optimization (PSO) is a nature-inspired algorithm that efficiently addresses optimization in various dynamic scenarios. Algorithms for mobile base station (MBS) vehicle loading have been evaluated within the broader context of the deployment problem. The PSO algorithm is utilized to maximize MBS vehicle loading from a systemic and holistic perspective.

The loading of MBS vehicles is managed by the decision support system (DSS), which configures each truck or MBS vehicle to carry a predetermined number of unmanned aerial vehicles (UAVs).

Table 9.2: Comparison of GA and ACO

Feature / Input	**gamultiobj() (Built-in GA)**	**Custom ACO Implementation**	**Common**
Population Size	`PopulationSize`	Number of Ants `numAnts`	Same
Num of Generations / Iterations	`MaxGenerations`	Number of Iterations `numIterations`	Same
Bounds	`lb, ub`	Not Applicable	Not Same
Fitness / objective function	Built into function	Implicit (cost, time, etc. matrices)	Similar
Multi-objective handling	Pareto ranking / NSGA-II (Non-dominated Sorting genetic algorithm II)	Not built in. Weighted values can be used for cost, time, etc.	Similar but GA is better
Crossover Operator	`CrossoverFcn`	Not Applicable	Not Same
Mutation Operator	`MutationFcn`	Not Applicable	Not Same
Selection Operator	`SelectionFcn`	Implicit in probability rules	Similar
Pheromone Parameters	Not Applicable	α, β, ρ, Q	Not Same (ACO specific)
Problem Encoding	Vector of real and integer values	Permutation of nodes	Not Same
Weights for scalarization	Not Applicable (uses Pareto front)	Weighted values can be used for cost, time, etc.	Not Same (ACO specific)
Elitism or archive of solutions	`ParetoFraction`, internal	Unless implemented / Custom	Not Same (GA specific)
Constraint handling	`Constraint Tolerance`	Not easily visible but can be implemented	Not Same (GA specific)
Parallel support	`UseParallel`, automatic	Unless implemented / Custom	Not Same (GA specific)
Plot functions	`PlotFcn`, built-in options	Unless implemented / Custom	Not Same (GA specific)

Note:

[1] Genetic algorithm has been picked for first stage optimization.

[2] Ant Colony Optimization algorithm has been picked for second stage optimization.

Optimizing for maximum wildfire detection capability may result in MBS vehicles not being filled to capacity. The initial scenario assumes one UAV per MBS vehicle. Further integration of PSO-based optimization logic into this component is feasible. Preliminary work in this area has been completed, and additional development is under consideration for future commercialization.

Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) is a nature-inspired metaheuristic optimization algorithm introduced in 2016 by Seyedali Mirjalili [82]. It is designed to solve complex optimization problems where traditional mathematical methods struggle (nonlinear, multimodal, high-dimensional problems). The WOA mimics the hunting strategy of humpback whales, especially their famous bubble-net feeding behavior, as shown in 9.4 [5].

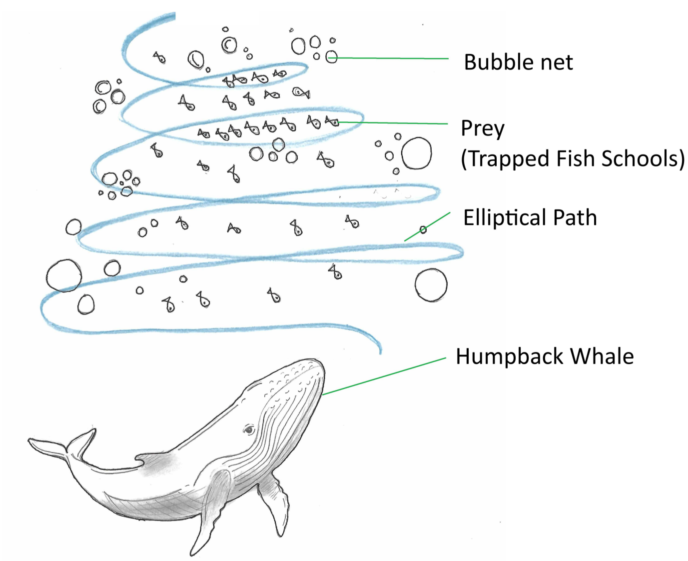


Figure 9.4: Humpback Whales behavior inspired WOA can be effective for Wildfire Applications

WOA Pros and Cons The pros and cons of the WOA algorithm are discussed below.

Pros

- Simple to implement

[5] The author gratefully acknowledges Ariana Bokhtier for creating this figure for the Whale Optimization Algorithm (WOA).

- Few parameters to tune
- Good balance between exploration and exploitation
- Competitive performance with PSO, GA, and DE

Cons

- Can converge slowly on some problems
- May still get trapped in local optima (like most metaheuristics)
- Performance depends on parameter tuning and problem type

9.6 Chapter Conclusions

This chapter documented several opportunities for future research and commercial adaptation of the proposed framework for wildfire UAV design and UAV fleet deployment. Key areas for continued work include improving the execution efficiency of the genetic algorithm based optimization machinery, expanding scalability across higher dimensional Pareto fronts or multiple operational objectives, and integrating emerging technologies such as large language models, autonomous or semi autonomous ATC communication systems, and SATCOM latency mitigation strategies. The chapter also presented broader reflections on the applicability of layered defense methodologies, large-scale aerospace deployment processes, and nature-inspired algorithms as effective approaches for addressing complex real-world engineering and operational challenges.

9.7 Chapter Summary

Future work focused on improving execution efficiency and expanding the capabilities of the proposed research framework will further strengthen the impact and applicability of this research. The reflections presented in this work also provide transferable knowledge that may benefit adjacent fields, including air defense systems, large-scale commercial aircraft deployment, and other complex aerospace applications. The insights and methodologies developed through this research are hoped to contribute positively to the broader research community and support continued innovation to solve complex real-world challenges.

Chapter 10

Conclusions

As wildfire threats progressively increase worldwide, early detection and effective communication become crucial in minimizing the adverse impact to wildlife, humans, and the overall environmental consequences. The deployment of a fleet of UAVs specifically designed for wildfire detection and communication is the transformative breakthrough to solve this complex real world problem. The holistic solution from this research work includes specialized features for effective optimal deployment strategies (ODS), flight paths/ wildfire points optimization (WPO) with accessibility to difficult terrains which require high altitude and extended range capability.

10.1 Summary

Wildfires are often more prevalent in rough terrain with mountains and forests. This challenge requires a fleet of UAVs capable of high altitude and long range. Existing commercially available off-the-shelf (COTS) small UAVs do not meet these requirements and are not practical for wildfires, as we identified as research gap. As generic small UAVs are not the go-to system for optimal aircraft performance (cost, range, and weight).

In Chapter 2, the mathematical specifications were detailed to capture the deployment of a complex real-world wildfire UAV fleet. Our research study develops this problem construct that includes Multi-Objective Optimization (MOO) with human-in-the-loop (HITL) and includes two stages of optimization. The first stage is focused on more MBS/CBS based. The second stage is designed towards run-time issues and wildfire points/flight paths. The construct of this mathematical model thus serves as a step towards real world implementation and commercialization. We have demonstrated that, by applying principles of system thinking such as *Learning Principle* and *Architecture Principle*, mental models can be transformed from the MBST framework to mathematical specifications. Thus, we can conclude that a novel mathematical specification for an optimizer machinery that includes CBS fleet coordinator(s), MBS operator(s) and wildfire systems analysts enables human-in-the-loop (HITL) interface by taking input and comparing with optimizer solution. Previously, there was no other mathematical specification in which HITL could provide input to a UAV-based solution for wildfire detection and communication.

In Chapter 3, we developed model-based systems engineering (MBSE) architectural model, specifically focusing on SFC. In this chapter we showed how to integrate an Architectural Trade Study into a Model-Based Systems Architecting Processes (MBSAP) for the real-world application of wildfire detection using a fleet of locally owned and operated, cost effective hybrid electric/gas turbine-propelled UAVs. Our MBSAP included cases of inadvertent misuse and cybersecurity misuse to ensure the robustness of the architecture of the system of interest. We also showed how this approach uncovered a novel architecture for the system of interest, namely the surface-less flight controls (SFC) system. This flight control architecture trade study drops all classical flight control surfaces, actuators, and mechanical linkages to reduce weight and cost, while recognizing the potential of lift systems to also serve flight controls: FIW and thrust vectoring nozzle (TVN). We have demonstrated that, by applying principles of system thinking such as *3-systems Principle*, mental models can be transformed from mission goals to effective MBSE models.

Traditional flight control does meet the requirements and is feasible for Wildfire detection. However, the novel architecture developed during our integrated model-based systems engineering (MBSE) approach appears very promising, as it can halve the specific cost of the UAV. This is very intriguing, as classical flight controls are normally not the go-to system for factors improvement in aircraft performance (cost, time, risk-reduction capability, range/area coverage). We therefore listed anticipated issues, potential unknowns, and risks associated with the surface-less architecture that we will analyze in depth going forward.

In Chapter 4, we performed computational fluid dynamics (CFD) analysis to identify the aerodynamics that are needed in order to establish the core foundation of the UAV architecture and effectively support the fleet deployment problem. Our study has identified an advanced, efficient fan-in-wings (FIW) UAV design that offers a high lift-to-drag (L/D) ratio while reducing weight, thus optimizing its aerodynamic characteristics for wildfire scenarios. We have demonstrated that by applying principles of system thinking, such as the *Holism Principle* and *Evolution Principle*, mental models can be transformed from mission goals into effective aerodynamic models, keeping both fleet deployment and UAV design coupled.

Using CFD within a holistic systems-oriented design optimization approach, we found a detailed 3D design of the airframe that can reach the high lift-to-drag ratio targets determined during preliminary design optimization and sizing for the Wildfire detection and communication mission. We could quantify the significant sensitivity of the lift-to-drag ratio to fan speed, number of fan blades, and angle of attack (AoA). This high level of sensitivity leads to the conclusion that SFC may indeed be feasible for our long-endurance hybrid electric/gas turbine-propelled wildfire detecting and communicating UAV. This is exciting because any structural weight saved by removing ailerons/rudders and the associated actuation systems would allow more fuel or payload to be carried onboard to improve endurance, range / coverage area, or the specific cost metric \$/(kg.km). Of course, this gain would also imply a more complex advanced primary flight control strategy that uses differential fan speed, differential fan acceleration, angle of attack, and variable nozzle angle to control roll, yaw, and pitch. A caveat is that we have not yet included FEA-based structural optimization in our holistic design optimization strategy. Joint optimization of the structure and aerodynamics would produce more realistic results. We have also not flown this configuration into the harsh gusty flying conditions typical of major wildfires.

In Chapter 5, we study systems dynamics of flight profile of a UAV and what parameters have the significant impact and cause contributions of the objective functions of the deployment problem. The principles of systems thinking are the critical philosophies for having an effective implementation of Systems Dynamics simulation for Wildfire UAV fleet deployment. We have demonstrated that, by applying systems thinking principles such as the *Human Principle* and understanding different types of systems, including the *3-Systems Principle*, we can identify game-changing parameters in the management flight simulator (MFS). The highly impactful factors are environmental factors, such as altitude and temperature, which significantly affect the UAV's flight dynamics and can also affect the timing of wildfire deployment, thereby influencing overall mission performance. This study serves as well, we will step into extensive prototyping and formulating the optimization problem for fleet deployment of the app MBST model, the system dynamics (SD) model demonstrated opportunities to minimize coverage time due to environmental aerodynamic and operational constraints such as failure rate, maintenance, fleet sites, etc. Next 3 chapters will detail developing and using the wildfire detection and communication optimizer to identify additional efficiencies in the deployment problem.

Research question 1 was thoroughly addressed in Chapter 6. The set of mathematical specifications was developed in Chapter 2 and implemented through two stages of optimization in the experiments presented in this chapter. The system methodology involving HITL outlined in this chapter effectively generates models for Operational Deployment Strategies (ODS) and identifies parameters with leverage points for these models. This serves as a valuable step toward extensive prototyping of the optimization problem for fleet deployment. The model identifies opportunities to minimize coverage time by addressing environmental, aerodynamic, and operational constraints (failure rate, maintenance, fleet size, etc.). In the wildfire case study for Colorado, the ODS optimizes timing sufficiently to cover southwest Colorado, the San Juan River region (District 43), for wildfire monitoring and detection. The operational model also identified the components necessary to efficiently manage deployment intervals to maximize area coverage and described details of fleet size management, noting a range of optimization opportunities. This model can be enhanced in the future by incorporating additional elements such as fuel efficiency, battery performance, high-risk scenarios, no-fly zones, and access-road availability. Such an enhanced model can yield more refined conclusions on minimizing risk factors and operational costs. The output of the DSS can be used to develop mathematical expressions for the ODS, enabling evolution toward optimized MBS deployment. The DSS will utilize topographical maps, geographical conditions, varied operational scenarios, and communication and other constraints. Future work will involve developing and applying this wildfire detection and communication optimizer model to achieve additional efficiency in addressing the deployment problem. A mathematical specification or problem construct can be developed that includes MOO with HITL and incorporates two stages of optimization. The first stage focuses on MBS/CBS-based coordination. A novel mathematical specification for an optimizer machinery, including CBS fleet coordinators, MBS operators, and wildfire systems analysts, enables a HITL interface by incorporating input and comparing it with optimizer solutions. Previously, no mathematical specification allowed HITL to provide input to a UAV-based solution for wildfire detection and communication. Combining *Boundaries Principle*, which identifies different parts of the system and who is included within the system, with *Human Principle*, which explains how humans impact and are affected by the system, helps create a more realistic and effective optimization problem.

In Chapter 7 we address research question 2 for run-time wildfire points optimization (WPO). Wildfire operating conditions and scenario-based constraint optimization improve flexibility in managing diverse run-time scenarios within UAV wildfire points optimization (WPO). Simultaneous optimization of launcher deployment and UAV wildfire points or flight paths offers a comprehensive solution to the deployment problem. The proposed methodology addresses run-time challenges in wildfire UAV fleet deployment and UAV design through a two-stage optimization process. In this framework, the second stage receives the first stage solution as input and subsequently returns its output to the first stage. This iterative feedback mechanism allows launcher deployment and UAV optimization to be performed independently while maintaining integration as a unified system for wildfire detection. System performance is assessed using optimal UAV wildfire points. Operational configurations and design decisions must adapt to run-time challenges by distinguishing between issues that impact individual solutions and those that influence the entire solution set. The resulting improvements are substantial, and the technology is feasible with current capabilities. Thus, the findings of this study represent progress towards real-world implementation and commercialization. Experiments from these chapters demonstrated that applying system thinking principles, such as *Emergence Principle* and *Learning Principle*, allows mental models to integrate runtime and dynamic systems into effective optimization models. As a result, the system can not only operate effectively, but also take advantage of favorable emergent behavior, learn from runtime situations, and adapt accordingly.

Research question 3 was fully answered in Chapter 8 while we explore the trade space between UAV design and UAV fleet deployment. The research presented in this chapter demonstrates that UAV design is integral to maximizing the effectiveness of wildfire detection missions. Specifically, effective design enables rapid, cost-efficient, and accurate coverage of extensive areas, as exemplified by the Southwest Colorado test case. Recognizing the flexibility and modularity of UAV design, as well as the capability for straightforward deployment, allows adjustments to deployment strategies or UAV configurations in alignment with mission objectives. This methodology establishes a trade space that facilitates implementation by CBS fleet coordinators or MBS vehicle operators. Multiple system methods were employed to illustrate this capability during wildfire modeling and simulation. This chapter demonstrates that applying systems thinking principles, such as *Learning Principle* and *Human Principle*, enables the development of solutions that effectively balance the deployment and design factors. Facilitating these trade-offs optimizes mission objectives. Thus, human operators are able to provide more comprehensive solutions for wildfire fleet deployment operations. The chapter examines the potential commercialization of this concept, which would allow deployment decisions to be translated into design decisions more rapidly and support the availability of additional modular options.

In Chapter 9 we discuss path commercialization of this research. Also we discuss any adjacent research reflections that are not in scope of the research study but we still can draw vital path forward solving those complex problems. This chapter documented several opportunities for future research and commercial adaptation of the proposed framework for wildfire UAV design and UAV fleet deployment. Key areas for continued work include improving the execution efficiency of the genetic algorithm–based optimization machinery, expanding scalability across higher dimensional Pareto fronts or multiple operational objectives, and integrating emerging technologies such as large language models, autonomous or semi autonomous ATC communication systems, and SATCOM latency mitigation strategies. The chapter also presented broader reflections on the applicability of layered defense methodologies, large-scale aerospace deployment processes, and nature-inspired algorithms as effective approaches for addressing complex real-world engineering and operational challenges.

Our research study to date has indicated that the unique needs of wildfire detection require the deployment of a fleet of UAVs using optimal deployment strategies (ODS) that has the potential to address the specific challenges of areas prone to high-risk wildfires. The (WPO) strategy adds an additional layer of efficiency to an UAV to reduce energy consumption and extend range. UAVs that are specifically designed for this application, with custom flight controls, are an essential component of this fleet deployment, as we have seen in our preliminary results.

10.2 Verification and Validation (V&V) of the Research Study

A comprehensive verification and validation (V&V) strategy was employed in the development of the DSS. New features are systematically evaluated against the overall system, and the V&V processes are repeated as additional capabilities are integrated, as illustrated in the framework in Figure 10.1.

The MITRE developed model validation method is followed, along with established simulation model validation strategies. These include: (i) comparison to other models, (ii) face validity, (iii) historical data validation, (iv) sensitivity analysis, and (v) predictive validation [190].

10.2.1 Continuous Verification and Validation (V&V)

The optimization framework within the DSS was developed using continuous Verification and validation processes (V&V) to ensure the integrity of the system, as illustrated in Figure 10.1.

This research study involved collaboration with the Colorado Division of Fire Prevention and Control, District 4 (San Juan River Region), located in Southwest Colorado and encompassing Montezuma, La Plata, San Juan, and Archuleta counties. When a new capability is developed for the DSS, such as a calculator for time or risk (for example, *CalculateTime.m*), a corresponding test (for example, *testCalculateTime.m*) is implemented to independently validate the associated

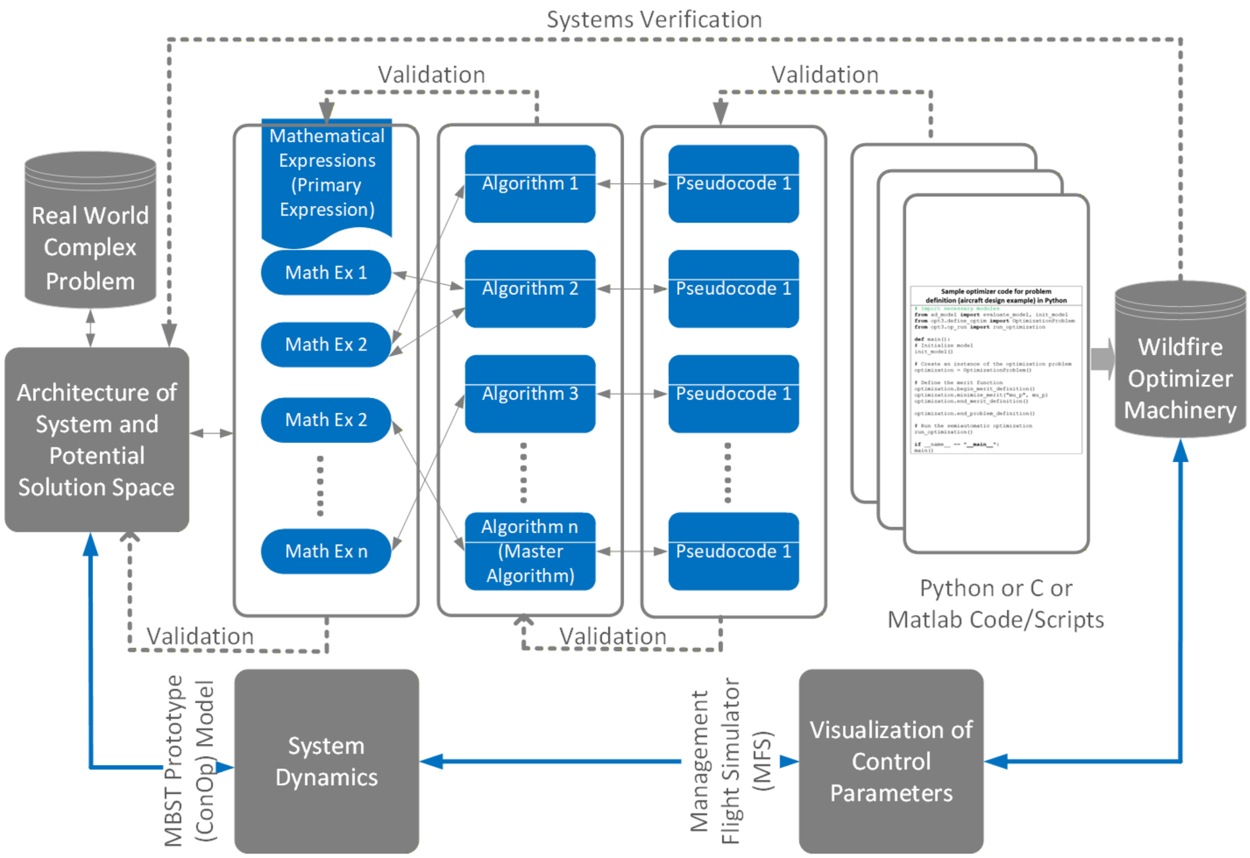


Figure 10.1: Verification and Validation

file using a range of parameters. This approach supports continuous verification and validation, eliminating the need to wait for full system integration.

Testing Monte Carlo simulations with varying parameter values provides valuable insights. Adjusting the number of points and parameter values demonstrates the robustness of the simulations and serves as a verification step, ensuring that the script produces logical results. Executing multiple configurations confirms that the observed behavior aligns with expectations.

10.2.2 Verification of DSS Modules

Seventeen key features of the DSS were verified by face validity. Most features of the DSS are also supported by additional tests or validation, increasing confidence in the overall research. Several features present test results alongside face validity, providing further support for the findings.

Table 10.1: Verification and Validation - Individual Means of V & V - 1 of 2

Section No.	Requirement Name	Priori	Typ	Model: File::Function (Tracing)	Means of Verification (IDA	Model Validation Metho	Scenarios/Use Cases
R1001	CBS Carrying Capacity	High	Req	objectiveFunction.m, FourobjGAMethod.m	Test	Face Validity	S1: 1 MBS vehicle carrying 2 UAVs to launch site for launching. S2: 2 MBS vehicles carrying 6 UAVs to launch site for launching. S3: 2 MBS vehicels carrying 5 UAVs (upto 6) to launch site for launching. S4: 10 MBS vehicles carryiing 25 UAVs to launch sites for launching.
R1002	Optimization Items	High	Req	FourobjGAMethod.m	Test	Comparison to Other Models	Use Case S01
R1003	HITL	Med	Req	objectiveFunction.m	Demonstration	Face Validity	Use Case S02
R1004	Feasiable Solution	Low	Text		N/A	N/A	N/A
	Objective & Constraints						
C2001	Objective & Constraints	High	Req	constraintsFunction.m, RiskCalc.m	Test	Face Validity	Use Case S02
C2002	Objective & Constraints	High	Req	constraintsFunction.m, RiskCalc.m	Test	Face Validity	Use Case S02
C2003	Objective & Constraints	High	Req	constraintsFunction.m, RiskCalc.m	Test	Face Validity	Use Case S02
C2004	Objective & Constraints	High	Req	constraintsFunction.m	Test	Face Validity	Use Case S02
C2005	Objective & Constraints	High	Req	constraintsFunction.m	Test	Face Validity	Use Case S02
C2006	Objective & Constraints	High	Req	constraintsFunction.m	Test	Face Validity	Use Case S03
C2007	Objective & Constraints - No Fly Zone	High	Req	constraintsFunction.m	Analysis	Historical Data Validation	Use Case S02
C2008	Objective & Constraints	High	Req	constraintsFunction.m	Demonstration	Historical Data Validation	Use Case S02
C2009	Objective & Constraints	High	Req	constraintsFunction.m	Demonstration	Parameter Variability – Sensitivity Analysis	Use Case S02
C2010	Objective & Constraints	High	Req	constraintsFunction.m	Demonstration	Parameter Variability – Sensitivity Analysis	Use Case S02

Several elements are further validated through testing with actual elevation data and ROC, L/D, and UAV speed data.

Similar models have also been deployed, including a system dynamics model that provides confidence in environmental impact, lift-to-drag ratio (L/D), vertical lift, and aerodynamic characteristics. In addition, parts of the architecture have been validated through trace studies and MBSE, while design decisions can also be validated.

Additionally, some validation has been performed as part of the CFD. So we have used CFD, SD, and MBSE. CFD gave us confidence in L/D and wing design utilizing the FIW concept.

MBSE gave us confidence in architecture, the use of fan-in-wings (FIW), and in system dynamics, which has given us confidence in some of the impacts of environmental parameters. So we can use some similar models that verify the high-level results.

Table 10.2: Verification and Validation - Individual Means of V & V - 2 of 2

Section No.	Requirement Name	Priori	Typ	Model: File::Function (Tracing)	Means of Verification (IDA	Model Validation Metho	Scenarios/Use Cases
	Optimization Algorithm						
A3001	Logical Implementation - GA	Low	Text	objectiveFunction.m	N/A	N/A	N/A
A3002	Logical Implementation - GA	Low	Text	objectiveFunction.m	N/A	N/A	N/A
	Pre-Flight and Run-Time Planning						
P4001	Pre-Flight Waypoints (PFWP)	High	Req	constraintsFunction.m	Test	Face Validity	Use Case S01
P4002	Pre-Flight Waypoints (PFWP)	Med	Req	constraintsFunction.m	Test	Face Validity	Use Case S02
P4003	Pre-Flight Waypoints (PFWP)	Med	Req	constraintsFunction.m	Test	Face Validity	Use Case S02
P4004	Run-Time Waypoints (RTWP)	High	Req	constraintsFunction.m	Test	Face Validity	Use Case S03
P4005	Run-Time Waypoints (RTWP)	Med	Req	constraintsFunction.m	Test	Historical Data Validation	Use Case S02
P4005	Run-Time Waypoints (RTWP)	Med	Req	constraintsFunction.m	Test	Historical Data Validation	Use Case S02
	Deployment Strategies						
S2001	Strategies - Base Case (scope)	Med	Req	objectiveFunction.m	Test	Historical Data Validation	Use Case S01
S2002	Strategies - Base Case Plus (not scope)	Low	Text		N/A		N/A
S2003	Strategies - Dynamic Case (not scope)	Low	Text		N/A		N/A
S2004	Strategies - Dynamic Case Plus (scope)	Med	Req	objectiveFunction.m	Test	Face Validity	Use Case S03

Including the model test, we can verify the impacts of environmental data and the dependency between design and deployment. We can see that environmental parameters are impacting the designs.

10.2.3 Verification Summary Report

Here is the verification summary report in Table 10.3. The primary validation method for this research study includes the following methods:

- First, Face Validity using our key SME
- Second, validation by a similar model
- Finally, Sensitivity Analysis

Table 10.3: DSS Validation

No	DSS Functionality	Dissertation Section	DSS Model	Validation
1	Decision Support System with Run-Time Data for wildfire UAV Fleet deployment	Section 6.4 to 6.7, Section 7.4	CBS Coordinator View, Main Capability	Face Validity
2	Wildfire Decision System with real-time data update	Section 7.5, Section 7.6	CBS Coordinator View, Main Capability	Face Validity
3	Ranking of Wildfire deployment related parameters from Deployment and Design	Section 8.5, Section 3.7	MBS Coordinator View, Main Capability	Face Validity, Sensitivity Analysis, Comp to other model
4	CBS Coordinator Deployment Planning (PFWP Plan and RTWP)	Section 6.6	MBS Coordinator View, Main Capability	Face Validity
5	Ability to compare the HITL decision with the optimized solution for wildfire UAV Fleet deployment sites.	Section 6.6	MBS Coordinator View, Main Capability	Face Validity, Sensitivity Analysis
6	Run-Time visualization for Wildfire Points navigation for UAVs	Section 6.6, Section 7.5 to 7.6	MBS Coordinator View, Main Capability	Face Validity
7	MBS Operator to be able to make a decision	Section 7.5, Section 7.6	MBS Coordinator View, Main Capability	Face Validity, Sensitivity Analysis

Continued on next page

Table 10.3 (continued)

No	DSS Functionality	Dissertation Section	DSS Model	Validation
8	Wildfire Mission Objective Identification and Finding Most beneficial points	Section 8.5, Section 8.6	CBS Coordinator View, Pareto Geometry	Face Validity, Sensitivity Analysis
9	Prominence (highest risk/etc) Point vs DSS Optimizer Machinery decisions	Section 6.6, Section 6.7	CBS Coordinator View, Pareto Geometry	Face Validity, Sensitivity Analysis
10	Feedback and learning from field operators, coordinators, and local wildfire experts as HITL	Section 6.6, Section 7.6, Section 8.5 to 8.6	CBS Coordinator View, Main Capability	Face Validity, Sensitivity Analysis
11	Identification of Urban corridor and Wildfire signature notions via DSS	Section 2.6, Section 6.5	Analyst View, Monte Carlo Simulation	Face Validity
12	Environmental Operational Impacts on Deployment and UAV Performance	Section 3.6, Section 6.6, Section 7.5 to 7.6	Analyst View, Monte Carlo Simulation	Face Validity, Sensitivity Analysis, Comp to other model
13	UAV Performance under Environmental Data	Section 4.8, Section 7.5 to 7.6	Analyst View, Monte Carlo Simulation	Face Validity, Sensitivity Analysis, Comp to other model
14	UAV Rate of Climb (ROC) Maximization and Altitude Impacts	Section 5.4 to 5.5, Section 7.6	Analyst View, Monte Carlo Simulation	Face Validity, Sensitivity Analysis, Comp to other model

Continued on next page

Table 10.3 (continued)

No	DSS Functionality	Dissertation Section	DSS Model	Validation
15	Flexibility to run the modularized Optimizer Machinery (Running part of the decision making system in order to save time and make fast decisions)	Section 6.6, Section 7.4 to 7.6	Analyst View, Tornado Charts	Face Validity
16	Input Dashboard for DSS using Contours to adjust to real-life scenarios and competing priorities	Section 6.5, Section 6.6	Analyst View, Tornado Charts	Face Validity
17	Single Digital Thread and usages of the same set of data for Wildfire deployment	Section 6.6, Section 6.7	Analyst View, Tornado Charts	Face Validity

We have developed an MBSE architecture model in Cameo in Chapter 3, a CFD model in ANSYS in Chapter 4, and a systems dynamics model in Chapter 5. These models are also often used as secondary verification for certain operational, environmental, and aerodynamic aspects and are also listed in this table.

Face validity

The validation and verification processes for models are often different from those for physically developed systems. The V&V process for the model includes the following MITRE systems engineering handbook guidance for model verification. The MITRE Corporation Systems Engineering Guide provides guidance that phase validity is a critical validation approach [190]. Research from MITRE and other verification efforts shows that face validation can be acceptable based on expert insight, which may not be captured solely in tests or models. Although there is a counter argument showing that face validation should not be a usable model [196], the evidence is much stronger on the side of SME and face validity.

Over time, expert SMEs can be incorporated into the validation process for high fidelity validation due to their significant amount of time expenditure and deep dive into the details of this process. We have adopted the face validation method for DSS to detect wildfires using a fleet of UAVs, recognizing that the life-cycle development of a UAV and its deployment are correlated. It requires a deeper understanding of the system and the SME level, which was critical for this research. We are confident that our SME validation provides a reliable assessment of our models. Evidence from both SME input and additional testing indicates a high degree of fidelity and validity of the model.

10.3 Remarks on Optimality for Deployment and Design With HITL

The goal is to determine what is optimal for the wildfire detection and communication system using a fleet of UAVs.

10.3.1 What Is Optimal for the System Problem of Wildfire Detection?

Clarifying the criteria for an optimal solution in wildfire detection requires addressing several fundamental questions:

- Is optimality determined by the specific objective assigned to the detection system?
- Does optimality merely reflect the objective designated for the detection system?
- How should trade-offs among multiple objectives governing system operation be managed?
- What challenges arise in balancing competing objectives, and which factors render these trade-offs significant?

In practice, optimality is determined by the trade-offs among competing objectives rather than by a single performance metric. The Pareto front delineates a set of feasible trade-off solutions, from which methods such as min-max optimization or least squares estimation (LSE) can be employed to identify a numerically favorable solution.

Finding a "Good" or the "Best" Solution

Assessing whether a solution achieves optimality for both the mission and the stakeholder is a critical consideration. An essential requirement is the capacity to navigate the Pareto geometry, with particular emphasis on the Pareto front. This process entails exploring various regions of the Pareto front to elucidate the trade-offs among competing objectives and to facilitate effective decision-making.

Selecting and comparing solutions generated by either the HITL process or the optimizer is essential to observe the evolution of associated trade-offs. In certain instances, parameters or constraints require re-evaluation. This process can be examined mathematically using Lagrange multipliers; a zero Lagrange multiplier indicates that the corresponding constraint is inactive. Within the context of a wildfire UAV system, this finding may indicate that specific constraints or decision variables should be adjusted.

This process may require selecting alternative solutions along the Pareto front or, in some cases, modifying the Pareto front itself. For instance, in a trade-off between time and cost, adjusting constraints, assumptions, or parameter values can shift the Pareto front and generate new feasible trade-offs. These adjustments offer a systematic approach to navigating the Pareto front to identify solutions that most effectively satisfy mission objectives and stakeholder preferences.

Trading Off Among Pareto-Optimal Solutions Versus Moving the Pareto Front for Wildfire Fleet Deployment

Selecting solutions along the Pareto front affords a structured method for managing trade-offs among competing objectives in wildfire fleet deployment. Each solution signifies a specific balance between objectives while preserving Pareto optimality.

In practice, decision-makers may choose solutions that are not located on the Pareto front. Such non-optimal selections may arise from human-in-the-loop (HITL) or AI-in-the-loop decision processes. It is therefore necessary to characterize these solutions, quantify their deviation from Pareto optimality, and determine the direction of adjustments required to improve performance. Evaluating the distance and direction from a selected solution to the Pareto front gives key guidance for improving deployment decisions.

In addition to selecting among Pareto-efficient solutions, it may be necessary to shift the Pareto front itself. This can be achieved by changing system rules, underlying assumptions, or model parameters. Such adjustments generate a new set of trade-offs that may better match evolving requirements or stakeholder objectives.

Effective navigation of the Pareto geometry requires both the selection of existing Pareto efficient solutions and the reshaping of the Pareto front when appropriate. Sensitivity analysis delivers the mathematical approach for this process through quantifying the effects of changes in parameters, constraints, and objective weights on the position and structure of the Pareto front. This methodology supports more informed decisions about wildfire fleet deployment.

10.3.2 Connecting Objective Trade-Offs with HITL, Field Events, and Feedback Loops

How can we make sense of trading objectives with respect to HITL, field events, and feedback loops? While Pareto solutions offer numerically optimal trade-offs, assessing the practical significance of these trade-offs requires human-in-the-loop involvement. CBS coordinators, MBS operators, and wildfire analysts contribute domain expertise and operational feedback to the DSS.

Feedback from the field, as emphasized by the wildfire subject matter expert (SME), is critical. Equally important is the presence of a structured framework to assess and incorporate such feedback. The proposed approach integrates feedback as an essential component by providing a systematic framework for its incorporation into the decision-making process.

Human-in-the-loop participation influences how the DSS generates solutions, evaluates their effectiveness, and learns from operational outcomes. This participation also facilitates the comparison and navigation of competing objectives. Addressing this challenge is particularly important because real-world problems frequently involve more than two objectives and may include three, four, or more. Thus, this study examines approaches to navigate complex objective spaces and outlines future research directions to simplify problems involving four or more objectives.

10.4 Research Contributions

The research contributions of this dissertation are summarized in this section.

10.4.1 Research Contribution (RC1.1)

This research study developed a set of novel mathematical specifications for an Optimizer Machinery that includes CBS fleet coordinator(s), MBS operator(s), and wildfire systems analysts, enabling a human-in-the-loop (HITL) interface by taking input and comparing with the optimizer solution. Previously, there was no other mathematical specification in which HITL could provide input to a UAV-based wildfire-detection and communication solution.

This research developed a holistic approach to the deployment of the UAV fleet and analyzed the systems architecture for wildfire detection and communication in Chapter 6. The novel ODS appraoch utilizes flexible optimization machinery for the wildfire UAV fleet and UAV aerodynamic design. This optimization machine incorporates a HITL interface, systems dynamics analysis using the Vensim SD model and model-based systems thinking (MBST) framework, architecture development with design structure matrix (DSM) or MBSE models, and computational fluid dynamics (CFD) analysis with an aerodynamic model, and thus contributes to the development of a fleet capable of high-altitude and long-range wildfire operations.

10.4.2 Research Contribution (RC1.2)

The research has developed a novel and quantitative optimization machinery that utilizes a structure consisting of base stations, launchers, and UAVs with an operating conditions scenario-based deployment structure for wildfire detection that utilizes a DSS for wildfire fleet deployment.

The fleet of UAVs we consider is a hybrid aircraft that uses power from both a lithium-ion battery and a fuel cell and is hauled to the launch site on a truck. We integrate knowledge from the research community and develop ODS for fleet operations, considering wildfire topology maps, geographic locations, operational constraints, communication requirements, and essential constraints on wildfire mitigation. The proposed systemic approach validates and pre-checks the decision support before launching the UAVs. We also consider where and when to retrieve the UAVs in both normal and abnormal operational cases.

10.4.3 Research Contribution (RC2.1)

Modularized / dynamic Pareto Front Framework: Operating Conditions Scenario-Based Optimization of the at Run-Time: This research has developed scenario-based optimization (operating conditions) and separated the optimization of the CBS & MBS vehicle and the flight path of the UAV within a continuous optimization loop with HITL, followed by their integration into a unified system to accomplish holistic wildfire detection tasks.

We have developed a set of mathematical expressions for fleet deployment and fleet paths/Wildfire Points Optimization. This research has developed an optimization engine with two stages that enables a wildfire-detection system based on UAVs.

We analyzed the impacts of fleet deployment on the planning of wildfire points and run-time issues in Chapter 7. We have experimented with environmental parameters for wildfire points optimization (WPO) efficiency. In addition to UAV flight paths and WPO efficiency, we also focus on a geographic map, environmental parameter characteristics, and wildfire likelihood to detect and communicate wildfires.

10.4.4 Research Contribution (RC2.2)

Modularized / dynamic Pareto Front Framework: We provide a novel framework and data-based modularized model to address complex problem-solving and provide a comprehensive solution for wildfire detection while maintaining adaptability to run-time scenarios. This approach uses a dynamic Pareto front, where only the affected portion of the optimization is re-executed at runtime rather than recomputing the entire solution.

This system method integrates fleet path or WPO strategies, PFWP, RTWP, and runtime decisions.

- Develop a prototype model for WPO strategies based on UAV fleet deployment.
- Develop strategies to perform the PFWP plan and RTWP (different strategies) and run in WPO.
- Run the strategies in the context of changes in field effects, mission goal, mission risk, and performance.

10.4.5 Research Contribution (RC3.1)

This research provides a novel systems method where we can integrate operating conditions with parameters from deployment and UAV design, so that priority and emphasis can be given to deployment or design/development.

We developed systemic methods in Chapter 8 for wildfire UAV Fleet deployment and UAV design. The identification of the leverage point between the deployment and the UAV design (SFC of the UAV) and the FIW (MBSE, trade study, CFD) is critical to finding a meaningful solution for detection and communication. An emergent, comprehensive understanding of the usage of MBSE, CFD analysis, systems dynamics modeling, and optimization problem-solving addresses the need for wildfire detection and communication.

- Contribution would be developing a method to identify the leverage point between “fleet deployment” and “UAV design”.

- We develop a SFC architecture to reduce weight to increase L/D, and increase the range. We perform an architecture trade study of different flight control options.
- Development of MBSAP for SFC utilizing MBSE. Also, review the MBSAP architecture for wildfire UAV.
- We develop a model for the UAV that uses the FIW concept, SFC, and understand the benefits of flight controls utilizing a CFD model.

10.4.6 Research Contribution (RC3.2)

This research has applied a set of Systems Thinking principles [42] that allow a human user to walk through the entire process from analysis to decisions, to design, to deployment, to site selection, and similar processes, but in reverse order, to understand the impact of each step for either deployment or design, or both.

We used case study data for the state of Colorado for wildfire scenarios for UAV fleet deployment, wildfire points planning, and advanced flight control architecture.

10.4.7 Research Contribution (RC3.3)

This research provides a novel and simulation-based DSS model where a fixed design can have realistic feedback and input from deployment scenarios, and understand the best trade-off points.

We used case study data for the state of Colorado for wildfire scenarios for UAV fleet deployment, wildfire points planning, and advanced flight control architecture.

By contributing the above items to the research community, we bridge several key gaps in the current state-of-the-art of fleet deployment body of knowledge.

10.4.8 Research Contribution Analysis

Integrating model-based systems thinking (MBST) [42] with optimizer machinery enables a DSS for multi-launcher and multi-UAV fleet deployment, where previously no run-time

human-in-the-loop (HITL) interface existed for UAV-based solutions for wildfire detection and communication.

The research study has used data from the state of Colorado for the deployment of wildfire UAVs, wildfire point planning, and an advanced fleet deployment architecture and UAV design. By contributing these items to the research community, this study has bridged key gaps in the current state of the art in fleet deployment for wildfire detection and communication using a fleet of UAVs.

10.5 Chapter Conclusions

It is a very effective approach to detecting wildfires using a fleet of UAVs specifically designed for that purpose. In particular, designing a specific component, such as SFC, is a game-changer for meeting the aerodynamic requirements associated with wildfire detection and communication mission goals.

The deployment problem of a UAV fleet is heavily dependent on the UAV platform and on having human operators (CBS coordinator or MBS operators) in the loop. The human operators are able to provide direct input to the optimizing machinery. We have made progress toward enabling CBS coordinators and MBS operators to become effective parts of the optimization loop, where they can provide direct input and control the optimization machinery. In particular, they can add or exclude wildfire launching and retrieval locations while the system is in motion. In addition, operational constraints can be effectively modified in real time.

The design activity is also heavily impacted by mission goals. We aim to ensure that there is no redundant design and that deployment optimization objectives related to cost, time, risk reduction, and area maximization are fully supported by UAV optimization metrics. We also seek to ensure that these optimization metrics support the overall mission optimization objectives.

This naturally raises the question of where the optimal trade-off or leverage point between UAV fleet deployment and UAV design optimization lies. We have shown that fleet deployment and UAV design are highly correlated (by changing UAV performance, impacting mission goals such as time reduction in Chapter 8) and that jointly optimizing both is the most effective way to maximize mission performance. Feedback from operational data should continuously inform the next generation of UAVs and, in some cases, reconfigurable UAVs. Reconfigurable UAVs can adapt to future mission requirements, and redesign inputs generated by the DSS can further improve UAV effectiveness. Thus, the HITL remains critical and can make crucial decisions to maximize mission objectives. These mission goals can vary depending on stakeholders' specific needs, and stakeholders should also be able to adjust objective functions to their operational needs.

As a comprehensive and holistic solution, we developed a close feedback loop between fleet deployment and UAV design. Such interconnectivity and dependencies highlight the systemic nature of this complex real-world problem of wildfire detection. It is also important to recognize that the DSS is intended not only for mission planning by coordinators and for UAV deployment, launching, and retrieval by MBS operators, but also for analysts who evaluate field operational data against design data to identify further optimization opportunities, as shown through the dashboards of the DSS. This proves how systemic principles are directly related to the real-world challenge of wildfire detection, and we further seek to determine and evaluate metrics that can make wildfire detection even more effective.

In addition, we reduce redundant weight of the UAV, time, costs, and avoid potential UAV overdesign that may not be compatible with mission requirements. We investigated ways to enhance the optimization machinery of the DSS by incorporating both operational feedback and UAV performance parameters. Several tornado charts illustrate the most critical parameters when jointly comparing fleet deployment parameters, DSS variables, UAV design parameters, and UAV performance metrics. As a result, coordinators can develop more effective mission plans, while analysts who provide feedback to UAV designers can continue to identify more effective approaches to addressing wildfire detection challenges.

This research study has bridged several critical research gaps between deployment and design. We have identified convergence systems methods for a comprehensive solution to wildfire detection and communication using a fleet of UAVs. Thus, the results of this research study show that the optimal benefit can be achieved when we utilize an efficient deployment strategy and an optimal-performance UAV. In addition, when we can leverage the trade space between these deployments and designs, we achieve the mission objective more effectively.

Data Availability

Data utilized to substantiate the findings of this wildfire UAV Fleet deployment research work can be obtained upon request.

Conflict of Interest

All data, methods and artifacts of this dissertation are the result of PhD research by the authors at the Colorado State University Systems Engineering Department. The author declare that there are no conflicts of interest with respect to the publication of this thesis.

Disclaimer

The views and opinions expressed in this dissertation, systems theories and the analysis of trade studies are solely the author. Views and opinions do not represent any position of Colorado State University, any employment entity, or any other organization, group, or individual.

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Appendix A

Integrated Dictionary

Central Base Station: Central base station (CBS) dispatches all the Mobile Base Station (MBS) and facilitates communication between CBS and an MBS. CBS is managed by a fleet coordinator who is part of the Human-in-the-loop (HITL) strategy.

Complex System: Complex system is a system that evolves, whose behavior can change over time, and which can exhibit emergent behavior. [42]

Enabling System: Enabling system is the system (or systems) that support the operation and maintenance of the System of Interest (SOI).

Design Structure Matrix (DSM:) Design structure matrix (DSM) is an architectural modeling and visualization tool that applies to process, project, product and service architectures. Multi-Domain Matrix is the aggregation of DSMs for the purpose of understanding how process, project, product, and service architecture are inter-related.

Decision Support Systems: Decision support systems (DSS) in this research are a key implementation that integrates the optimization machinery with the Graphical User Interface (GUI) to make decisions about UAV fleet deployment for wildfire detection and communication purposes.

Fans-In-Wings: Fans-in-wings (FIW) provides vertical lift and also controls roll axis maneuvering.

Human-in-the-loop: Human-in-the-loop (HITL), in the context of a decision support system (DSS), refers to the involvement of a human decision maker in the optimization process by modifying objective functions, constraints, and parameters within the numerical optimizer's iteration loop while the optimizer is running, thereby continuously contributing to improvements in the solution.

Mode-Based Systems Thinking: Model-based systems thinking (MBST) is a rigorous method (framework, languages & tools) that integrates various modeling methods that have proven their value to enhance our ability to understand real-world problems but were not previously directly aligned with adding rigor to the application of system principles [42].

Management Flight Simulator (MFS): A collaborative simulation tool in system dynamics used to analyze complex socio-technical systems and advance decision-making skills. It is based on the causal loop diagram (CLD) stocks and flows, feedback loops, and time delays, enabling scenario analysis for deployment, climb, and environmental parameters [42].

Mental Model: Mental models are the perspectives and frameworks that humans use to interpret the world.

Mobile Base Station: The mobile base station (MBS) is operated by an MBS Operator and can carry up to three UAVs that are folded into large pieces and ready for rapid assembly. The MBS Operator can participate if any human intervention is required.

Principle: Principle refers to a fundamental guideline or core concept [42].

Pareto Geometry The Pareto geometry (PG) is referred to as the structural construct of Pareto front, Pareto surface, Pareto manifold/hyper-surface that can show relations among dimensions, sensitive properties of the set of the objectives, enable systemic navigation, characterizes robustness. Pareto geometry is inclusive of Pareto front (PF), Pareto surface (PS) and Pareto hyper-surface and manifold but can help to visualize systemic decisions for deployment and design while focusing on robustness and sensitivity.

System: System is a set of interconnected elements that together form a structure and exhibit behavior that fulfills a purpose.

Systems Context: System context is the environment or the system that the System of Interest(SOI) fits into.

Systems Complexity: System complexity is the degree of interconnection and interdependence among the system's elements

Systems Dynamics: A methodology that uses computer modeling and simulation to analyze and understand the dynamic behavior of complex systems by focusing on the interrelationships between variables, feedback loops, and time delays.

Systems Engineering (SE) A multidisciplinary approach that utilizes holistic principles to design, develop, and manage complex systems throughout their life cycle by considering all components, interactions, and their relationships within the system and its environment [42].

System-of-Interest (SOI): System-of-interest (SOI) is the system that we are responsible for understanding, creating, developing, improving, buying, selling, or maintaining.

System of Systems: The system of Systems (SoS) is a group of systems that are significantly independent of each other, but collaborate, compete, or integrate to achieve a greater common purpose [42].

System Life Cycle: System Life Cycle refers to the series of stages that a system goes through from its inception to its retirement or death [42].

Systems Thinking (ST): *Systems Thinking* is an inter-relational trans-disciplinary*Philosophy*, enforced by rigorous *Methods*, for *Understanding* real-world *Complex* problems, and the *Systems* that may *Influence* them [42].

Surface-less Flight Control: Surface-less Flight Control (SFC) is the novel Flight Control design that is being developed to control the flight dynamics of the Wildfire UAV.

Thrust Vector Nozzle: A movable Thrust Vector Nozzle (TVN) is used to propel upward. It is selected to be multidirectional for this architecture.

Wildfire Point: The Wildfire Point (WP) refers to a geographic location characterized by a measurable risk of wildfire. These points may be specified using latitude and longitude coordinates, specific landmarks, or geo-location identifiers.

Appendix B

Abbreviations

The following is a list of acronyms used in this document. These abbreviations represent key terms and are referenced throughout the document with corresponding page numbers.

2D Two-Dimension. 185

3D Three-Dimension. 185

ACO Ant Colony Optimization. 223

AI Artificial Intelligence. 35

AI-ITL AI-in-the-Loop. 221

AIAA American Institute of Aeronautics and Astronautics. 15

AoA Angle of Attack. 86, 92, 231

ATC Air Traffic Control. 221

BDD Block Definition Diagram. 59

CBS Central Base Station. 2, 27, 28, 30, 117, 278

CFD Computational Fluid Dynamics. 73, 75, 84, 89

CLD Causal Loop Diagram. 63, 279

ConOps Concept of Operations. 9, 94

COTS Commercial-off-the-shelf. 229

DSM Design Structure Matrix. 278

DSS Decision Support Systems. 6, 9, 71, 164, 179, 278

FC Flight Controls. 56

FIW Fans-in-Wings. 2, 16, 62, 63, 67, 73, 237, 278

GA Genetic Algorithm. 222

GPS Global Positioning System. 53

GUI Graphical User Interface. 131, 278

H-UAV Hybrid UAV. 167

HITL Human-in-the-Loop. 6, 9, 15, 179, 249, 278

ICE Internal Combustion Engine. 62, 73

INCOSE International Council on Systems Engineering. 15

L/D Lift-over-Drag ratio or Lift-to-Drag ratio. 67, 68, 75, 85, 186

LDM Logical Data Model. 57

LiDAR Laser Detection and Ranging. 56, 57

LRDL Launch and Retrieval from Different Location. 29, 165, 166

LRSL Launch and Retrieval from Same Location. 29, 164, 166

LRU Line Replaceable Unit. 60

LV Logical Viewpoint. 204

MBS Mobile Base Station. 2, 12, 30, 117, 161, 278, 279

MBSAP Model-Based Systems Architecture Processes. 3, 57, 59

MBSE Model-Based Systems Engineering. 15, 59

MBST Model-Based Systems Thinking. iii, 1, 15, 25, 94, 99, 279

MC Monte Carlo. 187

MEA More Electric Aircraft. 52

MFS Management Flight Simulator. 94, 103, 279

MOE Measure of Effectiveness. 63

NFZ No-Fly Zone. 160, 164

ODS Optimal Deployment Strategies. iii, 15, 115, 229, 235

PCA Principal Component Analysis. 216

PF Pareto Front. 279

PFWP Pre-Flight Waypoints. 13, 14, 149, 160

PG Pareto Geometry. 279

PS Pareto Surface. 279

PSO Particle Swarm Optimization. 223

PV Physical Viewpoint. 59

ROC Rate of Climb. 11, 95, 102, 166

RTWP Run-time Wildfire Points. 13, 14, 149

SATCOM Satellite Communication. 3, 12, 52

SD Systems Dynamics. 100, 232

SE Systems Engineering. 280

SFC Surface-less Flight Controls. 2, 3, 56, 59, 177, 187, 280

SOI System-of-Interest. 19, 98, 278, 280

SoS System of Systems. 280

ST Systems Thinking. 280

TVC Thrust Vector Control. 59

TVL Thrust Vector Launcher. 60

TVN Thrust Vector Nozzle. 56, 59, 60, 62, 280

UAV Unmanned Aerial Vehicle. ii, 117

VTOL Vertical Take Off and Landing. 73, 82, 87

WOA Whale Optimization Algorithm. 223, 226

WP Wildfire Points. 7, 281

WPO Wildfire Points Optimization. iii, 15, 155, 221, 229, 235