

**Value-based model and analysis of autonomous unmanned aircraft systems based on
operational scenario**

by

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The student author and the program of study committee are solely responsible for the
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NOMENCLATURE

UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
NAS	National Airspace System
SHM	Structural Health Monitoring
NDE	Non-Destructive Evaluation
FAA	Federal Aviation Administration
NTIA	National Telecommunications & Information Administration
IRB	Institutional Review Board
SE	Systems Engineering
MDO	Multidisciplinary Design Optimization
MOO	Multi-Objective Optimization
VDD	Value-Driven Design
DSM	Design Structure Matrix
DV	Design Variables
AL	Autonomy Level
TRL	Technology Readiness Level
ATRA	Autonomy and Technology Readiness Assessment
GNC	Guidance Navigation Control
GPR	Ground Penetrating Radar
GPS	Global Positioning System
IMU	Inertial Measurement Unit
FPV	First Person View

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ABSTRACT

In recent years, the use of UAS has moved much beyond the realm of military operations and has made its way into the hands of consumers and commercial industries. Although the applications of UAS in commercial industries are virtually endless, there are many issues regarding its operations that need to be considered before these valuable pieces of equipment may be allowed to run free in the skies. Currently, UAS operations in public domain is guided and controlled by the FAA Part 107 rules after overwhelming public pressure caused by the earlier 333 exemption [1]. In order to approach such larger issues, this thesis will exploit the use of value models, which will help to quantify how the different environmental and operational scenarios play a role in UAS operations based on the task being performed.

The primary aim of this research is to use the attributes of key factors of the UAS such as the Autonomy Levels (AL) and Technology Readiness Levels (TRL) along with its operating scenario factors such as the environmental complexity and task complexity, based on the operating environment in which the UAS performs its task. To analyze the performance of autonomous UAS in different operational scenarios, the physical characteristics and class of the UAS may be linked to its AL and TRL. Using these parameters, the risks faced by the UAS in a particular mission are quantified and a value is assigned to the abstract entities involved. Although there are many critical questions with respect to good practices to be followed by UAS operators in order to obtain valuable data and information on the structures being scanned and monitored, there are many other major challenges with regards to large scale operations of UAS such as the ethical, legal and societal implications that have to be addressed.

CHAPTER 1

INTRODUCTION

The introduction of UAS technology on a large scale may very well be the next major technological breakthrough in the field of aviation for performing a wide variety of applications in a relatively safe and cost effective manner. This breakthrough is projected to create thousands of new jobs and billions of dollars of economic development [2]. The introduction of UAS into the National Airspace System (NAS) comes with a lot of advantages and some disadvantages which translates to gains and losses for different stakeholders involved. Unfortunately, the challenge faced by the government and multiple stakeholders who wish to use UAS technology on a large scale are the issues tied to safety, policy, law, ethics and privacy. This research study involves understanding the different factors that affect the deployment of UAS on a large scale by taking into account operational constraints and issues associated with it. Understanding these factors from the viewpoints of the users and operators may be used to aid in amending and developing policies for UAS operations, which is directly related to the ongoing controversy regarding the regulations of UAS.

With the recent increase in the number of UAS in the skies, measures have to be taken to properly regulate and safely carry out the transition into this new realm of aerial vehicles. This process will require the coordination and involvement of academia, industry, government agencies like the Federal Aviation Administration, Department of Defense, local authorities and private sectors alike in order to successfully implement a safe, efficient and robust system for commercial UAS operations [3]. The ultimate goal of such a high level partnership between these agencies would be to successfully integrate sUAS operations into the NAS in order to

enhance the use of UAS for commercial applications, while heavily weighing on the ethical, legal societal and environmental implications of these technologies. The current UAS boom for civil applications must be cautiously carried out without violating any rights or safety of individuals or the environment.

The primary goal of this research study is to create a value model for UAS by taking into account the technical, environmental and operational scenarios involved in order to possibly create a decision analysis simulation to analyze and rate different UAS based on its components, autonomy level and technology readiness level. This in turn may be used in the future to understand the dilemma between the preferences of the stakeholders and the regulations to model the inefficiencies induced in UAS operations due to policy requirements. The research will involve using a combination of various tools and frameworks such as Multidisciplinary Design Optimization (MDO), Value-Driven Design (VDD), and Decision Analysis (DA) to analyze and understand the various factors involved while designing and operating UAS on a large scale for the use of SHM and civil applications.

The methodology for this research will necessitate identifying different classes and types of UAS that can be used for commercial purposes and connecting the physical characteristics of these UAS to virtual characteristics such as AL and TRL in order to evaluate these system for the purpose of SHM, while staying compliant with the FAA Part 107 regulations. These evaluation methodologies of the software and hardware of UAS can in turn be used to rate their performance and guide operational activities based on the task being performed around the different operational scenarios. This way, the value model will be able to correlate the UAS to the operational environment that it performs tasks in. These characteristics can be represented in the form of attributes and design variables to create a value model that can capture and

incorporate the technical design aspects of the UAV to the societal and legal aspects of deploying UAS. In order to rate the performance capability of the UAS in its operational scenario and to abide by the legal and societal constraints, the autonomy level and technology readiness levels of the associated and relevant components play a key role in the value model.

The new Part 107 rules put forth by the FAA regarding the operations of sUAS will be used as the primary platform to setup the different scenarios to use either a single UAV or a swarm of UAVs to monitor different types of structures autonomously in order to provide a holistic view of the condition of the structure being surveyed. The use of UAS will open up new domains of unexplored potential in the field of SHM and provide an efficient solution to the current techniques being employed. In order to implement this system in an efficient manner, we will use the VDD approach of SE. This methodology will provide an interdisciplinary approach to the implementation of the system while being able to communicate the design and operational requirements with the preferences of the stakeholders including the UAS pilots, operators and the FAA. This will help in identify relationships between the subsystems of the overall system while including economic theories to better optimize the design and operation of the UAS swarm based on the mission scenario, while incorporating the preferences of the stakeholders [4].

The focus of the next chapter is to concisely describe the three research questions developed for this research project and the approach to addressing each of the questions, as well as the subtasks involved in each of these studies.

CHAPTER 2

RESEARCH QUESTIONS

This chapter explains the research questions and tasks that were formulated in order to initiate the search to form a value model that can be used to improve and optimize the operations of a UAS based on its operational scenario.

Research Question 1

“How do the different environmental and operational scenarios play a role in UAS operations with regards to the task being performed?”

This research question will be address with the task of first creating an ‘operational scenario complexity’ list of different types of infrastructure that will be scanned by the UAS in a typical mission, this list will be formed by rating the different infrastructures with a system of metrics backed by a list of attributes that contribute to the complexity of the operational scenario. Each of the attributes will have a weight based on the volume of impact that it has on the infrastructure being tested. The second task will be to create a ‘task complexity’ table which will rate the different methods of data acquisition that can be used by the UAS to scan the infrastructures. Similar to the ‘operational scenario complexity’, attributes will be used to create a system of weights for the different tasks in the list based on the primary factors affecting the process of collecting the different types of data remotely using a drone. These attributes will be supported by metrics in order to assign weights to the list of data acquisition methods to link back to the operational scenario, thus creating a connection between these parameters.

Research Question 2

“How are the physical characteristics and class of UAS linked to the AL and TRL to performance in different operational scenarios?”

This research question will be used to draw relationships between the hardware and software elements of the UAS. This will be done with the help of a value model that will separate out the primary parameters of the UAS, such as size, class, technology readiness level and autonomy level. The primary challenge of this research question will be to link the autonomy levels and technology readiness levels to the size and class of the UAS to enable a performance based evaluation of the UAS with regards to the operational scenario.

The software elements, namely AL and TRL will be linked together by the ATRA framework whose primary aim would be to create a link between the software components of the UAS. The ATRA can then be used to further connect to hardware elements to the different types of UAS such as fixed wing, hybrid or multirotor. The size class of the UAS will also be used in the model to study the feasibility between the size and class of the drone with respect to the AL and TRL required for the different mission scenarios and objectives to be performed by the UAS.

The task for this research question will be to investigate a meaningful sequence of relationships between the class, size, AL and TRL of a UAS with respect to its performance in the different operational scenarios discussed in the previous research questions. This will be done with the formulation of a value function that will be capable of evaluating the required levels of autonomy for different mission scenarios based on environment and task to be performed.

Research Question 3

“Can this value based model be used to perform risk analysis on autonomous UAS operations based on ethical, legal and societal issues?”

The value based models that have been developed in the previous two research questions can be stretched to further to investigate a bargain model over the system attributes to understand the risks that may occur during UAS operations in different mission scenarios. In order to understand the trade-offs, heuristic methods may be used to incorporate the existing FAA rules and regulations to perform the analysis between UAS ratings model and operational scenario models to extract an estimate risk value in a particular scenario. Once this has been achieved, checks and balances can be used to control, avoid and eliminate the risks and can be supported with thorough consideration of ethical, legal and societal issues.

A primary task of this research question will be to incorporate the existing Part 107 FAA rules in the form of constraints on the design variables of the UAS itself. This will help to not only base the design of the UAS within the legal constraints, but also formulate an optimization function for the UAS based on the minimization of mass. In order to expand this into a value model, the stakeholders and their true preferences may be listed out by studying multiple sources that provide the viewpoints of the different stakeholders; values may also be assigned to the key regulations put forth by the FAA and penalties may be imposed on operations that violate these regulations. This way, ethical, legal and societal issues may be used to determine the risks in autonomous UAS operations and quantify the penalties involved.

Organization of Thesis

Chapters 1 and 2 provided an overview of the current state of UAS operations in the commercial setting and a glimpse into the motivation behind the research along with a set of well defined research questions that may be used as a starting point to solve some of the potential issues with the sUAS commercial operations for SHM purposes. Chapter 3 will provide a detailed background on the subjects of unmanned aircraft systems, structural health monitoring, systems engineering, multidisciplinary design optimizations and value-driven design, which is necessary for proceeding through this thesis and understanding the core topics addressed in this research. Chapter 4 will focus on explaining and describing the breakdown of a fixed wing and multicopter UAS model which will be used as examples to link to the operational scenarios for SHM. Chapter 5 will provide an initiation to the linkages between the different tasks the UAS will be performing and the environmental scenario of the operations. This chapter will also help to quantify the links between the physical characteristics of a UAS such as its class and size to its AL and TRL in order for it to perform assigned tasks in the different operational scenarios. Chapter 6 will delve into the different types of traditional SHM techniques and quantifying their effectiveness against the proposed UAS-SHM method, supported by detailed studies and discussions of the pros and cons of the different techniques. Last but not the least, Chapter 7 will summarize the final conclusions of this research and lay the foundations for future work that could be extended from this research and the possible new areas that it may be expanded into.

CHAPTER 3

BACKGROUND

The operations of UAS in the civil environment is an extremely difficult issue to address due the large amount of ambiguity surrounding its position in the vast and complex activities occurring in the civil airspace. Value models will be used extensively in this thesis to highlight the advantages of connecting the different attributes of the physical components of a UAS to its levels of autonomy and operational conditions in order to create synergy between the operation, equipment and personnel involved and thus overcome the need to use traditional requirements based methods to set constraints on UAS operations. This value based systems approach to the operations of UAS in civil airspace will help facilitate a comprehensive view of the issues and better align the discussions within the appropriate scope of topics.

A fixed wing and multicopter UAS models will be used to address the couplings between the UAS hardware & software components to the infrastructure it will be performing SHM on and the tasks that the UAS will be performing. This model can be used to obtain system and operational correlations to further investigate the impact that UAS operations could have on the environment by performing multiple studies using simulations. The content in this chapter gives a detailed background of the key topics of this thesis such as the history and development of the fields of UAS and SHM. It also gives a detailed overview regarding the supporting frameworks required to understand the formulation of this research methodology such as traditional systems engineering, multidisciplinary design optimization and value-driven design.

Unmanned Aircraft Systems

Unmanned Aircraft Systems (UAS) also known as Unmanned Aerial Vehicles (UAV) or drones are basically aircrafts that don't have a human pilot on-board. These aircrafts are usually controlled remotely by a human operator and can have varying levels of control autonomy between the human operator and the on-board flight computer and control systems based on their capabilities [5]. UAS provide greater mobility to further the potential for exploration by effectively providing three dimensions of motion control to the user. Although the origins of UAS applications can be traced back to military purposes, as of today, it has the potential to play a key game changing role in applications pertaining to many different industries such as security surveillance, search and rescue, photography, mass media, agriculture, package deliveries and recreational uses [6].

Recently, UAS have taken to the skies in large numbers and is poised to have a major impact on the US and global economy as a whole. There are many credible sources that provide evidence of multiple billions of dollars of economic development and activity generated by the induction of UAS in civil applications, this in turn will help to create thousands of new well paying jobs across the world [7]. According to a report by the Association for Unmanned Vehicle Systems (AUVSI) in 2013, the expansion of UAS in civil industries could create up to 103,776 jobs by 2025 and the tax revenue to the states could reach up to \$462 million in the first 11 years after its integration into the NAS. Every year that UAS integration into civilian airspace is delayed, the US loses more than \$10 billion in positive economic impact, this amounts to losses of about \$27.6 million per day [8].

The first large scale commercial use of UAS started in Japan for agricultural applications in the 1990s. The primary UAS used for this purpose was the Yamaha R-Max, which was commissioned as an industrial-use unmanned helicopter in 1987, these efforts took place due to a request from the Ministry of Agriculture, Forestry and Fishery of Japan for the development of a UAV for crop-dusting purpose [9]. The Yamaha R-Max is a highly capable first generation UAV, which is equipped with a 2-cylinder, water cooled gasoline engine that is capable of lifting a payload of approximately 35 lbs for 60 minutes without refuelling. The electronic systems include a 500 Mb embedded flash drive for data storage, IMU, 3-axis Magnetometer, SONAR altimeter and RADAR altimeter for altitude control and stabilization [10]. The Yamaha R-Max is capable of spraying up to 2 acres of land in 6 minutes and has sprayed almost 310,000 hectares of Japanese farmland since 1995.



Figure 1. Hexacopter and Quadcopter UAS in flight

Today, the trend of UAS design has changed from a helicopter style system to multirotor hexacopter and quadcopter designs as seen in Fig. 1. These new designs of UAS provide it with more dynamic stability and lift capability for relatively smaller size of the rotor blades. Currently, the largest drone manufacturer is DJI with a net valuation of \$10 billion, followed by Parrot and the Berkeley based 3D Robotics which had net sales worth \$50 million in 2015 [11].

Structural Health Monitoring

Testing civil infrastructure manually is an expensive and relatively dangerous task. Many times a lift or a crane is used to allow manual access to inspect the ‘hard to reach’ locations where damage may have occurred [12]. Structural Health Monitoring (SHM) is an important tool to help improve the safety and maintainability of vital civil and transportation infrastructures. Due to the deterioration of civil infrastructure caused by time and other factors, the importance of SHM cannot be underemphasized. The primary aims of SHM is to provide the diagnostics or state of an infrastructure during every moment of its life of all the different parts and of the full assembly of all the parts constituting the structure. SHM is more than just an improved way of performing Non-Destructive Evaluation of a structure, it is a complex and multidisciplinary process comprising of visual monitoring, integration of sensors, smart materials, data transmission, computation and even predictive modelling of the entire structure itself [13].

As of today, SHM is performed manually by engineers, technicians and inspectors spending vast amounts of field time mapping and inspecting the structure for defects with the help of tripod or vehicle mounted equipment which have limited reach. Advances in bridge SHM have been enhanced with the help of stationary sensors that are strategically placed under or on the surface of the structure, capable of monitoring stresses and vibrational loads. Unfortunately, infrastructures that are old or located in remote areas cannot be monitored using such embedded sensor techniques [14]. Current inspection practices involve visual inspections, acoustic emission, ultrasonic testing .etc. These techniques revolve around previous knowledge of where the damage is in order to perform a detailed study of the holistic condition of the structure.

Systems Engineering

Systems Engineering is a field of engineering that is concerned with identifying relationships between the elements or subsystems of an overall system. It is an interdisciplinary approach and means to enable the realization of successful systems. Focusing on the relationships between the elements or subsystems, decision theory, statistics and optimization are used as the underlying frameworks in designing a successful system [15]. Using the basic framework, systems engineering focuses on the stakeholder's preference and handles issues that can arise during the development cycle. The procedure involves documenting requirements, synthesizing designs and validating the system while considering the complete problem and needs of the stakeholder. These processes have been used and practiced for over half a century, allowing designers to track the requirements given by the stakeholders [16]. However, failures still occur, although sometimes, in the long run they may be unavoidable.

It is the role of systems engineering to learn from these failures and find ways to improve the design of a system. Developing, understanding and control of the system interface, development of test and verification plans, and proper allocation of requirements are crucial to good systems engineering [17]. In a detailed design phase, the role of systems engineering is to guide, coordinate, and facilitate component design engineering activities. Using good practices and learning from our failures, we may develop methods to solve the issues that may occur during a system's life cycle. Systems engineering brings back the sense of art and excitement into engineering, as we examine the human interactions with the physical aspects of engineering [15]. Capturing the interactions of human decisions through the development of engineered systems may cause arise in complication as the size of the design team increases. Systems engineering

takes into account logical human organization and manages the complexity incorporated into the design process [15].

Presently, Systems Engineering is heavily requirements based. The current approach to using systems engineering method involves communicating the requirements down the organizational hierarchical order of the corporation [18]. The requirements for the system are set by the stakeholders in the highest level of decision making in an organization. The requirements are formed based on physical interferences, environmental limitations, legacy, knowledge. etc. The failure to form requirements properly is the main reason that systems fail [19]. The requirements made by the stakeholders are based on the needs of the customer, but these requirements fail to highlight the true preferences of the stakeholder. The primary requirements are then passed down the levels of the organizational hierarchy to the teams of their respective subsystem. In each level of the hierarchy, the subsystem teams form their own set of requirements and continue to pass them down to smaller subsystem teams. The design is considered to be achieved once all the requirements are satisfied at a component level. These requirements based systems engineering methods does not capture the stakeholders' true preferences and are susceptible to time and cost overflows [4]. Another traditional method of systems engineering is using the standard systems engineering V process and the waterfall processes shown in Fig. 2. The V process involves flowing down the V from the left and allocating requirements to every component until the lowest level, and then climbing up the right-hand V and implementing these requirements at each component level. The problem with this method is the lack of an objective function which limits its practical application in a detailed design process [20].

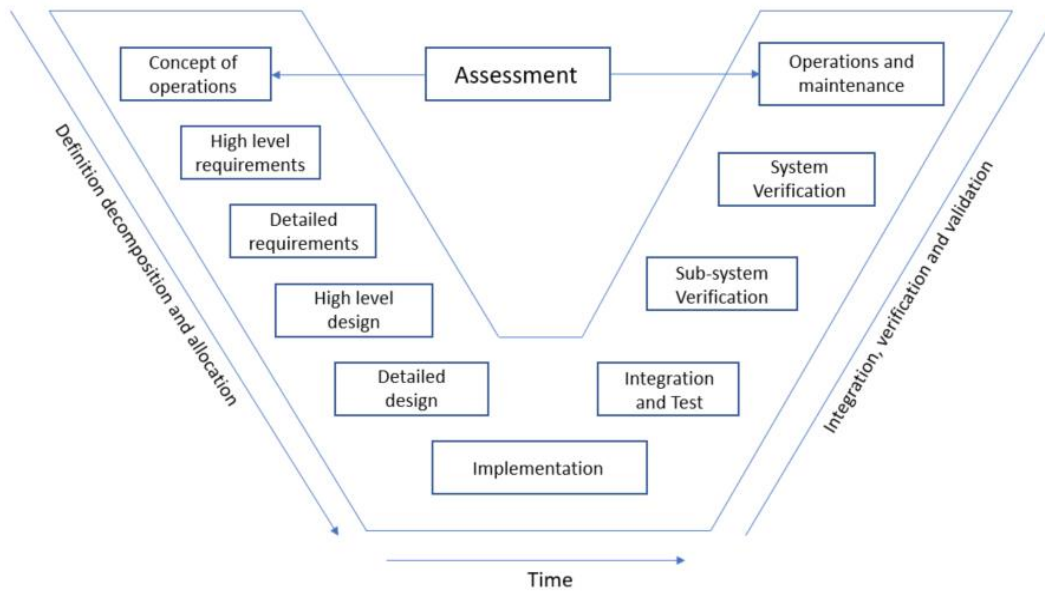


Figure 2. Systems Engineering V-Model

The waterfall method is a sequential development model and the requirements for one phase are set before moving to the next phase. It is a linear process and is easy to implement. Each step is frozen before the moving on to the next step. This allows the requirements to be clear before the development begins. The problem with this method is that issues with one phase of the design may be carried over to the next phase; since the requirements cannot be changed once the process has started, it may lead to a badly structured system [21]. The traditional systems engineering and optimization processes have limitations in determining the best system design while being unable to capture the preferences of the stakeholders and customers.

Multidisciplinary Design Optimization

The term Multidisciplinary Design Optimization (MDO) was created in 1947 by Arthur Roderick Collar “*as the study of the mutual interactions that take place within the triangle of the initial, elastic, and aerodynamic forces acting on structural members*” [22]. During the 1980s, MDO arose from structural optimization [4]. The huge jump in computation since the 1980’s enabled the inclusion of aerospace engineering companies, agencies, and academic researchers into optimization. As engineered systems become more detailed in complexity, new methods need to be implemented to help designers get an optimum system design. MDO focuses on the numerical optimization for design on systems which involve a number of disciplines or subsystems [18]. The main function for MDO is to optimize a system that has multiple subsystems that interact with each other. To achieve the optimum system, each subsystem has to be captured to understand how it affects the overall performance of the design. A well-known example where MDO is used is with the interaction of aerodynamics and structures. There was a strong interaction with these two subsystems; therefore, aeroelasticity was created to analyze these interactions [22]. As systems grow in size and complexity, it is important to incorporate the use of MDO into the design process as we capture the interactions that occur between the many subsystems. Using the MDO problem early in the design process and taking advantage of the advanced computational analysis tools, designers can improve a design while reducing the time and cost of the design cycle [15]. However, as designs become more dependent on the stakeholder, designers need to take preferences into account while working in the design cycle.

Value Driven Design

Value Driven Design (VDD) is a movement that uses economic theory to transform systems engineering and better use optimization to improve the designs of large systems, particularly in aerospace and defense [23]. Value Driven Design captures the preferences of the stakeholders by adding new elements into the design process. The process of Value Driven Design used in the design of large scale complex engineered systems is represented in Fig. 3. Instead of having requirements flow down to the subsystems, the preferences of the stakeholder are prioritized. This expands the design base, as requirements that are generally passed down in traditional SE methods may limit the overall design. By not limiting the design to requirements, all areas of the design can be explored to find the optimum design for the stakeholder.

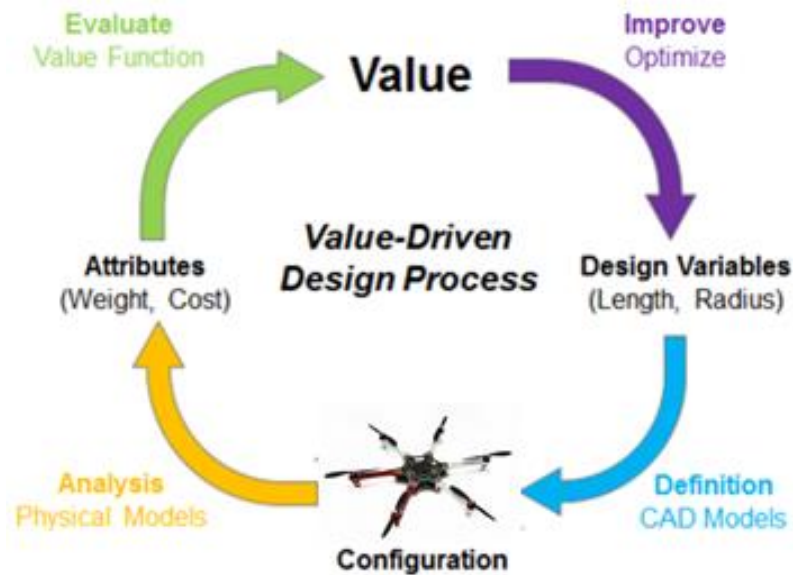


Figure 3. Value-Driven Design Process

VDD is involved with defining a process that provides a value to a detailed design when components are designed in relative isolation [24]. This is done through the creation of a value function, similar to an objective function; however, there are significantly lower constraints on

the design. This value given to the design has no meaning to anyone else except the stakeholder, as it monitors and expresses the stakeholder's preference. Typically, this value is monetary depending on if the stakeholder wants to maximize profit or minimize cost. The designer can create a value function that is not monetary; it is up to the stakeholder and designer to understand their system and discover ways to begin the design process. Value-Driven Design is an approach to systems engineering originally intended for use during the detailed design phase of systems development. VDD focuses on providing an objective function to each component to guide design work [25]. Value Driven Design is a framework that can be applied to MDO and aims to reduce the number of requirements applied to attributes of components of the system. It also attempts to reduce the number of constraints applied to optimization techniques and captures the true preference of the stakeholders.

Furthermore, VDD enables design optimization of the entire system as well as each component. It does so by using a value function to search for the best design and a higher number from the value function indicates a better design. It also helps to prevent design trade conflicts thereby preventing dead-loss trade combinations. When teams work at cross purposes in an organization to meet each requirement for their subsystems, it may lead to a net increase in cost and also decrease the performance and reliability of the system. VDD helps to prevent this 'dead loss' by creating a value function that encompasses all the attributes and trade factors which are consistent among components at all levels. Finally, it prevents cost growth and performance erosion by eliminating requirements at component levels and improving system attributes, thereby eliminating the source of cost growth and associated delay [26].

CHAPTER 4

UNMANNED AIRCRAFT SYSTEM MODEL

The following UAS model will lay the groundwork required to demonstrate the use of traditional SE approach along with the formulation of a multi-objective optimization function. A basic two tiered breakdown of a fixed wing and multicopter UAS model has been developed as a part of this research in order to serve as a test bed for the execution of different operational scenarios required to perform different tasks critical to SHM. The hierarchical model shown in Fig. 4 describes a two-tiered decomposition of a fixed wing UAV subsystems. This will be used to further explore the attributes and design variables along with their impact on operations. For a fixed wing UAV, each of these subsystems are further broken down into subsystems in lower tiers and are defined by 24 design variables shown in Table. 1. This model created will help to further our knowledge on the understanding of a UAV system and will be valuable in connecting key attributes to performance parameters in the different operational scenarios being tested.

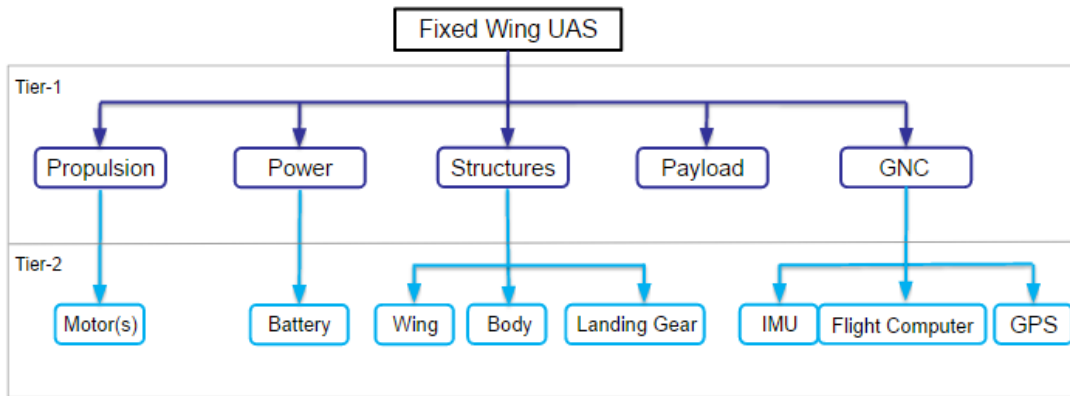


Figure 4. Hierarchical decomposition of a fixed-wing UAV system

Similarly, a hierarchical decomposition for a multicopter UAV along with its subsystems in two tiers are shown in Fig. 5, we see that the simplified model of a multicopter UAV has five

primary subsystems in its first tier: Propulsion, Power, GNC, Structures and Payload. The subsystem components of a UAS that has been broken down hierarchically can be used to further to explore a second level of components that create the makeup of the multirotor UAV. These levels can then be used to understand the connection between each of the disciplines of the UAV. The second tier of subsystems comprise of motors, battery, IMU, GPS, flight computer, 3D FPV camera, SONAR, arms, body and landing gear [27]. Since this is a relatively large model, each of the primary disciplines and their subsystems namely GNC, structures, power, propulsion and payload will interact with each. In order to capture the couplings of these interactions, a DSM will be used as shown in Fig. 6.

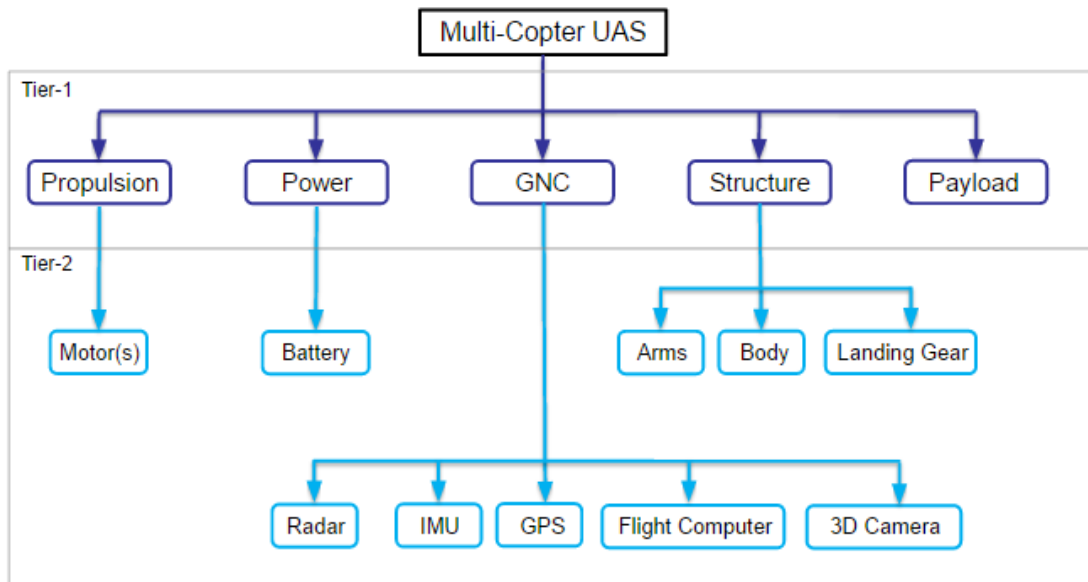


Figure 5. Hierarchical decomposition of a multi-copter UAV system

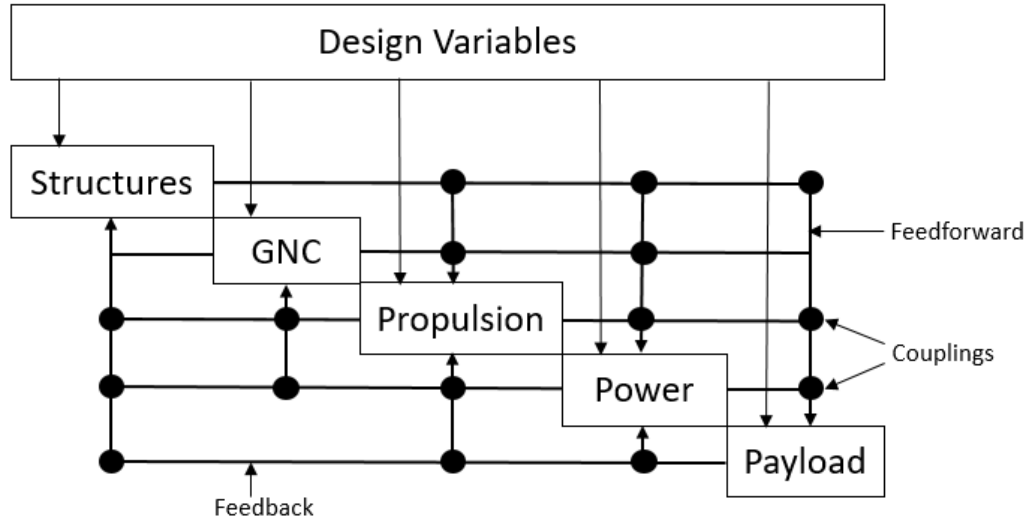
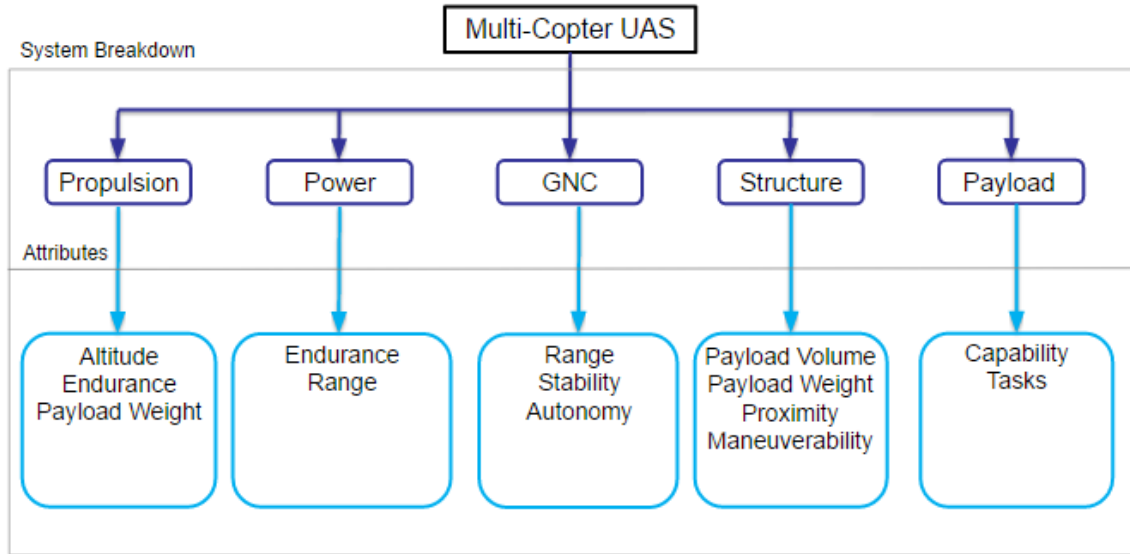


Figure 6. Design Structure Matrix of a multirotor UAS

The DSM shown above has the capability to visualize the connections between the subsystems as couplings, feed forwards, and feedbacks [28]. This makes it easier for the user to model and analyze the system and shows how the dependencies among the subsystems can be used to further improve the system as a whole. Using this DSM and the hierarchical breakdown models, we can list out the performance attributes that are affected by the first tier subsystems as shown in Fig. 7. As seen from the figure below, propulsion affects the altitude, endurance and payload weight that can be carried by the UAS; power from the battery affects endurance and range; GNC affects range, stability and autonomy level; while the structure affects payload volume, payload weight, proximity and maneuverability. The payload attached to the UAS can be removed based on its mission profile and task, thereby affecting the capability and tasks that can be performed by the UAS. The payload attributes can be changed based on the types of sensing equipment that will be attached to the UAS.



Figures 7. Multicopter UAS breakdown and connection to performance attributes

The fixed wing UAV being studied in this case will have the primary mission of surveying and performing SHM on infrastructure, while abiding by the FAA Part 107 regulations. The hierarchical model breakdown of a fixed wing UAV to assign attributes and design variables to each of the subsystem parts will be focused on setting guidelines and aiding the UAV designer to stick to the legal limits set by the government, while also catering to needs and preferences of the UAS operators from different industries as discussed earlier. The first tier of subsystems comprise of propulsion, power, structures, GNC and payload. This first tier is further broken down into a second tier of components such as motor, wing, body, landing gear, IMU, flight computer and GPS. Each of the individual subsystem levels of the fixed wing UAV and their associated design variables that could be used for analysis in a value model are described in Table 1 below.

Table 1. List of attributes and design variables of a fixed-wing UAS

Tiers			Attributes	Design variables
SYSTEM (Unmanned Aerial System)			AL, TRL, RV, Cost	Single UAV / UAV swarm
Subsystem level 1	(SS1) Wing		C_{wing}, M_{wing}, RV_1	Type of wing
	(SS2) Fuselage		$C_{fuselage}, M_{fuselage}, RV_2$	Type of fuselage, $L_{fuselage}$
	(SS3) Electronics		C_{elec}, M_{elec}, RV_3	Type of electronics
	(SS4) Motors		$C_{payload}, M_{payload}, RV_4$ Altitude, Range	Type of motor, n_{motor}
Subsystem level 2	Wings	(SS1) Spar	C_{spar}, M_{spar}	$Material_{spar}, L_{wing}, L_{chord}$
		(SS2) Skin	C_{skin}, M_{skin}	$Material_{skin}, L_{wing}, L_{chord}$
	Fuselage	(SS1) Frame	C_{frame}, M_{frame}	$Material_{frame}, L_{frame}, M_{payload}, n_{frame}$
		(SS2) Skin	C_{skin}, M_{skin}	$Material_{skin}, M_{payload}$
	Electronics	(SS1) Battery	$C_{battery}, M_{battery}$ Range	Type of Battery
		(SS2) Camera	C_{camera}, M_{camera}	Type of Camera
		(SS3) GNC	$C_{sensors}, C_{microprocessor}, C_{software}, HI, EC, MC, RV$	Antenna Type, Sensor Type Microprocessor & Software Type

In order to set up the optimization process, we needed to develop an objective function that captures the goals of the stakeholders and abide by the legal constraints set by the FAA. Equation. 1 is the formulation for the minimization of mass approach. These constraints need to have a sense of meaning due to its interaction with other objects, laws of physics, and mission success criteria. The mass is assumed to be a summation of all of the subsystems that have a mass which could affect the system.

$$\begin{aligned}
\min f(x) &= Mass_{total} = \sum_{i=1}^N Mass_{Ai} \\
g_1: Mass_{total} - 25 \text{ kg} &\leq 0 \\
g_2: V_{max} - 44.7 \text{ m/s} &\leq 0 \\
g_3: Range - 5000 \text{ m} &\leq 0 \\
g_4: Altitude - 122 \text{ m} &\leq 0 \\
1\text{m} &\leq wing \leq 2\text{m} \\
0.2\text{m} &\leq L_{chord} \leq 0.6\text{m} \\
0.5\text{m} &\leq L_{fuselage} \leq 2\text{m} \\
1 \text{ kg} &\leq Mass_{payload} \leq 5 \text{ kg} \\
X &= [X_{discrete} \ L_{wing} \ L_{chord} \ L_{fuselage} \ Mass_{payload}]
\end{aligned}$$

Equation 1. Formulation of minimization of mass approach

The side constraints that are introduced in this example are: length of the wing, chord, fuselage, and mass of the payload. These side constraints are developed to fit within physical bounds, such as to keep the mass of the UAS from dropping below zero or making it too heavy for takeoff. The inequality constraints on the other hand are based directly on the FAA Part 107 rules for UAS operations, such as maintaining a total mass of the UAV to be less than 55 lbs, maximum speed less than 100 mph, maximum flight altitude of 400 ft above ground level and flight missions must be carried out within visual line-of-sight [29]. These constraints used in the traditional MDO formulation represent the desires of the stakeholder, which in this case is the government, and highlights the regions in the design space that are deemed infeasible to use while designing the fixed wing UAS.

We can assume the stakeholders in this setup to be the government (FAA), UAV designer and the UAV operator. Based on the preferences, each stakeholder will have a different value, so the value given only makes sense to the stakeholder. The true preferences of the stakeholders interested in taking advantage of UAS can be obtained by analyzing the viewpoints of

stakeholders obtained from multiple sources and summarized in Table. 2. This table is a representation of the true preferences of UAS operators from different industries, the data presented in the table is extracted from the NTIA convened multi-stakeholder discussions due to a Presidential Memorandum issued by former President Obama for "*Promoting Economic Competitiveness While Safeguarding Privacy, Civil Rights, and Civil Liberties in Domestic Use of Unmanned Aircraft Systems.*" [30]. This meeting comprised of members and entities from academia, industry, government sectors and civil society, thereby giving a holistic view of their combined opinions for the development of regulation with regards to UAS.

Table 2. Preferences of UAS operators from various industries

	Farmers & Ag associations	Energy & Construction	University Researchers	Media Houses & Journalists
Operation	Precision Agriculture	Inspection & Maintenance	Research & Education	Photojournalism
Task	Photos - RGB, IR, NDVI Spraying	Power line inspect Gas leaks detection Thermography	Tool for R&D in multiple fields	Photo and video footage for news
Environment	Rural Farmland	Urban & Rural areas	Confined zones	Busy urban areas
Issues	Ownership of scan data. Intrusion over private land.	Current rules are too constraining Privacy laws need to be loosened	Treat institutes different from commercial entities	No reqs to disclose details. Time for training & registration
Requirements	Training programs needed UAS must have ID for tracking.	Special operations exemptions for inspection & maintenance	Use IRB regulations for schools not FAA	No additional privacy regulations for drone use

CHAPTER 5

VALUE MODEL AND ANALYSIS

The primary aim of this chapter will be to provide a detailed overview of the relations that were drawn between different tasks that the UAS will be performing with respect to the environmental scenario of the operations as well as the physical characteristics of a UAS such as its class and size to its AL and TRL. This chapter will also explain the approaches to quantifying the relationships between the UAS characteristics and operational scenarios, this way showing how all the parts of the puzzle fit together and explaining their effects on one another. This chapter could serve as a launchpad for the creation of risk and bargain models.

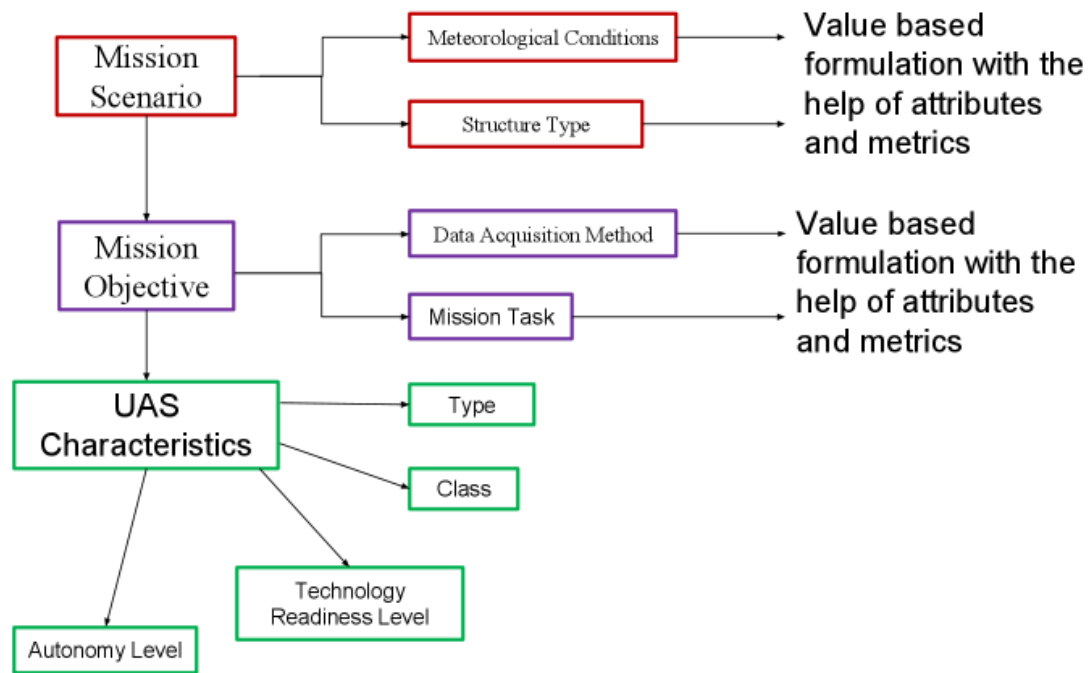
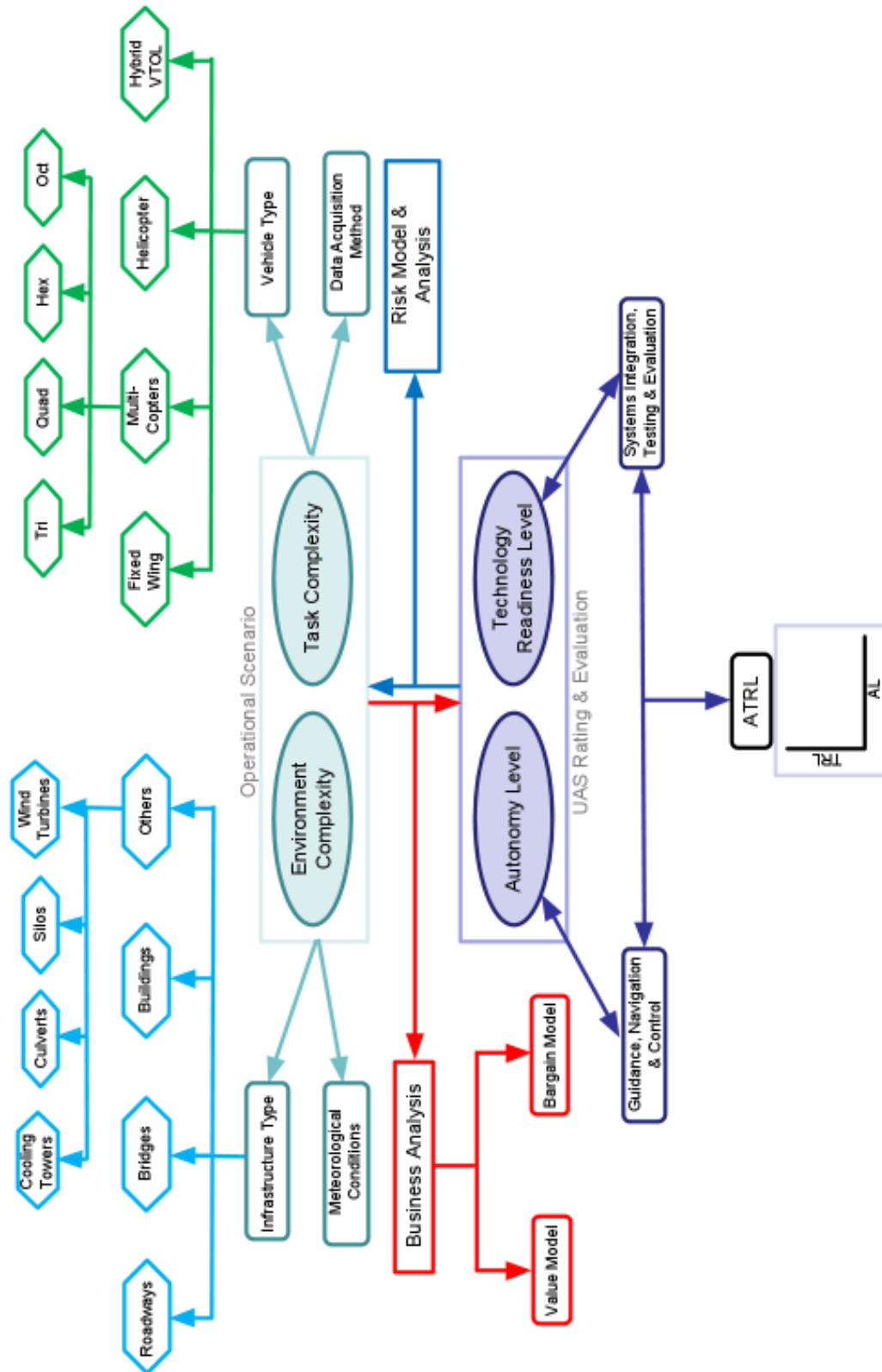


Figure 9. Parameters for operational scenario and UAS rating

The primary parameters involved in the operations involving a UAS are: The mission scenario, mission objective and the UAS characteristics, as shown in Fig. 9 above. The mission

scenario is defined by the meteorological conditions and the structure type; the mission objective is defined by the data acquisition method used and mission tasks and the UAS characteristics are divided by its size, class, AL and TRL. The structure type and the data acquisition method will have a set of attributes and metrics that will help to determine its complexity. This methodology can be used as a universal model for analyzing the operational scenarios for UAS in other applications such as precision agriculture or photojournalism, but in this research project, we will use the example of SHM to understand the effects of the operational scenario on the UAS. This example will be used to demonstrate the amount of complexities involved in the process of UAS based SHM and how optimal performance may be achieved.

The Fig. 10 below shows an elaborated model for performing decision analysis on UAS operations. We see that this model is divided into two main parts: Operational scenario and UAS evaluation. The operational scenario is further divided into environmental complexity and task complexity, while the UAS evaluation is divided into AL and TRL. The operational scenario and UAS evaluation can be used in the future to perform risk modelling and analysis on operations based on the UAS autonomy. This can also be used to create a bargain model for the comparison of UAS based SHM with other forms of traditional SHM based on quality v/s dollar comparison. The next two subtopics of this chapter will elaborately explain the creation of the value models for the operational scenario and the UAS evaluation separately along with the types of metrics and ratings that were used to evaluate the parameters involved.



Figures 10. Model for decision analysis of UAS operations

Value Model for Operational Scenario

This topic will focus on explaining the operational scenario aspect of the decision analysis model explained earlier. The two main parameters that are used to evaluate the operational scenario in our model are: Environment Complexity and Task Complexity. The environment complexity is further subdivided based on the meteorological conditions and the infrastructure type around which the UAS will be operating. The task complexity is subdivided into data acquisition type and vehicle type. This model with the subdivisions of each of the categories of operational scenario is illustrated in Fig. 11 shown below. A combined analysis of each of these parameters will be used to understand the effects of operational scenario on the UAS while performing its tasks. In order to quantify each of these parameters, common types of scenarios were studied based on their tasks and environment, then metrics were created for the two main subdivisions of these parameters that define operational scenario: Infrastructure Type and Data Acquisition Type. These metrics are supported by weighted attributes and these weights are assigned based on the value of its relevance to the attributes.

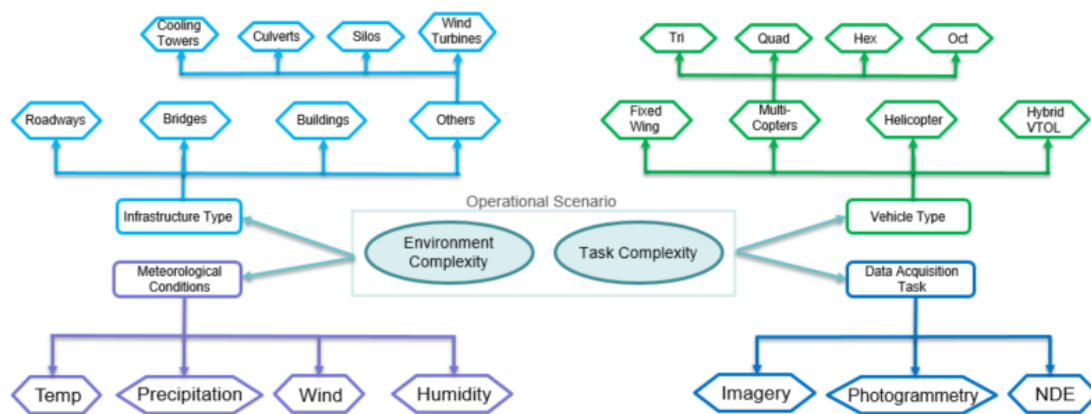


Figure 11. Model representing relation between environment and task complexity

The infrastructure type is divided based on the structure that will be surveyed by the UAS while performing SHM, for example, buildings, roads, bridges .etc. The meteorological conditions will be based on factors surrounding the infrastructure type where the UAS will be performing and will be evaluated based on temperature, precipitation, wind speeds and humidity. In our model, we will integrate the weather conditions as one of the attributes contributing to the infrastructure type's complexity. As for task complexity, vehicle type describes the types of UAS that will be used to perform the operations, such as, fixed wing, multicopter, hybrid VTOL, Lighter Than Air (LTA) or a helicopter. The data acquisition types are broadly divided into four different categories: Imagery, 3D modelling, non-contact NDE and contact NDE. These data acquisition types vary in levels of difficulty and are selected based on tasks that a UAS may be capable of performing in order to collect information regarding the health of a structure.

Although there are four major subdivisions for the two parameters pertaining to the operational scenario, in this model, we will only be quantifying the subdivisions that directly affect the UAS operating environment and not the type or class of UAS itself. This analysis will focus on quantifying the infrastructure types and data acquisition methods to compare it to the AL and TRL of the UAS. The reason for using select subdivisions in our analysis is to directly co-relate the environment factors to the autonomy and reliability of the UAS. The UAS type differs from its class; UAS type describes its physical build, while UAS class depends on its size. In this analysis, we will not consider the class or type of UAS for performing applications, instead, focus will be placed on assisting a UAS operator in decision making while using a UAS with a particular AL and TRL in a particular environment or scenario. The next section will explain the creation of the metrics and attributes for the main parameters.

The first parameter we will explore in detail with regards to operational scenario is the environmental complexity, this table was put together with a list of different infrastructure types that can be scanned by the UAS. This table of infrastructure type will have a set of metrics ranging from 1 to 10 for a broad range of infrastructures varying in complexities. The value of the metrics increases as the complexity of the infrastructure type increases from open unpaved rural roads to suspension bridge superstructures. These metrics will be supported by attributes that contribute to the complexity of the infrastructure as seen in the table below, such as size of the structure, physical obstacles around the structure, weather when the UAS operations will be conducted, geography of the surrounding location and factors that may cause signal interference to the link between the UAS and the pilot or ground station. These attribute weights will further be rated from 1 to 10 based on the comparative impact it has on each of the attributes. The list of the different infrastructure types with its metrics and attributes are compiled in Table. 3 below.

Table 3. List of infrastructure types with attributes and metrics

Metric	Infrastructure Type
1	Open Unpaved Rural Roads
2	Paved Urban Roads
3	Highways
4	Houses / Small Buildings
5	Skyscrapers
6	Dams
7	Wind Turbines
8	Regular Beam & Truss Bridges
9	Off-Shore Oil Platforms
10	Suspension Bridge Superstructures

Attributes	Weight
Size of Structure	0.2
Physical Obstacles	0.2
Weather	0.2
Geography	0.2
Signal Interference	0.2

Once we have these metrics and attributes for these infrastructure types setup, we can use it to create a function that can provide us with a value by combining these metrics, attributes and weights. In this model, we assigned equal weight of 0.2 to all the five attributes for the types of infrastructure, although the weights assigned to each of the attributes can be changed based on its importance compared to other attributes. It must be noted that the total sum of the weights of all the attributes must add up to be 1. Each of these attributes also has its own set of metrics ranging from 1 to 10, and this will be based on the impact of that particular attribute on the infrastructure type. For example, the metric value for the ‘size of structure’ attribute for a wind turbine depends on the comparative size of the wind turbine being inspected with regard to other wind turbines.

$$E(x) = \sum_{i=0}^n M_E * [w_i * A_i]$$

$$E_{max} = 10 * [5 * (0.2 * 10)]$$

$$E_{max} = 100$$

Equation 2. Formulation of environmental complexity function

Once the infrastructure being scanned is identified and all the metrics and weights have been assigned to the attributes, a mathematical function is formulated as seen in Eq. 2, which quantifies the environmental complexity. This was done by multiplying the infrastructure type metric (M_E) with the summation of the product between the assigned attribute weights (w_i) and the attribute metric (A_i). This formula quantifies the environmental complexity value from a minimum of 1 to a maximum value of 100 as shown in Eq. 2.

The next parameter we will explore in detail with regards to the operational scenario is the data acquisition method, this table was put together with a list of different types of data that may be performed by the UAS as a part of its SHM tasks. This table of data acquisition methods will have a set of metrics ranging from 1 to 10 for SHM tasks that the UAS performs based on its complexity. The value of the metrics increases as the difficulty the task increases from something as simple as distant low resolution imagery to a very complex task like ultrasonic contact NDE. These tasks are subdivided based on the type of data it obtains such as: Imagery, 3D modelling, non-contact NDE and contact NDE. Each of these different classes of data acquisition methods has its own set of attributes based on the way data is collected and due to the different nature of the classes of tasks. The list of the different data acquisition methods with its metrics and sub-divisions are shown in Table. 4 below.

Table 4. List of data acquisition methods with metrics

Metric	Data Acquisition Method	
1	Distant Low Res Aerial Imagery	Imagery
2	Close-up Aerial Imagery (<2m)	
3	Distant HD Aerial Imagery (18MP+)	
4	Close-up HD Aerial Imagery	
5	3D Photogrammetry Rendering	3D Modelling
6	Light Detection & Ranging (LiDAR)	
7	Non Contact NDE: Infrared Thermography	Non-Contact NDE
8	Non-Contact NDE: GPR	
9	Non-Contact NDE: Laser Shearography	
10	Contact NDE: Ultrasound	Contact NDE

Similar to the environmental complexity, the data acquisition methods are supported by attributes that contribute to the complexity of the data acquisition methods seen in Table. 5 below. There are four different sets of attributes for each data acquisition class. The attributes for imagery include equipment weight, image composition, proximity of the UAS to the object and stability required for acquiring good quality data, while attributes for 3D modelling include equipment weight, precision of the data collected, point density of the 3D renders and acquisition time needed to collect substantial amount of dense points of the structure being scanned. For non-contact NDE, the attributes include the weight of the NDE equipment such as the thermal camera or ground penetrating radar (GPR), accuracy of the data collected, minimum proximity required for data collection and the time needed for collecting the data, while for contact NDE, the attributes are equipment weight, precision of the transducers, penetration depth under the surface being scanned and the surface area that can be scanned in one flight.

Table 5. List of attributes with weights for data acquisition methods

Imagery		3D Modelling		Non-Contact NDE		Contact NDE	
Attributes	Weight	Attributes	Weight	Attributes	Weight	Attributes	Weight
Equipment Weight	0.3	Equipment Weight	0.3	Equipment Weight	0.3	Equipment Weight	0.3
Composition	0.2	Precision	0.3	Accuracy	0.3	Precision	0.3
Proximity	0.3	Point Density	0.2	Proximity	0.2	Penetration	0.2
Stability	0.2	Acquisition Time	0.2	Acquisition Time	0.2	Scanned Area	0.2

Once the metrics and attributes weights for the different data acquisition methods have been set up, we can use it to create a function that can provide us with a value by combining these metrics, attributes and weights. In this model, we have assigned different weights to all the attributes for the data acquisition methods based on its importance compared to other attributes. The total sum of the weights of all the attributes of each data acquisition class must add up to 1. These attribute weights of all the four classes is further rated by metrics ranging from 1 to 10

based on the comparative impact of that particular attribute on the data acquisition method. For example, the metric value of ‘equipment weight’ attribute for collecting imagery data depends on the weight of the camera mounted on the UAS compared with the weight of other cameras.

$$T(x) = \sum_{i=0}^n M_T * [w_i * A_i]$$

$$T_{max} = 10 * [(0.3 * 10) + (0.2 * 10) + (0.3 * 10) + (0.2 * 10)]$$

$$T_{max} = 10 * [3 + 2 + 3 + 2]$$

$$T_{max} = 100$$

Equation 3. Formulation of task complexity function

Once the task to be performed on the infrastructure has been identified and all the metrics and weights assigned to the attributes are finalized, a mathematical function is formulated as seen in Eq. 3, which quantifies the task complexity based on the data acquisition methods. This is done in a similar way the formula for environmental complexity was derived, which is by multiplying the data acquisition type metric (M_T) with the summation of the product between the assigned attribute weights (w_i) and the attribute metric (A_i) of the task type. If more than one task will be performed in a single mission, the same formula can be applied for the other tasks and the greatest task complexity value amongst the multiple tasks may be used as the final task complexity value to conduct any further analysis. This way, the formula developed in Eq. 3 quantifies the task complexity value from a minimum of 1 to a maximum value of 100, thereby allowing task complexity to be scaled to the environmental complexity.

Value Model for UAS Rating and Evaluation

Autonomous mobile robotic technology has rapidly evolved over the last decade and has begun to impact multiple sectors across various industries [31]. In order to characterise, compare and evaluate the advancements in autonomy of a vehicle, common taxonomies and terminologies will need to be put in place. As of now, multiple government agencies such as the Department of Defense Joint Program Office (JPO), the U.S. Army Maneuver Support Center, and the National Institute of Standards and Technology (NIST) have separate but related on-going efforts to describe levels of robotic behaviors [32]. Although most of these are military related projects for combat systems, similar autonomous behavioural models can be modified for commercial operations. Although there are multiple references and metrics that have been created for UAS autonomy evaluation, here, we will create a version of the ATRA that can be retrofitted into the larger model for decision analysis of UAS operations explained earlier.

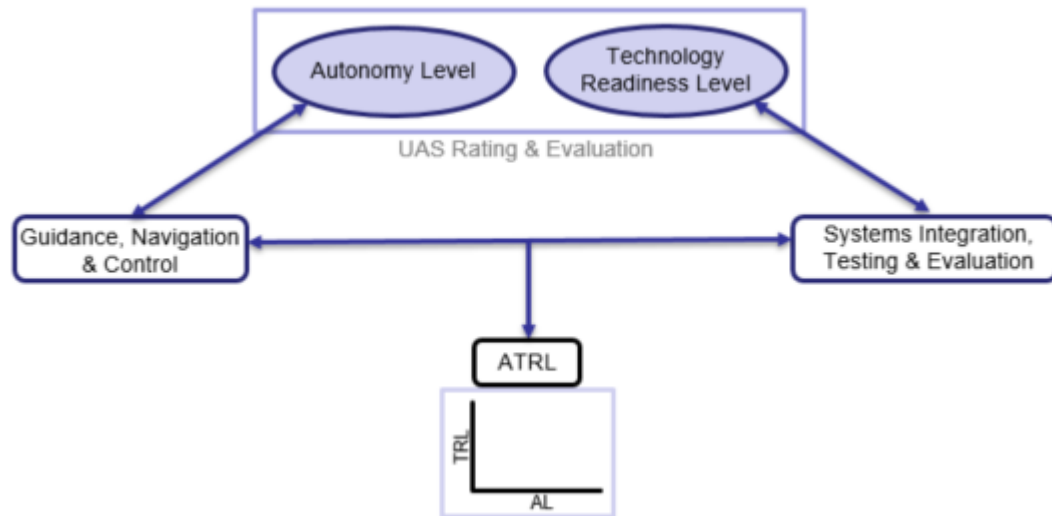


Figure 12. Model relating autonomy level and technology readiness level

The two parameters that are used to evaluate the autonomy and robustness of a system being implemented are: Autonomy Level (AL) and Technology Readiness Level (TRL). These parameters are unified to form the Autonomy and Technology Readiness Assessment (ATRA), which can be used to provide a holistic view of the software component of UAS [33,34]. The formation of the network between the AL and TRL to form the ATRA is shown in Fig. 12 above. The use of this framework to evaluate autonomous UAS can be used to make both qualitative and quantitative comparisons that may be accomplished with the help of a formulated value function. The reason for the creation of such a framework is to enable the UAS community with a common set of evaluation that can be systematically used to compare the autonomy of one UAV to another, no matter the physical components that were used to make it.

The ATRA framework can be used to measure the maturity and robustness of not just UAS, but can also be used for any other vehicle that uses autonomous technology, such as Unmanned Underwater Vehicles (UUV), Unmanned Ground Vehicles (UGV) or even self-driving cars if this framework can be modified appropriately to be utilized universally [35]. In this thesis, we will just use this frameworks to investigate how they can be used in SHM applications to determine the optimal level of autonomy for different tasks to be performed. Here, we will use the definitions of AL, TRL and the ATRA, defined by NiST as Autonomy Levels for Unmanned Systems (ALFUS) [36,37] with necessary modifications from other sources to fit our SHM applications agenda. In this chapter, will use the example of a UAV that was assembled with off the shelf components and control system and evaluate it based on the ATRA framework developed to demonstrate its usage and effectiveness in the evaluation of autonomous UAS, while also keeping track of its operational environment.

The first parameter we will explore in detail is the Autonomy Level (AL), this is a set of metrics that is used to systematically evaluate and measure the autonomous capabilities and limitations of a UAS [38]. This metric ranges from 1 to 10, representing the accession of autonomous behaviour from remote controlled UAS with rudimentary first order flight control up to fully autonomous capabilities with no human pilot decision making involved at all. The AL of a UAS is mainly based on its GNC functions, which is the primary attribute to enabling autonomy in the hardware component of the UAS. As the GNC capabilities of the UAS is directly proportional to the autonomous capabilities of the UAS, as the GNC functionalities increases, the AL of the UAS will also increase alongside. The list of the different levels of autonomy for our example is compiled in Table. 6 below.

Table 6. List of Autonomy Levels (AL) with descriptions

Autonomy Levels	
Level	Description
1	Remote Control
2	Automatic Flight Control
3	System Fault Adaptive
4	GPS Assisted Navigation
5	Path Planning & Execution
6	Real Time Path Planning
7	Dynamic Mission Planning
8	Real Time Collaborative Mission Planning
9	Swarm Group Decision Making
10	Fully Autonomous

The next parameter we will explore is the Technology Readiness Level (TRL), which is a set of metrics that is used by many companies and government agencies to systematically evaluate and assess the reliability and maturity of the technology being used, which in this case is the autonomous UAS [32]. This metric ranges from 1 to 10 and is related to the advancement of systems development, integration, validation and deployment, ranging from the formulation of basic principles of the system up to its deployment and fully operational status. The TRL of a UAS is mainly based on its systems integration, test environment, mission scenario and performance, which goes hand in hand with the reliability of the combination of autonomy and hardware that can be implemented in the UAS [32]. The levels of TRLs that we will be using for our example here is shown in Table. 7 below.

Table 7. List of Technology Readiness Levels (TRL) with description

Technology Readiness Levels	
Level	Description
1	Basic Principles
2	Application Formation
3	Technology Concepts & Research
4	Tech Development & Proof of Concept
5	Low Fidelity Component Testing (Labs)
6	System Integration & Flight Tests
7	Prototype Demonstration & Operation
8	Prototype Operation in Realistic Mission Scenario
9	UAS Mission Deployment
10	Fully Operational Status

Example of ATRA formulation for a Hexacopter

We will use the example of a DIY hexacopter UAV created by assembling off the shelf components to demonstrate the use of the AL and TRL evaluations in order to create an ATRA graph. In order to evaluate the AL of this UAV, we will need to evaluate its GNC capabilities of its flight controller component. The flight controller used in this UAV is the 3DR Pixhawk mini [39], which is a commercially available flight controller for UAS designed and manufactured by Berkeley based drone company 3D Robotics [40]. This flight control system comes with an inbuilt auto flight stability system, which is assisted by a gyroscope and altimeter to adapt to dynamic changes in its environment such as varying wind speeds to keep it stable during flight.

This flight controller allows for the addition of a modular GPS and compass unit to the main flight controller CPU to allow it to provide accurate positioning via its ground station software - px4 autopilot pro [41]. This mission planner uses GPS assisted waypoint navigation that allows a user to pre-program a path and allow the UAS to execute it autonomously. On referring to the AL table and based on the GNC capabilities of the Pixhawk mini flight controller, we see that it is fully capable of performing tasks up to AL 5, which is ‘Path planning and execution’. As we move up the AL scale to level 6 and so, capabilities such as real time path planning and dynamic mission planning can only be tested and experimented on by modifying the flight control system or ground station software and by the addition of more hardware such as obstacle avoidance sensors to the flight control system that will be capable of enabling these autonomous capabilities into the UAS. Since these capabilities have not been implemented, the AL for ‘safe operations’ will be set at 5 as shown in Table. 8 below.

Table 8. Selection of AL and TRL values for ATRA

Technology Readiness Levels		Autonomy Levels	
Level	Description	Level	Description
1	Basic Principles	1	Remote Control
2	Application Formation	2	Automatic Flight Control
3	Technology Concepts & Research	3	System Fault Adaptive
4	Tech Development & Proof of Concept	4	GPS Assisted Navigation
5	Low Fidelity Component Testing (Labs)	5	Path Planning & Execution
6	System Integration & Flight Tests	6	Real Time Path Planning
7	Prototype Demonstration & Operation	7	Dynamic Mission Planning
8	Prototype Operation in Realistic Mission Scenario	8	Real Time Collaborative Mission Planning
9	UAS Mission Deployment	9	Swarm Group Decision Making
10	Fully Operational Status	10	Fully Autonomous

In order to back our earlier statement of ‘safe operations’ based on AL, we will take advantage of the TRL scale. Since TRL does not only depend on the critical autonomy enabling GNC components, but also on the systems integration and operational reliability of the whole UAS itself, we will have to consider the other hardware components used in the assembly of the UAV when we evaluate the TRL. In this scenario, we see that for AL 5, this UAS has been flown on a regular basis to capture images and videos using its integrated gimbal and camera system using a pre-planned path. This puts its TRL at 8, which according to the metric is ‘Prototype operation in realistic mission scenario’, since path planning operations were used to execute its mission of capturing images and videos and has been carried out only using this one prototype. If a full UAS mission deployment must be considered, the UAV must be mass produced and its missions must be carried out on a regular basis with a track record exhibiting proof of operational success in performing its tasks. Based on this, the hexacopter used in this example receives a TRL of 8 for AL of 5 as highlighted in Table. 8 above.

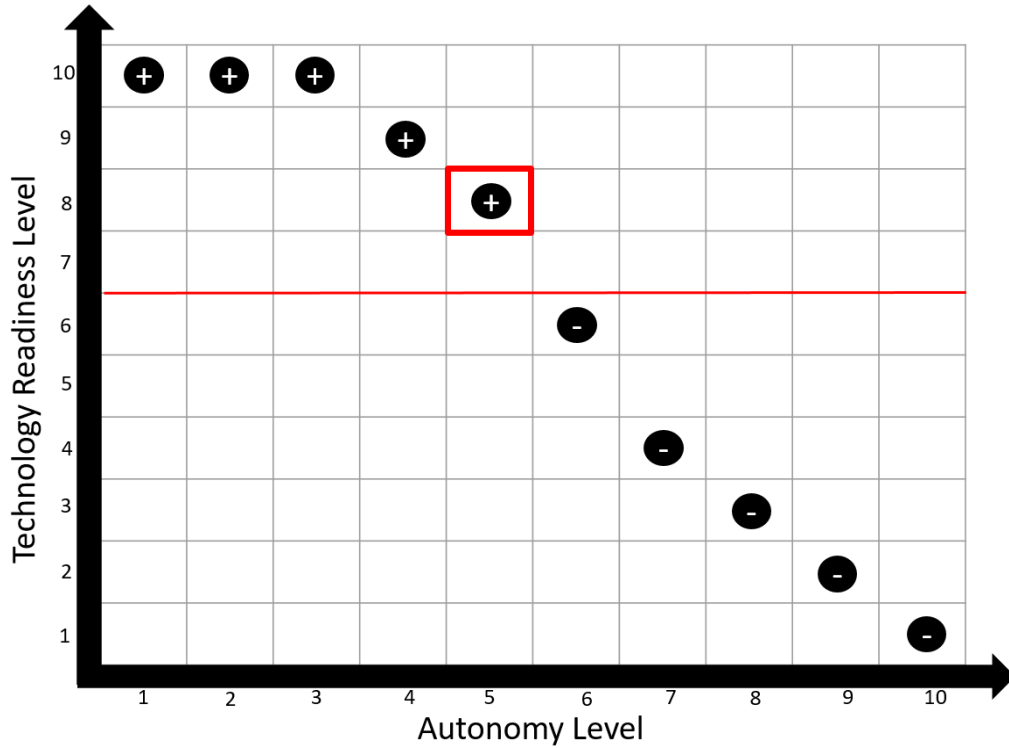


Figure 13. ATRA graph for the Hexacopter UAV

From the results obtained using the AL and TRL metrics, we can create the ATRA graph by plotting the AL in the X-axis and the TRL as the Y-axis. The Fig. 13 above illustrates the ATRA graph for the hexacopter, here we have highlighted circle in the block of AL 5 and TRL 8 with a red square to signify the extent of safe operational autonomous capabilities of the UAV. The '+' and '-' subscripts in each of the blocks are used to denote whether that AL and TRL has been implemented on the system. In this ATRA graph, for all ALs above 6, the TRL remains below 6 due to the fact that it does not fulfill the requirements needed to be implemented on the UAS. For a system to be able to be implemented, the TRL of the UAS must be at least, therefore a UAS with TRL below 7 may only have a '-' subscript, this threshold is demarcated using a red line under the TRL 7 row.

CHAPTER 6

APPLICATION OF DEVELOPED VALUE MODEL

In the previous chapter, we created metrics and functions that helped to quantify abstract factors such as the environment, difficulty of tasks, autonomy and reliability of the UAS performing the mission. In this chapter, we will use the functions and metrics created to evaluate risks and the value of a particular operation, which can then be used to guide the UAS operators before the flight missions. The risk analysis and operations value that we will discuss in the next part of this chapter can be used for purposes ranging from authorizing UAS flights safely based on different operational scenarios to aiding in pricing and cost analysis of missions based on the environment and tasks. The application and usage of the value model that we developed earlier will be applied and demonstrated in the following operational scenarios.

The operational scenarios that we will explore in the following examples will use a variety of different realistic mission scenarios defined by the task performed, payload carried, the type of infrastructure being scanned and the flight conditions, which are abstract entities that will be quantified to provide a mission operation value and a risk value. The resulting operations value can be used as a basis for the creation of dollar based pricing model for commercial UAS operations, while the risk value can be used as a model used to aid in decision making for the UAS operator prior to the UAS operation by using the balance between the UAS characteristics and the operational scenario. In this study, the ‘risk analysis’ will merely be used as a measure of likelihood of operational mishap occurring. The results from these models can be used as a starting point to research and understand effects of other factors on UAS operations such as the human factors, ergonomics, detailed UAS physique and failsafe mechanisms.

Operations Value and Risk Analysis

Every UAS operation is different in its own way and in order to create a standardized method that can be used to quantify the value of these operations, we have created an operations value formulation. This formulation is made by combining the four major metrics developed in the previous chapter, which are, the environment complexity - $E(x)$, task complexity - $T(x)$, autonomy level - AL and technology readiness level - TRL. In order to effectively incorporate these different metrics and provide us with the operations value, the environmental complexity value and task complexity value are added to each other and this is then added to the sum of 10 times the AL and TRL in order to scale up the raw values obtained from the respective metrics.

$$\begin{aligned}
 V(x) &= E(x) + T(x) + 10 * [AL + TRL] \\
 V_{max} &= 100 + 100 + 10 * [10 + 10] \\
 V_{max} &= 400
 \end{aligned}$$

Equation 4. Formulation of operations value function

The mathematical formulation of the operations value function is shown in Eq. 4 above. This way, all the four primary parameters are equally represented in the operations value formulation and thereby plays an equal role in determining the final operations value. Using this formulation, the total operations value can range from a minimum value of 22 to a maximum value of 400. The operations value $V(x)$ in Eq. 4 quantifies the overall difficulty and complexity of the UAS operations to be performed by taking into account the both the physical and autonomous UAS attributes along with the operational scenario, thereby aiding the user in obtaining a holistic view in terms of operational decision making. The ‘risk analysis’ in this case is used as a decision making mechanism and does not include probability of occurrences.

Similar to how the different metrics that we developed were used to assign a single value that quantified the UAS operations, we will take advantage of the same set of metrics value to perform risk analysis on the UAS operations that will help the UAS operator in the decision making process before flight. The main purpose of this risk analysis will be to provide valuable information to the UAS operator about whether the capabilities of the UAS he will be using to perform the respective mission is appropriate to complete the mission operations in the particular operating environment. Therefore, the risk analysis model used here will focus on simply balancing the operational scenario parameters to the UAS evaluation parameters.

$$\begin{array}{l}
 \text{IF} \\
 0.1 * [E(x) + T(x)] \leq AL + TRL \\
 \text{THEN} \\
 \text{Operation safe with UAS configuration} \\
 \text{ELSE} \\
 \text{Operation NOT safe with UAS configuration}
 \end{array}$$

Equation 5. Risk Analysis logic

The exact risk analysis logic developed for this purpose is shown in Eq. 5 above, where the 0.1 times the sum of the environmental complexity value - E(x) and task complexity value T(x) on one side is balanced against the sum of AL and TRL on the other side. If the value obtained from the operational scenario parameters on the left side is less than or equal to the UAS evaluation parameters on the right hand side of the inequality formula, then the UAS operation may be considered safe to execute, else the operational scenario is too difficult for the UAS to perform and hence is unsafe for operations unless a more advanced UAS can be used.

Evaluation of UAS Operational Scenario using Value Function

In this section, we will use the developed operations value and risk analysis formulations and use it on different mission scenarios to demonstrate the benefits of these value models for handling pricing and decision making in the UAS operations for performing SHM applications.

Operational Scenario 1

A state department of transportation wants to perform aerial high definition survey of 5 miles length of an inner city road using a Canon EOS 70D DSLR camera mounted underneath a fixed wing UAV. The UAV is capable of executing a pre-planned path from the ground station and the operation is planned to take place on a high visibility and low wind speed day.

To conduct this type of analysis, we will start by using the operational scenario metrics of the infrastructure types and data acquisition methods to obtain the environmental complexity and task complexity values. The inner city roads to be scanned in this case comes under the ‘paved urban roads’ category that has a value of 2 in our infrastructure metrics. All the attributes in this analysis is equally weighted and the attribute values are determined by comparing the paved city road being scanned in this scenario to other paved city roads. The length of this inner city road is assigned an attribute value of 5 based on the length of the road to be surveyed, since the UAV will be operating above the road in the city, there may be a few obstacles and hence the physical obstacles attributes value is 4. Since the survey is conducted on a relatively pleasant day above the city, the weather is assigned a value of 2 and the geography is given a value of 4. Due to the amount of metallic structures such as antennas and telecom towers present in the surroundings that may cause radio interferences, the signal interference may be moderate and is assigned a value of 5. The Table. 9 shown below contains the attribute weights and values for each of the

five attributes that help us quantify the environment complexity. Using these weights and values of the attributes obtained from Table. 9, we can calculate the environment complexity value as shown in Eq. 6 below. The final environmental complexity obtained using this equation is 8.

Table 9. Attribute weights and values for paved urban road

Paved Urban Road		
Attributes	Weight	Value
Size of Structure	0.2	5
Physical Obstacles	0.2	4
Weather	0.2	2
Geography	0.2	4
Signal Interference	0.2	5

$$E(x) = \sum_{i=0}^n M_E * [w_i * A_i]$$

$$E(x) = 2 * [(0.2 * 5) + (0.2 * 4) + (0.2 * 2) + (0.2 * 4) + (0.2 * 5)]$$

$$E(x) = 8$$

Equation 6. Environmental Complexity Value of Urban Road

Similarly, we can calculate the task complexity value using the data acquisition metrics and the set of attribute weights and values associated with it. On referring to the list of data acquisition metrics, the ‘distant HD aerial imagery’ task being performed here has a value of 3. For this task, the four different attributes along with its assigned weights and values are shown in Table. 10 below. The equipment weight attribute is assigned a weight of 0.3 and given an attribute value of 7 due to the *Canon EOS 70D DSLR* [42] being quite heavy as compared to other HD cameras. The image composition is assigned a weight of 0.2 and an attribute value of

5, since HD aerial imagery requires a medium level detail of composition to capture the larger defects on the road. The proximity is weighted at 0.3 and assigned a value of 2, since the fixed wing will be flying at a relatively high altitude above the road while performing aerial survey. Since the stability of the image from this mission need not be highly stable and is supplemented by the relatively stable flight characteristics of the fixed wing aircraft, it is assigned a value of 4. Using these weights and values of the attributes shown in Table. 10, we can calculate the task complexity value using Eq. 7 below. The task complexity value obtained using this equation for distant HD aerial imagery is 13.5.

Table 10. Attribute Weights and Values for Distant HD Aerial Imagery

Distant HD Aerial Imagery		
Attributes	Weight	Value
Equipment Weight	0.3	7
Composition	0.2	5
Proximity	0.3	2
Stability	0.2	4

$$T(x) = \sum_{i=0}^n M_T * [w_i * A_i]$$

$$T(x) = 3 * [(0.3 * 7) + (0.2 * 5) + (0.3 * 2) + (0.2 * 4)]$$

$$T(x) = 13.5$$

Equation 7. Task Complexity Value of Distant HD Aerial Imagery

Once the operational scenario has been quantified, the factors to evaluate the UAS characteristics must also be quantified. In order to do so, we use the two parameters we use the Autonomy Level (AL) and Technology Readiness Level (TRL). Since this flight controller of the

UAS in this situation uses a pre-programmed waypoint navigation, it has an AL value of 5. The UAS used here is being deployed on a mission of capturing HD images, it is assigned a TRL value of 9. Using all the values obtained from the operational scenario and UAS evaluation, we can find out the final operations value for this mission. Using the formula shown in Eq. 8, we get the operations value to be 35.5, which implies that this UAS operation is simple and the UAS available for fulfilling this task is not sophisticated. Based on this low operations value, it is safe to assume that this mission will be relatively cheap to perform and the UAS needed for this task need not be highly sophisticated.

$$V(x) = E(x) + T(x) + 10 * [AL + TRL]$$

$$V(x) = 8 + 13.5 + 10 * [5 + 9]$$

$$V(x) = 35.5$$

Equation 8. Operations value for Operational Scenario 1

Using the environmental complexity, task complexity, AL and TRL values, a simple risk analysis can also be performed that may be used to determine if the mission being performed is safe to execute purely based on the operational scenario and the UAS characteristics. The risk analysis for this operational scenario is performed that by balancing the operational scenario and the UAS characteristics. In this case, the operation to be performed is safe with the available UAS configuration and the environment and task are not too complex to perform.

Operational Scenario 2

A builder wants to perform IR thermal test of a 3 story residential building located in a town to create a heat loss map using a FLIR A6750sc SLS thermal camera mounted on a self-built UAV controlled by a custom build controller which lacks a self-stabilization and altitude hold system. The operation is planned to take place on a high visibility and medium wind speed day with manual remote control from the ground.

Similar to the previous case, we will start by using the operational scenario metrics of the infrastructure types and data acquisition methods to obtain the environmental complexity and task complexity values. The three story building being scanned in this case comes under the ‘small buildings’ category that has a value of 4 in our infrastructure metrics. All the attributes in this analysis are equally weighted and the attribute values are determined by comparing the building being scanned in this scenario to other buildings. The size of this building is assigned an attribute value of 7 based on the size of the buildings being scanned, since the UAV will be operating in close proximity to the building, there may be few obstacles such as antennas, hence the physical obstacles attributes value is 5. Since the scan is conducted on a high visibility and medium wind day, the weather is assigned a value of 4 and the geography of the small town is given a value of 3. Due to the amount of metallic structures such as television antennas present near the building, the signal interference may be low to moderate and is assigned a value of 3. The attribute weights and values for each of the five attributes that help us quantify the environment complexity are shown in Table. 11 below. Using Eq. 9, the final environmental complexity value was computed to be 17.6.

Table 11. Attribute weights and values for a three story building

3 Story Building		
Attributes	Weight	Value
Size of Structure	0.2	7
Physical Obstacles	0.2	5
Weather	0.2	4
Geography	0.2	3
Signal Interference	0.2	3

$$E(x) = \sum_{i=0}^n M_E * [w_i * A_i]$$

$$E(x) = 4 * [(0.2 * 7) + (0.2 * 5) + (0.2 * 4) + (0.2 * 3) + (0.2 * 3)]$$

$$E(x) = 17.6$$

Equation 9. Environmental Complexity Value of three story building

We can calculate the task complexity value using the data acquisition metrics and the set of attribute weights and values associated with it. On referring to the list of data acquisition metrics, the ‘infrared thermography’ task being performed here has a value of 7. For this task, the four different attributes along with its assigned weights and values are shown in Table. 12 below. The equipment weight attribute is assigned a weight of 0.3 and given an attribute value of 7 due to the weight of the FLIR A6750sc SLS [43] thermal camera being heavier compared to other thermal cameras. The accuracy is assigned a weight of 0.3 and has an attribute value of 8, due to the camera’s excellent image quality of 640×512 pixels [43]. The proximity is weighted at 0.2 and assigned a value of 7, since the quadcopter will need to fly at least 10 feet close to the building walls to perform this scan. Since the acquisition time of the data from this camera mounted on the UAS is slightly above average compared to other thermal cameras, it is assigned

a value of 6. Using these weights and values of the attributes shown in Table. 12, we can calculate the task complexity value using Eq. 10 below. The task complexity value obtained using this equation for distant HD aerial imagery is 49.7.

Table 12. Attribute Weights and Values for Infrared Thermography

Infrared Thermography		
Attributes	Weight	Value
Equipment Weight	0.3	7
Accuracy	0.3	8
Proximity	0.2	7
Acquisition Time	0.2	6

$$T(x) = \sum_{i=0}^n M_T * [w_i * A_i]$$

$$T(x) = 7 * [(0.3 * 7) + (0.3 * 8) + (0.2 * 7) + (0.2 * 6)]$$

$$T(x) = 49.7$$

Equation 10. Task Complexity Value of Infrared Thermography

Once the operational scenario has been quantified, the factors to evaluate the UAS characteristics must also be quantified. In order to do so, we use the two parameters we use the Autonomy Level (AL) and Technology Readiness Level (TRL). Since this is a self-built UAV and it lacks a flight controller that is capable of auto stabilization and can only perform remote control operations, it has an AL value of 1. The UAV used here has been put together using off-the shelf components with not much formal testing and is therefore assigned a low TRL value of 5. Using the values obtained from the operational scenario and UAS evaluation, we can find out the final operations value for this mission. Using the formula shown in Eq. 11, we get the operations value to be 73.3, which implies that this UAS operation and environment is

intermediate and the UAS available for fulfilling this task is very rudimentary. Based on this operations value, it is safe to assume that this mission may be moderately valuable to perform and the UAS needed for this task may need to be slightly sophisticated as well.

$$V(x) = E(x) + T(x) + 10 * [AL + TRL]$$

$$V(x) = 17.6 + 49.7 + 10 * [1 + 5]$$

$$V(x) = 73.3$$

Equation 11. Operations value function for Operational Scenario 2

Using the environmental complexity, task complexity, AL and TRL values, a simple risk analysis can also be performed that may be used to determine if the operation being performed is safe to perform purely based on the operational scenario and the UAS characteristics. From this risk analysis, we see that on balancing the operational scenario and the UAS, the operation is not safe to be performed with the available UAS configuration. In this situation, the environment and task are much more complex than what the UAS technology used here can handle. One way to solve this issue would be to perform some major upgrades to the autonomy and robustness of the UAS itself or wait for the wind speed to reduce for safer operations.

Operational Scenario 3

A wind turbine company wants to perform ultrasonic NDE on the blades of the wind turbine to identify and locate delaminations and micro cracks present on a 350 ft tall wind turbine located in a rural area. A custom built quadcopter UAV that uses an Ardupilot flight control system assisted by GPS navigation will be remotely operated by a pilot to accomplish this task.

In this scenario, we will start by using the operational scenario metrics of the infrastructure types and data acquisition methods to obtain the environmental complexity and task complexity values. The wind turbine being scanned in this case comes under the ‘wind turbine’ category that has a value of 7 in our infrastructure metric's. All the attributes in this analysis is equally weighted and the attribute values are determined by comparing the wind turbine being scanned in this scenario to other wind turbines. This wind turbine is 350 ft tall, it is assigned a high attribute value of 9. Since this wind turbine does not have too many obstacles around it other than its blades, the attribute value is 5. The weather around wind farms are usually very windy and therefore is assigned a value of 8 and the geography of wind farms is given a value of 6 due to the non flat lands where they are located. Around wind farms, there are very few antennas and telecom towers in the surroundings, so signal interferences against the UAS radio signal is very low and therefore assigned a value of 2. The Table. 13 shown below contains the attribute weights and values for each of the five attributes that help us quantify the environment complexity. Using the weights and values of the attributes obtained from Table. 9, we can calculate the environment complexity value as shown in Eq. 12 below. The final environmental complexity obtained using this equation turns out to be 42.

Table 13. Attribute weights and values for a Wind Turbine

Wind Turbine		
Attributes	Weight	Value
Size of Structure	0.2	9
Physical Obstacles	0.2	5
Weather	0.2	8
Geography	0.2	6
Signal Interference	0.2	2

$$E(x) = \sum_{i=0}^n M_E * [w_i * A_i]$$

$$E(x) = 7 * [(0.2 * 9) + (0.2 * 5) + (0.2 * 8) + (0.2 * 6) + (0.2 * 2)]$$

$$E(x) = 42$$

Equation 12. Environmental Complexity Value of a Wind Turbine

Similarly, we can calculate the task complexity value using the data acquisition metrics and the set of attribute weights and values associated with it. On referring to the list of data acquisition metrics, the ‘contact ultrasonic NDE’ task being performed here has a value of 10. For this task, the four different attributes along with its assigned weights and values are shown in Table. 14 below. The equipment weight attribute is assigned a weight of 0.3 and given an attribute value of 9 due to ultrasonic NDE equipment being heavier compared to other inspection equipments. The precision is assigned a weight of 0.3 and an attribute value of 8, since carrying out ultrasonic NDE using UAS requires a high level of stability and constant contact pressure between the transducer and the wind turbine blades. The depth penetration is weighted at 0.2 and assigned a value of 6, since the ultrasonic waves must pass through multiple layers of composite in order to obtain valuable data regarding the damages underneath the turbine blade. The amount

of area that the transducer can scan in a single pass is assigned a weight of 0.2 and a value of 8, since it is an important aspect in determining the surface area scanned in a single flight. Using these weights and values of the attributes shown in Table. 14, we can calculate the task complexity value using Eq. 13 below. The task complexity value obtained using this equation for contact ultrasonic NDE is 79.

Table 14. Attribute Weights and Values for Ultrasonic Contact NDE

Ultrasonic NDE		
Attributes	Weight	Value
Equipment Weight	0.3	9
Precision	0.3	8
Penetration	0.2	6
Scanned Area	0.2	8

$$T(x) = \sum_{i=0}^n M_T * [w_i * A_i]$$

$$T(x) = 10 * [(0.3 * 9) + (0.3 * 8) + (0.2 * 6) + (0.2 * 8)]$$

$$T(x) = 79$$

Equation 13. Task Complexity Value of Ultrasonic Contact NDE

Once the operational scenario has been quantified, the factors to evaluate the UAS characteristics must also be quantified. In order to do so, we use the two parameters we use the Autonomy Level (AL) and Technology Readiness Level (TRL). The Ardupilot flight controller [44] of this UAV is operated using GPS assisted remote controlled navigation, so has an AL value of 4. The quadcopter used here is deployed to perform contact ultrasonic NDE for the mission and is assigned a TRL value of 8, since the quadcopter is a prototype performing in a

realistic mission scenario. Using all the values obtained from the operational scenario and UAS evaluation, we can find out the final operations value for this mission. Using the formula shown in Eq. 14, we get the operations value to be 133, which implies that this UAS operation is highly complex and the UAS required for fulfilling this task must be highly sophisticated in terms of autonomy and robustness. Based on this high operations value, it is safe to assume that this mission will be expensive to perform and the UAS needed for this task must be highly sophisticated in terms of technology and robustness.

$$\begin{aligned}
 V(x) &= E(x) + T(x) + 10 * [AL + TRL] \\
 V(x) &= 42 + 79 + 10 * [4 + 8] \\
 V(x) &= 133
 \end{aligned}$$

Equation 14. Operations value function for Operational Scenario 3

Using the environmental complexity, task complexity, AL and TRL values, a simple risk analysis is performed that may be used to determine if the operation being performed is safe to perform purely based on the operational scenario and the UAS characteristics. The risk analysis for this operational scenario shows that the operation to be performed is not safe with the available UAS configuration and the task is too complex to perform in the given environment. The solution to this issue would be to improve the autonomy and robustness of the UAS that will perform the ultrasonic testing operations on the wind turbine.

Operational Scenario 4

A bridge inspection company wants to perform a routine LiDAR scan of a large suspension bridge located in a major city using a Rutescene LiDAR mounted on a DJI MATRICE 600 for performing this survey. This UAV is equipped with an obstacle avoidance system and will be pre-programmed a path to scan the bridge while facing wind speeds of 19 mph.

To conduct this analysis, the operational scenario metrics of the infrastructure types and data acquisition methods will be used to obtain the environment complexity and task complexity values. The large suspension bridge to be scanned in this scenario comes under the ‘suspension bridge superstructure’ category of our infrastructure type metrics and has a value of 10. All the attributes in this analysis is equally weighted and the attribute values are determined by comparing the large bridge in this scenario to other suspension bridges. The size of this large bridge is assigned an attribute value of 9, and since this suspension bridge has many obstacles surrounding it, the physical obstacles attributes value is assigned to be 10. Since the survey is conducted on a very windy day above a busy city, the weather is assigned a value of 8 and the geography is given a value of 7. Due to the large amount of metallic structures such as suspension wires and steel beams on the bridge, radio and signal interferences will be extremely high and therefore assigned a value of 8. The Table. 15 shown below lists out the attribute weights and values for each of the five attributes that help us quantify the environment complexity. Using these weights and values of the attributes obtained, we can calculate the environment complexity value as shown in Eq. 15 below. The final environmental complexity obtained using this equation is 84, which is an indication of a very difficult environment.

Table 15. Attribute weights and values for Suspension Bridge Superstructure

Suspension Bridge Superstructure		
Attributes	Weight	Value
Size of Structure	0.2	9
Physical Obstacles	0.2	10
Weather	0.2	8
Geography	0.2	7
Signal Interference	0.2	8

$$E(x) = \sum_{i=0}^n M_E * [w_i * A_i]$$

$$E(x) = 10 * [(0.2 * 9) + (0.2 * 10) + (0.2 * 8) + (0.2 * 7) + (0.2 * 8)]$$

$$E(x) = 84$$

Equation 15. Environmental Complexity Value of Suspension Bridge Superstructure

Similarly, we can calculate the task complexity value using the data acquisition metrics and the set of attribute weights and values associated with it. On referring to the list of data acquisition metrics, the ‘LiDAR scan’ task being performed here has a value of 6. For this task, the four different attributes along with its assigned weights and values are shown in Table. 16 below. The equipment weight attribute is assigned a weight of 0.3 and given an attribute value of 7 due to the *Routescene LidarPod* [45] being significantly higher than other UAV based LiDAR units. The precision is assigned a weight of 0.3 and an attribute value of 7, since this LiDAR unit is capable of <20mm accuracy at a distance of 100m [46]. The proximity is weighted at 0.2 and assigned a value of 8, since the LiDAR can collect 700,000 3D points per second while surveying any structure. Since the acquisition time needed for this LiDAR to map this structure would be lower due to its high speed of data collection, is given a weight of 0.2 and is assigned a

value of 4. Using these weights and values of the attributes shown in Table. 16, we can calculate the task complexity value using the Eq. 16 below. The task complexity value obtained using this equation for this LiDAR survey is 37.8, which is lower than the previous case of ultrasonic NDE.

Table 16. Attribute Weights and Values for LiDAR

Light Detection and Ranging (LiDAR)		
Attributes	Weight	Value
Equipment Weight	0.3	6
Precision	0.3	7
Point Density	0.2	8
Acquisition Time	0.2	4

$$T(x) = \sum_{i=0}^n M_T * [w_i * A_i]$$

$$T(x) = 6 * [(0.3 * 6) + (0.3 * 7) + (0.2 * 8) + (0.2 * 4)]$$

$$T(x) = 37.8$$

Equation 16. Task Complexity Value of LiDAR

Once the operational scenario has been quantified, the factors to evaluate the UAS characteristics must also be quantified. In order to do so, we use the two parameters we use the Autonomy Level (AL) and Technology Readiness Level (TRL). Since the DJI A3 flight controller [47] of the MATRICE 600 UAV [48] used in this situation uses a dynamic obstacle avoidance system coupled with a path planning software, it is assigned an AL value of 7. The commercially available UAS used here has undergone a large amount of testing by the manufacturers before its release in the market to perform the task of performing LiDAR survey for this mission, it is assigned a value of 10. Using the values obtained from the operational

scenario and UAS evaluation, we can find out the final operations value for this mission. Using the formula shown in Eq. 17, we get the operations value to be 138.8, which implies that this UAS operation is quite complex and the UAS used for fulfilling this task must be sophisticated to counter this. Based on the high operations value, we can assume that this mission will be relatively expensive to perform and the UAS needed for this task needs to be highly advanced in terms of both autonomy and reliability.

$$\begin{aligned}
 V(x) &= E(x) + T(x) + 10 * [AL + TRL] \\
 V(x) &= 84 + 37.8 + 10 * [7 + 10] \\
 V(x) &= 138.8
 \end{aligned}$$

Equation 17. Operations value function for Operational Scenario 4

Using the environmental complexity, task complexity, AL and TRL values, a simple risk analysis is performed that may be used to determine if the operation being performed is safe to perform purely based on the operational scenario and the UAS characteristics. The risk analysis for this operational scenario is performed by balancing the operational scenario and the UAS characteristics to each other. Based on the analysis, this operation is safe to be performed with the available UAS configuration in the given environmental conditions. In this situation, although the task and environment are exceptionally complex, the UAS is very competent and robust, thereby capable of performing this complex LiDAR survey without any need for changes or modifications in the high wind weather above a busy city environment.

CHAPTER 7

VALUE FUNCTION SENSITIVITY ANALYSIS

In the previous chapters, we created and applied the value function to four different operational scenarios to calculate the operations avalue and perform a preliminary risk analysis. In this chapter, we will use two operational scenarios from the previous chapter and perform a sensitivity analysis on each of the scenarios to observe if the results of the risk analysis changes and the amount of change to the operations value. The sensitivity analysis is conducted by changing the value of the assigned weights of the task complexity attributes of two different scenarios. In order to maintain simplicity while performing this analysis, the primary list of metrics such as the infrastructure types metrics and data acquisition type metrics will not be changed. Similarly, the assigned attribute values of the environmental complexity and task complexity will also remain same as what was used in the earlier chapter. This setup is meant to ensure fair comparison of results obtained by only changing the assigned attribute weights.

The primary aim of the sensitivity analysis is to investigate the robustness of the results obtained from value functions pertaining to the environmental and task complexities in order to understand how the change in weights assigned to the attributes affect the final results. The sensitivity analysis can be further studied to rate the impact of each of the attributes on the risk analysis results and final operations value to perform uncertainty analysis on the different parameters of this model. Based on the observations from this analysis, changes can also be made to improve the consistency of the value model, so that even if minuscule changes are made to the assigned weights, substantial changes to the final results do not occur.

Operational Scenario 1 Sensitivity Analysis

A state department of transportation wants to perform aerial high definition survey of 5 miles length of an inner city road using a Canon EOS 70D DSLR camera mounted underneath a fixed wing UAV. The UAV is capable of executing a pre-planned path from the ground station and the operation is planned to take place on a high visibility and low wind speed day.

In order to conduct the sensitivity analysis, we will start by using the same operational scenario metrics and attribute values of the infrastructure types and data acquisition types. This analysis will be carried out by changing the balance of the weights between each of the attributes of the data acquisition type to find whether the original risk analysis results changes. The attribute weights of the environmental complexity will not be change in this analysis since all the five attributes are equally important and the main purpose of this test is to identify if any major changes occur in the final risk analysis results if minor changes are made to the task complexity weights. In order to do so, five different sets of weights are assigned to the perform calculations and identify any deviation of risk analysis results from the originally assigned attribute weights.

Table 17. Sensitivity analysis of Operational Scenario 1

Attributes	Value	w ₁	w ₂	w ₃	w ₄	w ₅
Equipment Weight	7	0.3	0.4	0.3	0.2	0.2
Composition	5	0.2	0.3	0.3	0.2	0.3
Proximity	2	0.3	0.2	0.2	0.3	0.2
Stability	4	0.2	0.1	0.2	0.3	0.3
Risk Analysis Results		Safe	Safe	Safe	Safe	Safe

IF

$$0.1 * [E(x) + T(x)] \leq AL + TRL$$

$$0.1 * [8 + 13.5] \leq 5 + 9$$

$$2.15 \leq 14$$

THEN

Operation safe with UAS configuration

ELSE

Operation NOT safe with UAS configuration

Equation 18. Risk Analysis of Operational Scenario 1

The formulation of the risk analysis of operational scenario 1 using the original assigned weights from the previous chapter is shown in Eq 18 above. From this analysis, we see that if the inequality formed by balancing the operational aspect and the UAS characteristics are fulfilled, then the operation is safe to perform based on the available UAS configuration. On changing the weights of the task complexity attributes, we see that although the value on the operations side of the equation changes, the final risk analysis results does not change from the original analysis in either of the five different cases as shown in Table 17. This occurrence is due to the value of the left hand side of the risk analysis equation is significantly smaller than the value of the right hand side of the equation, no change in the final analysis was made by changing the attribute weights, thereby proving the robustness of the risk analysis formulation.

Operational Scenario 2 Sensitivity Analysis

A builder wants to perform IR thermal test of a 3 story residential building located in a town to create a heat loss map using a FLIR A6750sc SLS thermal camera mounted on a self-built UAV controlled by a custom build controller which lacks a self-stabilization and altitude hold system.

The operation is planned to take place on a high visibility and medium wind speed day with manual remote control from the ground.

Similar to the previous case, we will start by using the same operational scenario metrics and attribute values of the infrastructure types and data acquisition types. The sensitivity analysis will be carried out by changing the balance of the weights between each of the attributes of the data acquisition type to find whether the original risk analysis results changes. In order to do so, five different sets of weights are assigned to the perform calculations and identify any deviation of risk analysis results from the originally assigned attribute weights. Similar to the previous case, the environmental complexity attribute weights will not be changed to perform sensitivity analysis tests to maintain simplicity and only understand the the effects of variable weights.

Table 18. Sensitivity Analysis of Operational Scenario 2

Attributes	Value	w ₁	w ₂	w ₃	w ₄	w ₅
Equipment Weight	7	0.3	0.4	0.3	0.2	0.2
Accuracy	8	0.3	0.3	0.2	0.2	0.3
Proximity	7	0.2	0.2	0.3	0.3	0.2
Acquisition Time	6	0.2	0.1	0.2	0.3	0.3
Risk Analysis Results		Unsafe	Unsafe	Unsafe	Unsafe	Unsafe

$$\begin{array}{l}
 \text{IF} \\
 0.1 * [E(x) + T(x)] \leq AL + TRL \\
 0.1 * [42 + 79] \leq 4 + 8 \\
 6.73 \nless 6 \\
 \text{THEN} \\
 \text{Operation safe with UAS configuration} \\
 \text{ELSE} \\
 \text{Operation NOT safe with UAS configuration}
 \end{array}$$

Equation 19. Risk Analysis of Operational Scenario 2

The formulation of the risk analysis of operational scenario 2 using the original assigned weights from the previous chapter is shown in Eq 19 above. From this analysis, we see that if the inequality formed by balancing the operational aspect and the UAS characteristics is not fulfilled, then the operation is not safe to be performed based on either the available UAS configuration or the severe environmental or task complexities involved. On changing the weights of the task complexity attributes, we see that although the value on the operations side of the equation changes, the final risk analysis results does not change from the original analysis in either of the five different sets of weights as shown in Table 18. Here, we see that in all five cases the value of the left hand side of the risk analysis equation is larger than the value on the right hand side of the equation. Since no changes in the final risk analysis results were observed by changing their attribute weights, the robustness of the risk analysis formulation and results holds true when small changes in the attribute weights are introduced into the formulation.

Operational Scenario 3 Sensitivity Analysis

A wind turbine company wants to perform ultrasonic NDE on the blades of the wind turbine to identify and locate delaminations and micro cracks present on a 350 ft tall wind turbine located in a rural area. A custom built quadcopter UAV that uses an Ardupilot flight control system assisted by GPS navigation will be remotely operated by a pilot to accomplish this task.

Similar to the previous case, we will start by using the same operational scenario metrics and attribute values of the infrastructure types and data acquisition types. This analysis will be carried out by changing the balance of the weights between each of the attributes of the data acquisition type to find whether the original risk analysis results changes. The attribute weights of the environmental complexity will not be change in this analysis since all the five attributes are equally important and the main purpose of this test is to identify if any major changes occur in the final risk analysis results if minor changes are made to the task complexity weights. In order to do so, five different sets of weights are assigned to the perform calculations and identify any deviation of risk analysis results from the originally assigned attribute weights.

Table 19. Sensitivity Analysis of Operational Scenario 3

Attributes	Value	w ₁	w ₂	w ₃	w ₄	w ₅
Equipment Weight	9	0.3	0.4	0.3	0.2	0.2
Precision	8	0.3	0.3	0.2	0.2	0.3
Penetration	6	0.2	0.2	0.3	0.3	0.2
Scanning Area	8	0.2	0.1	0.2	0.3	0.3
Risk Analysis Results		Unsafe	Unsafe	Safe	Safe	Unsafe

$$\begin{array}{l}
 \text{IF} \\
 0.1 * [E(x) + T(x)] \leq AL + TRL \\
 0.1 * [42 + 79] \leq 4 + 8 \\
 12.1 \not\leq 12 \\
 \text{THEN} \\
 \text{Operation safe with UAS configuration} \\
 \text{ELSE} \\
 \text{Operation NOT safe with UAS configuration}
 \end{array}$$

Equation 20. Risk Analysis of Operational Scenario 3

The formulation of the risk analysis of operational scenario 3 using the original assigned weights from the previous chapter is shown in Eq 20 above. Similar to the two previous operational scenarios, if the inequality formed by balancing the operational aspect and the UAS characteristics is not fulfilled, then the operation is not safe to be performed. On changing the weights of the task complexity attributes, we see that the value on the operations side of the equation changes from the original analysis and this induces a change in the final risk analysis results in two out of five different sets of weights as shown in Table 19. Among the five cases studied, the value of the left hand side of the risk analysis equation is smaller than the value on the right hand side of the equation in two cases. These changes in the final risk analysis results can primarily be attributed to the fact that the value of the operations side of the equation (LHS) is very close to the UAV characteristics side of the equation (RHS), the proximity of these values cause the results obtained from the risk analysis to be very volatile as compared to the previous cases. Thus exhibiting a possible limitation in the weighted method of performing risk analysis.

CHAPTER 8

SUMMARY, CONCLUSION AND FUTURE WORK

Summary and Conclusion

This research project gives us a broad overview of the different types SHM applications using UAS and how the value and risk of these operations can be quantified using a value based analysis approach. The value model we constructed incorporates critical aspects of the UAS performing a SHM mission such as the environment of the mission, the objectives and task of the mission as well as the various physical, software and technical attributes of the UAS. The hardware and technical features of a fixed wing and multirotor UAS were broken down into its subsystems in a DSM to clearly show the relation between all the components. Similarly, in order to quantify the software and ‘intelligence’ attributes of the UAS, the table AL and TRL were used. The environment and task complexity were also represented as functions supported by attributes and metrics to incorporate into the final operations and risk values.

Using these four primary factors, the final value model that was created that laid the foundation for quantifying and analyzing the operations value and the risk value of the UAS operation. The risk model further evaluates in the decision analysis of whether the UAS operator must proceed to perform the flight mission while prioritizing safety. The operations value provides the UAS operator with a final numerical value that can be used to create pricing models for missions. Finally, the sensitivity analysis performed by changing the assigned weights of the attributes associated with the task and environment complexities on the value and risk models demonstrated the robustness and reliability of these models.

Future Work

The research relating to the evaluation of autonomy of UAS for different applications hold a large amount of value for years to come. The value model created in this thesis to broadly quantify the value of operations and perform an elementary risk analysis may be further researched and expanded to include a dollar based analysis for the different operational scenarios. This detailed value function can be used to determine insurance rates based on scenario, true cost of a UAS crash and the probability of mishaps that may lead to a catastrophic operational failure. An expected utility function may also be developed to perform risk analysis based on the probability and severity of possible occurrences, which may be supported by results from stochastic simulations that identify different failure modes during operations. This can be further iterated by creating a detailed value model comprising of the UAS subsystems along with a comprehensive list of all its major parts and how their characteristics affects the final performance of the UAS in an operational scenario.

Another form of research that could stem out of this could be to perform qualitative and quantitative comparison of UAS based SHM techniques to other traditional SHM methodologies such as manual inspection, embedded sensors and aircraft or helicopter based surveying. The pros and cons of each of these methods can be compared by using operations cost, accessibility, quality of data, total time required .etc. as some of the benchmark attributes. This can be used to synthesise a quality/dollar value contrast of data collected through the different methodologies and then using a bargain model to explore an optimized combined approach for performing effective SHM over a long period of time and on a larger multi-tiered scale.

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APPENDIX MATLAB CODE FOR OPERATIONS VALUE AND RISK ANALYSIS CALCULATIONS’.

```
% Akash Vidyadharan
% MS Thesis AerE
% Appendix A - Operations Value and Risk Analysis calculations
Clear,clc
```

```
% Scenario 1: DOT aerial survey of city road
E_1 = 2*((0.2*5)+(0.2*4)+(0.2*2)+(0.2*4)+(0.2*5));
T_1 = 3*((0.3*7)+(0.2*5)+(0.3*2)+(0.2*4));
AL_1 = 4;
TRL_1 = 9;
V_1 = E_1+T_1+AL_1+TRL_1;
if 0.1*[E_1+T_1]< AL_1+TRL_1
    disp('UAS Operation safe')
else
    disp('UAS Operation NOT safe')
End
```

```
% Scenario 2: Thermal map of building
E_2 = 4*((0.2*7)+(0.2*5)+(0.2*4)+(0.2*3)+(0.2*3));
T_2 = 7*((0.3*7)+(0.3*8)+(0.2*7)+(0.2*6));
AL_2 = 1;
TRL_2 = 5;
V_2 = E_2+T_2+AL_2+TRL_2;
if 0.1*[E_2+T_2]< AL_2+TRL_2
    disp('UAS Operation safe')
else
    disp('UAS Operation NOT safe')
End
```

```
% Scenario 3: Wind turbine blade Ultrasonic NDE
E_3 = 7*((0.2*9)+(0.2*5)+(0.2*8)+(0.2*6)+(0.2*2));
T_3 = 10*((0.3*9)+(0.3*8)+(0.2*6)+(0.2*8));
AL_3 = 4;
TRL_3 = 8;
V_3 = E_3+T_3+AL_3+TRL_3;
if 0.1*[E_3+T_3]< AL_3+TRL_3
```

```

    disp('UAS Operation safe')
else
    disp('UAS Operation NOT safe')
End

```

```

% Scenario 4: LiDAR scan of bridge superstructure
E_4 = 10*((0.2*9)+(0.2*10)+(0.2*8)+(0.2*7)+(0.2*8));
T_4 = 6*((0.3*6)+(0.3*7)+(0.2*8)+(0.2*4));
AL_4 = 7;
TRL_4 = 10;
V_4 = E_4+T_4+AL_4+TRL_4;
if 0.1*[E_4+T_4] < AL_4+TRL_4
    disp('UAS Operation safe')
else
    disp('UAS Operation NOT safe')
end

```