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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

OPTIMAL PAYLOAD DESIGN FOR THE NAVY'S FUTURE UAS

by

Stephen J. Ward

June 2018

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13. ABSTRACT (maximum 200 words)

The Tern is a future Navy unmanned aerial system that will deploy on and launch from surface ships such as destroyers. It is designed to be capable of performing multiple types of sorties such as anti-submarine warfare; information, surveillance, and reconnaissance; and acting as a node in a communication network. Each type of sortie has different operational and physical requirements manifested in the payload onboard the Tern. There are two forms a payload can take: fixed and modular. The fixed payload is hard-wired into the Tern while the modular payload space on the Tern supports the ability to change the payloads for each sortie. Multiple possible scenarios and operational postures add another level of complexity in determining optimal payload configurations. The overarching issue that we will address in this research is the general design of the Tern payload. This design must take into account the inherent stochasticity of the situations in which the Tern will operate. While conducting a primary task within a sortie, the Tern could also be called to carry out other tasks as the situation dictates. For every possible realization of a sortie a Tern is sent on, there is an optimal payload design that addresses the possible tasks in the sortie. Consequently, each design satisfies a given measure of effectiveness with a certain expected effectiveness. The objective is to find a global payload design that maximizes responsiveness over all possible sorties and scenarios.

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OPTIMAL PAYLOAD DESIGN FOR THE NAVY'S FUTURE UAS

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Submitted in partial fulfillment of the
requirements for the degree of

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(OPERATIONS RESEARCH)**

from the

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ABSTRACT

The Tern is a future Navy unmanned aerial system that will deploy on and launch from surface ships such as destroyers. It is designed to be capable of performing multiple types of sorties such as anti-submarine warfare; information, surveillance, and reconnaissance; and acting as a node in a communication network. Each type of sortie has different operational and physical requirements manifested in the payload onboard the Tern. There are two forms a payload can take: fixed and modular. The fixed payload is hard-wired into the Tern while the modular payload space on the Tern supports the ability to change the payloads for each sortie. Multiple possible scenarios and operational postures add another level of complexity in determining optimal payload configurations. The overarching issue that we will address in this research is the general design of the Tern payload. This design must take into account the inherent stochasticity of the situations in which the Tern will operate. While conducting a primary task within a sortie, the Tern could also be called to carry out other tasks as the situation dictates. For every possible realization of a sortie a Tern is sent on, there is an optimal payload design that addresses the possible tasks in the sortie. Consequently, each design satisfies a given measure of effectiveness with a certain expected effectiveness. The objective is to find a global payload design that maximizes responsiveness over all possible sorties and scenarios.

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Table of Contents

List of Figures

List of Tables

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List of Acronyms and Abbreviations

ASW Anti-submarine Warfare

BLOS Beyond Line Of Sight

DARPA Defense Advanced Research Projects Agency

EO/IR Electro-Optical/Infra-Red

GPS Global Positioning System

ISR Intelligence, Surveillance, and Reconnaissance

LOS Line Of Sight

MD-BPP Multi-Dimensional Bin Packing Problem

MEU Marine Expeditionary Unit

MOE Measure Of Effectiveness

NAVAIR Naval Air Systems Command

NPS Naval Postgraduate School

ONR Office of Naval Research

OTH Over The Horizon

RADAR Radio Detection And Ranging

SAG Surface Action Group

SME Subject Matter Expert

UAS Unmanned Aeriel System

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Executive Summary

The use of unmanned aerial systems (UASs) has been growing in recent years within the U.S. military and its implementation brings a wide array of benefits to the Navy in particular. There exist many beneficial attributes of these unmanned aircraft in their reduced cost, increased endurance, limited need for training, ability to send into high-risk situations, and more. These systems are only being used more and thus there lies a need to analyze and optimize their potential.

The Tern is an upcoming UAS which will be used to supplement the resources available to Surface Action Groups (SAGs). The Tern has an advantage in its ability to vertically take off and land, consequently not requiring more than a helicopter launch pad on its home ship. Once it is airborn, the Tern can shift to flying horizontally with its fixed wing structure.The Tern is also capable of being stored in a compact manner, allowing for multiple Terns on each ship.

The problem this thesis investigates is the configuration of payloads onboard the UAS. A *payload* is an item which may be considered for attachment on the Tern. Payloads range from weapons to sensors and communication devices. A *sortie* is the specific mission the Tern is sent to conduct. Over the course of a deployment, the UAS is expected to conduct multiple unique sorties. Since certain payloads may only serve a purpose for some of the sorties, but not all, we consider attaching them as either fixed or modular. If such a payload is fixed, then that payload and all of its mechanisms will be attached in a particular slot for every sortie the Tern undergoes - including those sorties for which it is unneeded. If a payload is modular, then it can be attached and detached as needed according to the planned sortie and its associated tasks.

From a purely functional aspect, it would obviously be ideal for all payloads to be modular so as to maximize tactical flexibility. However, physical constraints such as weight, volume, time to prepare and other factors must be considered when evaluating the trade-offs between choosing modularity versus fixed installation. For example, a fixed payload is presumed to take up less space and be more robust to failure than a modular design which may require additional parts and attachments.

The model is a zero-one linear program where the decision variables are centered on the payloads. The model decides whether a payload will be fixed or modular. If it is fixed, it chooses where on the Tern it is fixed. If it is modular, then the model decides for which sorties it is placed and where. The model is implemented in Pyomo and solved using the CPLEX solver.

The purpose of this thesis is to provide a tool which can be used to better understand the intricacies of fitting a diverse set of objects in spaces with many physical limitations which must adhere also to the constraining factors of the system as a whole and meet a variety of demands. While our work focuses on the application of the model to the Tern, it could easily be used for many similar problems such as the payload configuration of other air platforms, personnel manning, or construction design.

We find in this thesis that the solutions produced by our model are sensible, but not simple. The results favor fixed payloads when possible while still striving for the best total value through the use of modular design. Often, we see results where the model makes trade-offs between various payloads that would take a great deal of analysis and enumeration by hand to arrive at the same solution.

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CHAPTER 1: Introduction

The use of unmanned aerial systems (UASs) has been growing in recent years within the U.S. military and its implementation brings a wide array of benefits to the Navy in particular. There exist many beneficial attributes of these unmanned aircraft in their reduced cost, increased endurance, limited need for training, ability to send into high-risk situations, and more (Rosa et al., 2016). These systems are only being used more and thus there lies a need to analyze and optimize their potential.

There have been multiple recent studies on the use of UAS and their optimal design. For example, it was found that UAS which can vertically take off and land are more beneficial than ones which require runways (Roth & Buckler, 2016). Furthermore, the authors argue that fixed wing designs provide more endurance than rotary, and modular design of payloads is more desirable from an operational perspective. The authors' idea was focused on a ground unit which could quickly exchange payloads as desired to conduct a variety of sorties. In a similar way, we seek in this thesis to design a configuration of payloads on a UAS to conduct a diverse set of sorties.

The Tern is an upcoming UAS which will be used to supplement the resources available to Surface Action Groups (SAGs) (Drones, 2013). The Tern has an advantage in its ability to vertically take off and land, consequently not requiring more than a helicopter launch pad on its home ship. Once it is airborne, the Tern can shift to flying horizontally with its fixed wing structure.The Tern is also capable of being stored in a compact manner, allowing for multiple Terns on each ship. Figure 1.1 shows an artist's rendition of the UAS launching from a helicopter pad.

Artist's rendition of a Tern taking off from a ship's helicopter pad.

Figure 1.1. Tern's vertical launch. Source: Irving (2016)

Each time a Tern launches with a unique set of *tasks*, we call this a *sortie*. The Tern is meant to support a diverse array of sorties from acting as a communication node to anti-submarine warfare (ASW). To meet the demands on each sortie, it would be ideal for the Tern to be loaded with certain *payloads*. For instance, if a sortie contains the task of locating a ship, a radar would be a necessary payload to have on board.

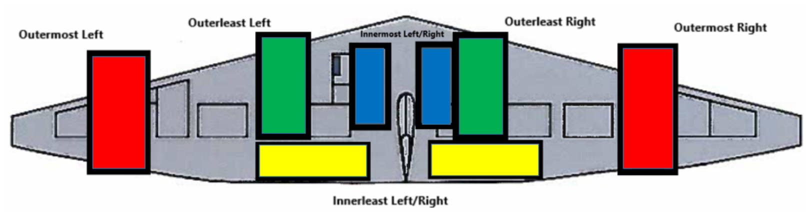
1.1 Background

In May 2014, the Defense Advanced Research Projects Agency (DARPA) and the Office of Naval Research (ONR) made work on the Tern a joint effort (Drozeski, 2018). By October of the same year, the preliminary design of the UAS was completed. The project is currently in the phase of conducting both on-land and at-sea take off and landing demonstrations as well as transitioning from vertical to horizontal flight. In addition, these tests are being done on launching platforms the size of a small naval vessel's flight deck, such as a destroyer.

Since the Tern needs to be capable of many different types of sorties, each type with various tasks that are either certain or uncertain, a diverse array of payloads must be considered for attachment on the UAS. These payloads can be placed in essentially eight slots where there are four different types of slots on each side of the Tern:

- Outermost Left/Right: Outermost racks on the wing $[Red]$
- Outerleast Left/Right: Innermost racks on the wing $[Green]$
- Innerleast Left/Right: Internal bays inside the wing $[Yellow]$
- Innermost Left/Right: Bays inside the wing's center $[Blue]$

These slots are visualized in Figure 1.2. Each type of slots is associated with some constraints affecting the payloads that can be attached.



Schematic representation of Tern's slots for payloads to be placed.

Figure 1.2. Design Layout of Tern's Slots

While the outer racks on the Tern's wings are not designed to hold multiple payloads simultaneously, the internal bays have the potential to hold more than one payload so long as it is feasible with regards to constraints associated with the slot which are manifested in factors such as weight, volume, and heat.

1.2 Description of the Tern

The Tern is essentially a flying unmanned wing with two 10-foot propellers on its nose. The Tern will be one of the largest drones in the U.S. military, capable of carrying up to 600 pounds of ordnance in addition to a variety of sensors (Smith, 2018). Smith (2018) also claims the Tern will "have enough endurance to carry out strike missions as far away as 600 miles." The Tern is capable of both strike and reconnaissance type sorties, providing many new capabilities to smaller navy vessels than in the past.

The slim design allows for easy storage in a ship's hangar. Our focus, however, is on the eight slots described in Figure 1.2. The two outermost slots on either side are racks where a single pod can be attached to each rack. The outermost of these racks can carry more weight than the innermost, but both can manage a great deal of weight.

The other four slots are internal to the UAS. These slots are relatively small areas where payloads can be attached. In these locations, it is possible to fit multiple small payloads in the same location if feasible with regards to various physical limitations.

A *payload* is an item which may be considered for attachment on the Tern. Payloads range from weapons to sensors and communication devices. Since certain payloads may only serve a purpose for some of the sorties, but not all, we consider attaching them as either fixed or modular. If such a payload is fixed, then that payload and all of its mechanisms will be attached in a particular slot for every sortie the Tern undergoes - including those sorties for which it is unneeded. If a payload is modular, then it can be attached and detached as needed according to the planned sortie and its associated tasks.

From a purely functional aspect, it would obviously be ideal for all payloads to be modular so as to maximize tactical flexibility. However, physical constraints such as weight, volume, time to prepare and other factors must be considered when evaluating the trade-offs between choosing modularity versus fixed installation. For example, a fixed payload is presumed to take up less space and be more robust to failure than a modular design which may require additional parts and attachments.

A *configuration* is the term we use when referring to the specific attachment of payloads on the Tern for a certain sortie. In other words, a configuration is both the knowledge of which payloads are fixed to what slots, but also which payloads are made modular to what slots for each sortie.

1.3 Motivation

While the final designs and exact uses of the Tern are not determined yet, the purpose of this research is to provide decision makers a framework to understand the trade-offs of various feasible designs of payloads. For instance, some of the operational constraints described later in this thesis require launch preparation time to be below a certain threshold or demand a minimum amount of fuel to be present before launching. Our research seeks to answer, for a given set of data about payloads, tasks, probabilities, etc., what is the optimal payload configuration on the Tern. A configuration consists of fixed payloads onboard for every sortie and modular payloads attached for particular sorties.

The ability to understand which payloads should be on the Tern always (fixed payload design) and which could be modularized is crucial to developing a versatile asset with maximum effectiveness. The fixed-modular dilemma stems from uncertainties associated with operational and tactical postures associated with the various sorties. These uncertainties relate to the likelihood of the sorties and their constituent tasks.

1.4 Sorties and Tasks

Throughout this thesis, we refer to *sorties* and *tasks*. Every time the Tern launches from the ship it is on a sortie until it lands back on the ship. While on a sortie, the Tern has various tasks to conduct.

While on deployment, many different types of sorties may be conducted and we refer to a particular type of sortie simply as a sortie. For example, a type of sortie could be for the Tern to act as a communication node while also monitoring the area for enemy targets. This sortie may happen multiple times during a deployment. We assume the exact number of a certain sortie is unknown beforehand, but the relative frequency of a sortie can be estimated.

Within a sortie, one or multiple tasks may be required of the Tern. Before the Tern is launched, however, some of these tasks may be unknown and will unfold only during the sortie. We assume that each of these tasks has a probability of becoming realized, which can be estimated by subject matter experts (SMEs) or from previous data.

Possible tasks could be defined as engaging a submarine or detecting an aircraft at high speeds. Some tasks will be known with certainty to occur on a particular sortie before launch. These could be tasks such as detecting surface combatants at long range on a sortie defined to be perimeter monitoring.

The given sorties and their tasks, along with associated probabilities, affect the decision regarding which modular payloads should be on the Tern for just certain sorties and which payloads should be fixed.

1.5 Configurations of Tern Payloads

We define that a configuration of payloads is such that every payload is either fixed to a slot, modular for a set of sorties, or never on the Tern at all. These configurations will be found through solving a zero-one linear program defined in Chapter 3 on a particular set of data. For each instance of data, there will be an optimal configuration. Decision makers can consequently find what design of the Tern will be best for an upcoming deployment. They can even vary parameters they are unsure of to see how the configuration changes.

Deciding to make payloads fixed comes with many advantages. As discussed in Section 1.2, a payload which is fixed takes up less space and weighs less due to fewer parts needed than in the modular case. Furthermore, a fixed payload can be installed in a way that provides robustness and little to no preparation before a launch. On the other hand, modular design of payloads allows for the flexibility of outfitting the Tern to meet tasks on the current sortie without superfluous payloads on board. The benefits and shortcomings must all be considered in deciding the loadout for the fixed design and each sortie.

Since most ships have the ability to house multiple Terns, it may be prudent to have different configurations for each of them in order to maximize their collective effectiveness. Furthermore, an entire SAG might find it useful to employ various groupings of Terns, each with a different distribution of configurations.

1.6 Literature Review

Many studies have been performed in recent years on the use of UAS. Payton (2011) analyzes the best application of UAS for the Marine Expeditionary Units (MEU) with an array of possible sorties. The author found through surveys that top sorties for MEUs included Intelligence, Surveillance, and Reconnaissance (ISR), strike, and communication relay. These are all sorties we discuss when considering the payload configuration for the Tern in Chapter 4.

Pearson (2008) discusses a model to schedule the flight plans for a UAS conducting multiple sorties. While this thesis also considers the demands of various sorties, we focus our model on how the configuration of payloads can better meet the demands within each sortie. Johnson (2004) explores the organizational structures that could be implemented to task unmanned vehicles, but does not delve into the design of the actual system as we do in this thesis.

The knapsack problem, which is at the core of our optimization model, is one of the most commonly known problems where there exists a container with a finite capacity and several items with associated weights and values. The goal is thus to achieve the highest value of the items in the container without exceeding its capacity. This problem is extended to multiple dimensions where weight is not the only constraint, but also volume, time, and several other necessary conditions for feasible, applicable solutions. The multidimensional 0-1 knapsack problem (as the one described in Chapter 3) has been studied thoroughly over the past half century and is known to be NP-hard (Fréville, 2004).

The problem we are studying is more than just that of the knapsack where only one container is present. Rather, there are multiple bins with varying characteristics which we refer to as slots. This structure is akin to the multi-dimensional bin packing problem (MD-BPP) where the goal is to fit all the objects demanded into a set of alloted bins much like we do in this research with payloads (Martins, 2003). The classical application of the MD-BPP is fitting objects which have physical dimensions into spaces which also have physical dimensions. For example, fitting spheres into cubical containers. Our application of this problem interprets the dimensions to be various physical considerations such as the heat of the payloads in each slot and the net torque of the Tern.

With focus on the design of ships, this problem has been approached via the use of MD-BPP in order to develop the layout of various compartments on a ship with regards to a multitude of constraining factors (Oslebo, 2014). In a similar manner we seek to develop a mapping of payloads to slots and sorties with regards to numerous physical constraints. However, we also address the uncertainty guiding which payloads will be made fixed and modular.

Further studies show the use of MD-BPP applied to the packing of boxes into containers on a cargo airplane (Paquay, Schyns, & Limbourg, 2016). Once again, the methodology and structure of the model hold close to the approach used in this research. However, we have extended the model to include the idea of sorties where the Tern in our case must be re-packed with modular payloads before each launch. Consequently, we must consider the frequency of sorties as well as the unknown demands on each sortie in order to decide which payloads will remain on the Tern and which will be re-packed.

With regards to the design and configuration of payloads onboard a UAS, there is little that has been studied. A thesis from 1993 produced an analysis on the difference between using a UAS with only electro-optical sensors versus multiple sensors as they related to the performance of search-related sorties (Keane, 1993). The model constructed to design the UAS with multiple sensors holds similarities to our model in that the decisions centralized on which payloads to bring onboard with considerations to the weight, volume, and power capacities of the UAS itself. However, this approach did not consider the location of each payload, nor many of the physical constraints we appended to our model. Furthermore, the approach from 1993 did not take into consideration the option of modularity and consequently the resulting payload configuration for each sortie and the uncertainties involved.

From reviewing similar previously studied problems, it appears that our approach is unique in our focus on the decision of making payloads fixed or modular. Previous work has considered this type of problem best modeled with a knapsack style approach and even more accurately with bin packing. Models have focused on the fixed design of UAS without heed for the uncertainties and varying demands that each launch entails. We claim in our research that the use of modularity within situational and physical constraints leads to far better solutions to meet the challenges faced on deployment.

1.7 Outline of Thesis

In this thesis, we begin in Chapter 2 by laying out the basics of our mathematical approach as well as a brief discussion on an alternative algorithmic approach. In Chapter 3 we describe in detail the formulation of our linear program and apply this in Chapter 4 on an example problem. We expand on these ideas in Chapter 5 by investigating the configuration of two and three Terns simultaneously and analyze the results. We then perturb the data from an example problem to investigate how the results can change with different parameters in Chapter 6. Finally, this thesis concludes in Chapter 7 with our final thoughts on the benefits of the model and possible ways forward.

CHAPTER 2:
Mathematical Approach

The basic mathematical approach we take in this research is based on the classical knapsack formulation (Kelly et al., 2003). Essentially we would like the Tern to be loaded with as many of the best payloads for the tasks of each particular sortie while maintaining feasibility regarding weight, volume, vibration, and other constraining factors. The goals for our model can be simplified to

- **Goal 1:** Choose a configuration of payloads to maximize performance potential across several different sorties, each of which conducts multiple tasks

- **Goal 2:** Choose a configuration of payloads that utilizes as many fixed payloads as possible to effectively execute sorties.

The full model in Chapter 3 has an objective which seeks to maximize the expected performance potential of the Tern for a deployment (**Goal 1**) while adhering to physical limitations. This approach tends to result in configurations with more modular payloads in order to achieve greater tactical flexibility.

In the next section we describe a simplified formulation of our model as a basis for our approach in Chapter 3. The objective of this simplified model is to demonstrate the modeling approach for capturing **Goal 2** in the presence of the uncertainties regarding sorties and tasks discussed in Chapter 1.4. To do this, we seek to maximize the number of fixed payloads used to meet sortie requirements. This promotes robustness in the sense that we reasonably assume fixed payloads are less likely to fail as well as require less preparation time before a sortie. Ideally, the best payloads could all be fixed, but this is rarely achievable. This chapter serves to highlight the trade-off between robustness and flexibility.

2.1 The Simplified Model

Consider a situation where a set of payloads (radar, EO/IR, etc.) is available for placement on the UAS for executing a given set of sorties, each with possibly different requirements and thus varying payload demands. For example, an ASW sortie needs a computer, radar, and torpedo. This simplification provides a binary effectiveness for each payload. However, there are only a finite number of payloads that will be able to fit on the Tern for each sortie launch.

Our decisions are thus to either *fix* a payload to always be on the Tern or *modularize* it in order to change it out for different sorties. We assume that ideally all payloads could just be fixed and consequently provide robustness and efficiency. This obviously could happen only if all sorties require the same set of payloads and those payloads can fit on the Tern. In this manner our objective (2.1.1) is to maximize the number of fixed payloads with the goal of obtaining a solution with the demand of each sortie met using as little modularity as possible. The solution is constrained by the sortie requirements in the form of necessary payloads (2.1.2) as well as the Tern's capacity to carry them (2.1.3).

2.1.1 Sets

$$P = \text{Set of all payloads}$$
$$S = \text{Set of all sorties}$$

2.1.2 Parameters

$$\delta_{p,s} = \begin{cases} 1 & \text{if payload } p \text{ is needed for sortie } s \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, s$$

$$C = \text{The number of payloads that can fit on the Tern}$$

2.1.3 Decision Variables

$$x_p = \begin{cases} 1 & \text{if payload } p \text{ is fixed to the Tern} \\ 0 & \text{otherwise} \end{cases} \qquad \forall p$$

$$y_{p,s} = \begin{cases} 1 & \text{if payload } p \text{ is modular and attached for sortie } s \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, s$$

2.1.4 Formulation

$$\max_{x,y} \quad \sum_{p \in P} x_p \qquad \big[\text{Maximize number of fixed payloads}\big] \tag{2.1.1}$$

$$\text{s.t.} \quad \delta_{p,s}\, x_p + y_{p,s} = \delta_{p,s} \quad \forall p, s \tag{2.1.2}$$

$$\big[\text{Each sortie must have required payloads}\big]$$

$$\sum_{p \in P} \left(x_p + y_{p,s}\right) \leq C \qquad \forall s \tag{2.1.3}$$

$$\big[\text{Total payloads per sortie must be less than capacity}\big]$$

While this is an oversimplified model for the problem at hand, it serves as an illustration to lead into the full model. In Chapter 3 we extend the data to include many more attributes related to the payloads as well as the slots themselves. Furthermore, the decisions are expanded to include the choice of which slot a certain payload will be attached to. The objective is no longer to maximize fixed payloads, but instead to maximize the expected value of the Tern over the entirety of a deployment.

2.2 Solution by Greedy Algorithm

At first glance, it appears that a simple greedy algorithm could be implemented to solve this problem without the use of optimization techniques. The proposed algorithm would be as follows:

Algorithm 2.2.1.

- ***Step 1:*** *Sort all payloads by how frequently they are needed (i.e. sort by* $\sum_s \delta_{p,s}$*).*

- ***Step 2:*** *Make the most frequently used payloads fixed as long as there is capacity on the Tern.*

- ***Step 3:*** *While there are still payloads unattached, make them modular for each sortie they are required, overfilling capacity if necessary.*

- ***Step 4:*** *While the number of payloads onboard the Tern exceeds capacity for any sortie, make the least frequently needed and currently fixed payload modular for only the sorties it is needed.*

We will illustrate these steps with examples to make things more clear. This method is simple however, with $O(p^2)$ runtime, but only comes to the same solution as the optimization in every case when there are two or fewer sorties. This can be proven as follows:

Theorem 2.2.2. *Algorithm 2.2.1 will produce the optimal solution for two or fewer sorties (*$|S| \leq 2$*).*

Proof. Let sortie 1 be the sortie with the most payloads required with m total payloads and sortie 2 be the second sortie with the number of payloads required defined as n. Let s be the number of payloads required by both sorties. Then, the total number of payloads is $m + n - s$. Let k be the number of slots such that $m \leq k \leq m + n - s$. The number of shared payloads s are made fixed, then the next $k - n$ payloads required by sortie 1 are made fixed. There are now $n - s$ slots left. We know the number of unattached payloads for sortie 1 is $(n - s) + (m - k) \leq (n - s)$ since $k \geq m$ and we know there are still $n - s$ payloads unattached for sortie 2. Consequently, the number of payloads unattached for sortie 1 is less than or equal to those unattached for sortie 2. Therefore, the algorithm chooses to fix the next $k - m$ payloads for sortie 2. There are now a total of $2k - (m + n - s)$ payloads fixed and $(m + n - s) - k$ slots left for modularity. Then, the remaining $(m + n - s) - k$ payloads needed by sortie 1 are made modular for sortie 1 and the remaining $(m + n - s) - k$

payloads needed by sortie 2 are made modular for sortie 2. Since there are exactly the same number of slots left for modularity as there are unattached payloads for both sortie 1 and sortie 2, any additional payload made fixed will cause infeasibility. Therefore, the solution is optimal. □

To show how this algorithm breaks down for more than two sorties, we consider the following example. Consider a scenario in which there is a set of five payloads: $\{p_1, p_2, p_3, p_4, p_5\}$ and three sorties: $\{s_1, s_2, s_3\}$. Table 2.1 shows the payload requirements for each of the three sorties. Since the maximum number of payloads needed for any sortie is four and having a capacity of five is trivial, we set the capacity of the Tern to four for this example.

Table 2.1. Greedy Algorithm: Sortie-Payload Requirements

		Sorties		
		s_1	s_2	s_3
Payloads	p_1	0	1	1
	p_2	1	1	1
	p_3	1	1	0
	p_4	0	1	1
	p_5	0	0	1

This table shows the initial payload requirements for each sortie ($\delta_{p,s}$).

Table 2.2 displays the ranking of payloads by the number of sorties that are required. When there is a tie, the payload with the higher subscript is taken to be more important.

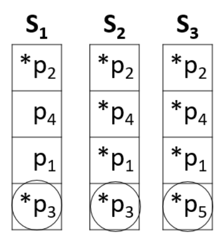
Figure 2.1 shows the optimal configuration found by solving the integer linear program from Section 2.1 in Pyomo with the CPLEX solver. Note that payloads p_1, p_2, and p_4 are fixed with one modular spot for p_3 and p_5 as modular payloads for their respective sorties.

Table 2.2. Greedy Algorithm: Step 1

Order of Importance

Payload	**Number of Sorties**
p_2	3
p_4	2
p_3	2
p_1	2
p_5	1

This table shows the first step of the greedy algorithm: sorting the payloads by the number of sorties they are needed.

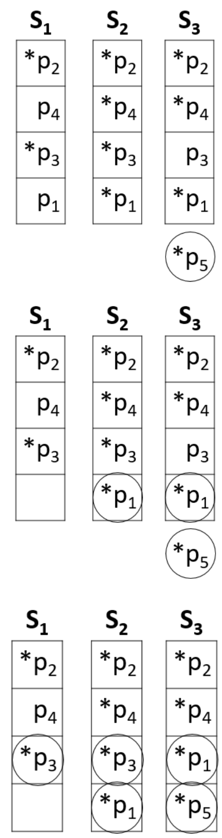


This figure demonstrates the optimal payload configuration for this example. The boxes represent the capacity of the Tern, the * indicates required payloads, and circled payloads are modular.

Figure 2.1. Optimal Payload Configuration

Figure 2.2 depicts the steps of the proposed greedy algorithm to find a solution. The payloads are listed in order in Figure 2.2 according to order in Table 2.2. In the algorithm, we iterate through payloads in reverse order, switching from modular to fixed until we arrive at a feasible solution.

At first, we fix all but p_5 because they are needed more frequently and thus p_5 is made modular for s_3. Since s_3 is over capacity, we make the least needed fixed payload (p_1) modular for sorties s_2 and s_3. As can be seen in Figure 2.2, this change does not solve the capacity issue. Consequently, another iteration is required to change p_3 to be modular for just sorties s_1 and s_2 which now allows for feasibility. However, the better choice would have been to make p_3 modular in the first place since that would have solved the capacity issue for s_3. It can be argued that this would not be problematic if p_1 was considered more important than p_3, but one can also imagine the same issue arising if the numbers in Table 2.1 remain the same and the names of the payloads are randomized.



This figure demonstrates the implementation of the greedy algorithm. The boxes represent the capacity of the Tern, the * indicates required payloads, and circled payloads are modular.

Figure 2.2. Greedy Algorithm: Steps 2-4

Numerical experimentation suggests that so long as there are no ties when constructing Table 2.2, the greedy algorithm will always find the optimal solution. For this to be the case, the number of payloads under consideration has to be equal to the number of sorties. Essentially, there must exist a way to rearrange the rows and columns in Table 2.1 in such a way that the lower triangle of entries is all ones and the upper is all zeros. Of course, it is certainly possible for the algorithm to find the optimal solution in other cases, but it is not guaranteed.

In order to address the ambiguity when there is a tie in payload importance, it is possible to construct a more complicated version of the greedy algorithm. This version allows for making more intelligent choices on which payload should be the next one to be switched from fixed to modular. The algorithm maintains the first three steps as previously discussed, but then in step 4 while a sortie exceeds capacity:

- **Step 4a:** Find the currently fixed payload that is least needed among the sorties which currently have more payloads than capacity allows.

- **Step 4b:** Change this fixed payload to be modular for every sortie it is needed. Repeat **4a** and **4b** until no sortie has more payloads on board than capacity allows.

- **Step 5:** Once feasibility has been reached, make each modular payload fixed if feasible, starting with the ones which are most frequently needed.

This modified greedy algorithm still runs on O(p^2) and is much better at finding the optimal solution than the original algorithm. Applying this modification to solving the example in Figure 2.2, the new algorithm would identify p_3 as the currently fixed payload which is least needed among the sorties which currently have more payloads than capacity allows. Making this payload modular allows for p_5 to fit within the Tern's capacity for s_3. Numerical experimentation reveals that as long as the number of sorties is less than five, this algorithm finds the optimal solution. However, the methodology does not work in every case when there are five sorties and works less frequently as the dimensions continue to increase. The reason for this is that the algorithm would have to iterate through every possible combination to be sure of obtaining the optimal solution. To prove this, we provide a counter-example with 10 payloads and 5 sorties. Table 2.3 details the payload requirements for each sortie in this example.

Table 2.3. Advanced Greedy Algorithm: Sortie-Payload Requirements

		Sorties				
		s_1	s_2	s_3	s_4	s_5
	p_1	1	1	0	0	0
	p_2	0	1	1	1	0
	p_3	1	0	1	0	0
	p_4	0	0	1	1	0
Payloads	p_5	0	1	0	1	0
	p_6	1	0	0	1	0
	p_7	0	0	1	0	0
	p_8	0	1	1	1	1
	p_9	0	0	1	1	0
	p_{10}	0	0	1	0	1

This table shows the initial payload requirements for each sortie ($\delta_{p,s}$).

Table 2.4 shows the first step of the algorithm for this example. As can be seen, there are a high number of payloads (7) which have an equal importance since they are needed for two sorties each. Since sortie s_3 requires the most payloads at seven total, we set the capacity of the Tern to be seven to allow a feasible solution.

Table 2.4. Advanced Greedy Algorithm: Step 1

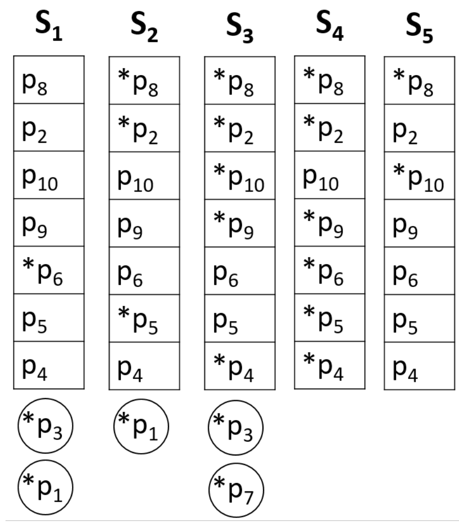
Order of Importance

Payload	**Number of Sorties**
p_8	4
p_2	3
p_{10}	2
p_9	2
p_6	2
p_5	2
p_4	2
p_3	2
p_1	2
p_7	1

This table shows the first step of the greedy algorithm: sorting the payloads by the number of sorties they are needed.

The optimization model yields a solution in which payloads p_2, p_3, p_4, p_8, and p_9 are fixed and the rest are modular as needed. Note that this is a total of five payloads fixed and two modular.

Figure 2.3 displays the second and third steps of the greedy algorithm. The first seven payloads from Table 2.4 are fixed to the available seven slots and the remaining three payloads are made modular where needed, creating excess on the first three sorties.



This figure demonstrates the implementation of the advanced greedy algorithm. The boxes represent the capacity of the Tern, the * indicates required payloads, and circled payloads are modular.

Figure 2.3. Advanced Greedy Algorithm: Steps 2-3

Figure 2.4 demonstrates the iterations taken by the algorithm to swap fixed payloads to be modular until the solution is feasible. In the first round, sortie s_1 is found to be the most overloaded and payload p_4 is the least needed amongst the sorties which are over capacity. Consequently, this payload is altered to be modular only for the sorties needed thus freeing space for sorties s_1 and s_2. Now sortie s_3 is the most overloaded and payload p_5 is not required by either of the overloaded sorties. Once this payload has been modified, sortie s_3 is the only one still exceeding capacity. Therefore, payload p_6 is made modular to allow for feasibility across all sorties. Attempting to fix any of the current modular payloads only results in infeasibility, so the algorithm is terminated.

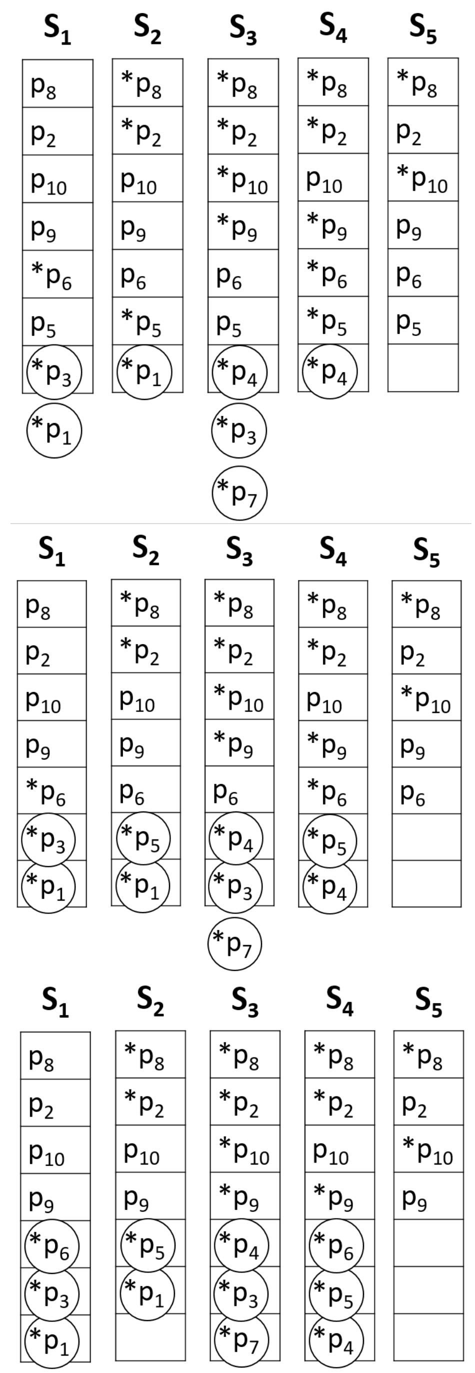
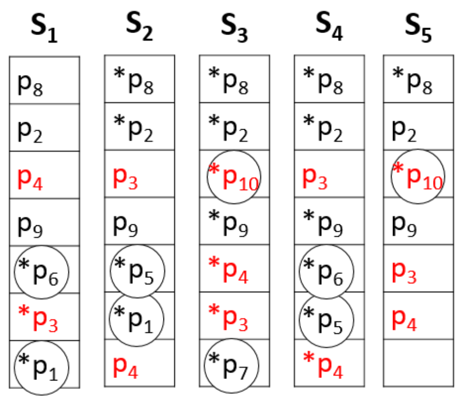


Figure 2.4. Advanced Greedy Algorithm: Step 4

Figure 2.5 shows the solution found by the linear program at optimality. The differences from the solution found using the advanced greedy algorithm are highlighted in red. As can be seen, it was possible to make payload p_{10} modular, allowing for both p_3 and p_4 to be fixed (which is a better solution since our goal is to maximize the use of fixed payloads to meet demand). The algorithm was not able to see this improvement to the final solution because it does not iterate through every possible combination of payloads.



This figure demonstrates the differences in the optimal solution and that of the advanced greedy algorithm with red text.

Figure 2.5. Optimal Solution

While using a greedy algorithm does not always find the “best" solution, as defined by our idea of maximizing robustness in the form of fixed payloads, it does find good solutions. Furthermore, it is of note that the final solution in Figure 2.4 has a total of four empty slots across the five sorties while the optimal solution in Figure 2.5 has only one empty slot across the five sorties. It can be argued that losing a little robustness is worth it to have fewer payloads on sorties s_2 and s_5. Consider a scenario in which sortie s_5 is one where speed, maneuverability, or endurance are paramount and this sortie happens twice as much as any of the others. Obviously, the model discussed in this chapter is too simple and does not account for numerous physical limitations and operational considerations. In the following chapter, we present a more involved model which does consider many pressing factors and requirements.

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CHAPTER 3: Optimization Model

In this chapter we formulate an optimization model for the design of a single-configuration Tern which has four types of slots for payloads. There are two slots of each type for a total of eight slots on the Tern. The goal of the optimization model is to find the optimal balance between fixed and modular payloads such that the Tern is best equipped for every possible sortie. First, we qualitatively describe the formulation and justify it. Then, we provide a detailed mathematical formulation of the optimization problem.

3.1 Physical Considerations

The majority of the constraints within our model are physical limitations with respect to the payloads, slots, the Tern as a whole, and even the ship itself. We assume that since the Tern is designed for use on smaller Navy vessels such as a destroyer, there will be limited space to store payloads.

In regards to the Tern as a whole, weight is the biggest concern. Each sortie has a maximum weight allowance in order to maintain the proper level of maneuverability, speed, and endurance as set forth by the sortie commander. In accordance with this, the balance of torque caused by the payloads must be within specified limitations as set by the engineers of the Tern to enable full control and operability.

There are multiple logical constraints associated with the slots of the Tern. The most simple are that each slot has weight and volume limitations. The slots further from the centerline of the UAS are capable of carrying much heavier payload systems than the slots close to the centerline.

Most of the physical factors limiting the decisions of where to place payloads and whether to attach them as fixed or modular components have to do with the payloads themselves. In order to model the difference in failure rates of payloads that are fixed and modular, each slot experiences a certain amount of vibration and each payload can withstand up to a threshold of vibration and still remain operational. If a payload is made fixed, we assume that it is secured better than if modular and can endure more vibration. In a similar way, some payloads are more sensitive to heat than others. Every slot has an inherent amount of heat and if there are multiple payloads placed in the same slot, their accumulated heat must be taken into consideration. We assume that the metric used for heat has an additive property such that the total heat within a slot is the baseline in summation with the heat produced by each payload. Another issue to be considered is power. Every payload has some level of power requirement and we assume that each slot has a finite supply of power to provide. However, we presume that most of the power supply will be central to the Tern instead of towards the wingtips.

3.2 Operational Considerations

In order to avoid a complex, multi-dimensional objective, we set certain operational requirements as constraints in the optimization model. The first of which is a fuel requirement for each sortie. Obviously, it would be ideal to have as much fuel as possible, but there are other payload necessities and we would also like to minimize the total weight of the Tern. Due to this fact, there is set a minimum amount of fuel each sortie needs in order to capture a time on station element in the model.

We might also want to minimize the time it takes to prepare for an upcoming sortie. To implement this in our model, we add constraints to keep this total time under a preset value for each sortie. While this may not be critical for some routine sorties, one can imagine quick launch times being highly desired for response sorties such as intercepting an enemy force detected over the horizon.

We also consider in our formulation that a sortie commander might want to require a payload from a certain *generic category* be on the Tern for a sortie. For example, a generic category might be radar and the sortie commander has learned from experience that there is no use sending a UAS to conduct an ASW sortie without a radar. If everything is valued properly in the data, the model should choose to attach a radar for the ASW sortie regardless, but this attribute of the model allows the user to be sure certain payloads are attached.

3.3 Counting Payloads

One of the challenges of our formulation is how to account for the value of payloads as they pertain to a particular task, the larger sortie, and the deployment in general. For the purposes of this research, we assume that subject matter experts are able to define what the value of a payload is for each task. We also assume that data exists on the probability of tasks occurring within a sortie and how frequently a sortie is expected to be conducted over the course of a deployment. With this in mind, our model seeks to maximize the expected value of the Tern as an effective asset for the ship it is stationed on.

There are two ways we consider counting payloads and each method has its benefits based on the situation. The first method is for the model to count every payload on board the Tern for an upcoming sortie as providing value. This option is simple and accounts for everything at the Tern's disposal. However, this method falls short when one considers the diminishing returns related to attachment of complimentary, but similar payloads. For example, a situation could exist where the sortie is to perform a search for an item gone overboard. The model sees that Radar A provides a 0.8 value for the task detecting small objects, but EO/IR C also provides a 0.9 value for the same task. In reality, perhaps their combined effect is 0.95, but it is certainly not 1.7. However, the model would choose to take both these payloads, even if it meant not taking additional fuel to be able to search for a longer period of time.

The second method for counting payloads is for every task within a sortie. The model can only count the value of one payload that is on the Tern. In this way, the model would only care about making sure EO/IR C is on the Tern for the sortie since it provides more value than Radar A. However, this method fails to account for synergies between payloads. Continuing with the current example, we say that the combined effect of Radar A and EO/IR C is 0.95 so if there is space on the Tern, it might be prudent to have both payloads to increase the likelihood of finding the lost object. This second method also requires the addition of a large number of binary variables to capture which payload is counted for each task.

An easy solution from a modeling perspective is to assume that there exists data for the value of every combination of payloads for every task. However, it is unrealistic to assume that anyone could accurately produce this information. Consequently, for the purposes of our study, we will assume that tasks are defined to a specificity such that there are no synergies for a task. In other words, for each task, there is no way that multiple payloads can work together to produce better results than the best payload working alone.

3.4 Formulation

What follows is the mathematical formulation of the problem discussed thus far as well as a description of the formulas defining the objective function and each set of constraints.

3.4.1 Sets

$$
\begin{aligned}
g \in G &= \text{Set of generic payload categories} \\
p \in P &= \text{Set of all payloads} \\
P_g \subset P &= \text{Set of specific payloads in category } g && \forall g \\
s \in S &= \text{Set of the eight slots on the Tern} \\
e \in E &= \text{Set of sorties} \\
G_e \subset G &= \text{Set of generic payloads required for sortie } e && \forall e \\
t \in T &= \text{Set of all possible tasks} \\
T_e \subset T &= \text{Set of tasks for sortie } e && \forall e, \\
A &= \{fixed, \; modular\}
\end{aligned}
$$

3.4.2 Parameters

δ_s	=	distance from center of Tern to slot s	$\forall s$
f_e	=	relative frequency of sortie of type e	$\forall e$
$q_{t,e}$	=	probability of task t given sortie e	$\forall e, t : t \in T_e$
$w_{p,a}$	=	weight of payload p with attachment type a	$\forall p, a$
W_s	=	max allowable weight at slot s	$\forall s$
τ	=	max net torque allowed	
ω_e	=	proportion of total weight allowed on Tern for sortie e	$\forall e$
$l_{p,a}$	=	volume of payload p with attachment type a	$\forall p, a$
L_s	=	max allowable volume at slot s	$\forall s$
N	=	total storage volume on the ship for payloads	
$k_{p,s,a}$	=	time to prepare payload p in slot s with attachment type a	$\forall p, s, a$
K_e	=	max time allowed to prepare for sortie e	$\forall e$
h_p	=	heat produced by payload p	$\forall p,$
H_s	=	maximum heat tolerable within any slot s	$\forall s,$
h'_p	=	how much less than the maximum H payload p can tolerate	$\forall p$
r_p	=	power required by payload p	$\forall p,$
R_s	=	power available at slot s	$\forall s,$
b_s	=	vibration at slot s	$\forall s,$
$B_{p,a}$	=	max vibration tolerable by payload p with attachment type a	$\forall p, a$
U_e	=	required volume of fuel for sortie e	$\forall e$
$u_{p,a}$	=	volume of fuel stored in payload p with attachment type a	$\forall p, a : p \in P_{fuel}$
$v_{p,t}$	=	value of payload p for conducting task t	$\forall p, t$

3.4.3 Decision Variables

$$x_{p,s} = \begin{cases} 1 & \text{if payload } p \text{ is fixed to slot } s \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, s$$

$$y_{p,s,e} = \begin{cases} 1 & \text{if modular payload } p \text{ is in slot } s \text{ for sortie } e \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, s, e$$

$$z_{p,a} = \begin{cases} 1 & \text{if payload } p \text{ has attachment type } a \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, a$$

$$m_{p,t,e} = \begin{cases} 1 & \text{if payload } p \text{ has the maximum value} \\ & \text{for task } t \text{ within sortie } e \\ 0 & \text{otherwise} \end{cases} \qquad \forall p, e, t : t \in T_e$$

3.4.4 Formulation

$$Q_e = \sum_{t \in T_e} q_{t,e} \qquad \forall e \in E \tag{3.4.1}$$

$$V(e) = \frac{1}{Q_e} \sum_{p \in P, t \in T_e} m_{p,t,e} \cdot v_{p,t} \cdot q_{t,e} \quad \forall e \in E \tag{3.4.2}$$

$$\max_{x,y,z,m} \qquad \sum_{e\in E} f_e \cdot V(e) \tag{3.4.3}$$

s.t.

$$\sum_{p\in P} l_{p,modular} \cdot z_{p,modular} \leq N \tag{3.4.4}$$

$$\sum_{p\in P} \left[w_{p,fixed} \cdot x_{p,s} + w_{p,modular} \cdot y_{p,s,e}\right] \leq W_s \qquad \forall e, s \tag{3.4.5}$$

$$-\tau \leq \sum_{p\in P, s\in S} \delta_s \left[w_{p,fixed} \cdot x_{p,s} + w_{p,modular} \cdot y_{p,s,e}\right] \leq \tau \qquad \forall e \tag{3.4.6}$$

$$\sum_{p\in P, s\in S} \left[w_{p,fixed} \cdot x_{p,s} + w_{p,modular} \cdot y_{p,s,e}\right] \leq \omega_e \sum_{s\in S} W_s \quad \forall e \tag{3.4.7}$$

$$\sum_{p\in P} \left[l_{p,fixed} \cdot x_{p,s} + l_{p,modular} \cdot y_{p,s,e}\right] \leq L_s \qquad \forall e, s \tag{3.4.8}$$

$$b_s \cdot x_{p,s} \leq B_{p,fixed} \qquad \forall p, s \tag{3.4.9}$$

$$b_s \cdot y_{p,s,e} \leq B_{p,modular} \quad \forall p, s, e \tag{3.4.10}$$

$$h'_p\left[x_{p,s} + y_{p,s,e}\right] + \sum_{\tilde{p}\in P} h_{\tilde{p}} \left[x_{\tilde{p},s} + y_{\tilde{p},s,e}\right] \leq H_s \qquad \forall p, s, e \tag{3.4.11}$$

$$\sum_{p \in P} r_p \left[x_{p,s} + y_{p,s,e}\right] \leq R_s \qquad \forall s, e \tag{3.4.12}$$

$$\sum_{\substack{p \in P_{fuel}, \\ s \in S}} \left[u_{p,fixed} \cdot x_{p,s} + u_{p,modular} \cdot y_{p,s,e}\right] \geq U_e \qquad \forall e \tag{3.4.13}$$

$$\sum_{p \in P, s \in S} \left[k_{p,s,fixed} \cdot x_{p,s} + k_{p,s,modular} \cdot y_{p,s,e}\right] \leq K_e \qquad \forall e \tag{3.4.14}$$

$$\sum_{p \in P_g, s \in S} x_{p,s} + y_{p,s,e} \geq 1 \qquad \forall e, g : g \in G_e \tag{3.4.15}$$

$$\sum_{s \in S} y_{p,s,e} \leq z_{p,modular} \qquad \forall p, e \tag{3.4.16}$$

$$\sum_{s \in S} x_{p,s} = z_{p,fixed} \qquad \forall p \tag{3.4.17}$$

$$z_{p,fixed} + z_{p,modular} \leq 1 \qquad \forall p \tag{3.4.18}$$

$$\sum_{p \in P} m_{p,t,e} \leq 1 \qquad \forall e, t : t \in T_e \tag{3.4.19}$$

$$\sum_{s \in S} \left[x_{p,s} + y_{p,s,e}\right] \geq m_{p,t,e} \qquad \forall p, e, t : t \in T_e \tag{3.4.20}$$

3.4.5 Description

Equation (3.4.1) is the summation of all conditional probabilities for a given sortie which will be used to weight the importance of selecting payloads. Equation (3.4.2) is the resulting value of a sortie based on the maximum value payloads for each non-zero probability task within that sortie. Consequently the objective function (3.4.3) seeks to maximize the expected value of the Tern over a deployment.

The decisions are constrained by a multitude of constraints. Constraint (3.4.4) ensures that the total volume of modular payloads is within the capacity of the ship's storage. Constraint (3.4.5) restricts the total weight within any particular slot to the specified capacity of that slot. Constraint (3.4.6) maintains the net torque within preset limitations. Constraint (3.4.7) enforces the total weight of the Tern's payloads for any sortie be under the alloted amount. Constraint (3.4.8) limits the total volume of payloads within a slot to the specified physical limitations of the slot. Constraints (3.4.9) and (3.4.10) restrict payloads from being placed in slots with vibration which exceeds manufactured tolerability. Constraint (3.4.11) ensures that no payload is placed in a slot with too much cumulative heat for its ability to withstand. Constraint (3.4.12) limits payload placement to slots where enough power is available to support all payloads attached.

Constraint (3.4.13) demands that there exist enough fuel onboard the Tern as required for each sortie. Constraint (3.4.14) enforces a limit on the amount of time it takes to prepare the Tern for each sortie launch to the amount specified. Constraint (3.4.15) ensures that at least one payload from the required generic categories is onboard the Tern before the corresponding sortie is launched. Constraint (3.4.16) specifies that a modular payload cannot be on the Tern if it was never brought on deployment. Likewise, constraint (3.4.17) requires that a fixed payload always be on the Tern for every sortie. Constraint (3.4.18) then follows that a payload can be at most fixed or modular, but not both. Constraint (3.4.19) provides a means of ensuring at most one payload adds to the value of a task within a particular sortie. Finally, constraint (3.4.20) requires that for a payload's value for a task to be added to the value of a sortie, it must be attached for that sortie.

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CHAPTER 4: Demonstration of the Model

While actual data is not available at this time for testing, we generated our own constructed data to experiment with the functionality of this model and provide a demonstration of its capability. In this chapter, we explore the performance and output of our model as the number of sorties increases.

4.1 Data Description

Since real data is not available for analysis in this thesis, we have constructed our own data set with values we believe to be realistic enough for the purposes of studying our model.

4.1.1 Payloads

In order to keep things simple for analysis, we create 9 generic categories of payloads, each with just two specific models of payloads. Table 4.1 details the various attributes of these payloads. In general, model A payloads are heavier, larger, produce more heat, need more power, and tolerate more vibration. Conversely, model B payloads are the lighter, smaller, produce less heat, require less power, and have a lower tolerance for vibration. As a penalty to choosing modularity, we assume that whatever extra parts need attachment to make a payload modular come with adverse effects. These effects manifest in 10% heavier payload weight, 10% larger payload volume, and 20% less tolerance for vibration.

Since the values used in experimentation are not based on any physical truth, we did not find it necessary to include units, but all metrics for the same attribute are on the same scale. For example, EO/IR A is always twice as heavy as EO/IR B.

Although not displayed in the table, Fuel Pods A and B can hold 100 and 150 gallons of fuel respectively. We assume that if one of these pods is chosen, the fuel will be filled to capacity. Also not displayed is the storage capacity of the ship for modular payloads (N), which we set to be 300 for this example.

Table 4.1. Payload Data

Payload	Weight Fixed	Weight Modular	Volume Fixed	Volume Modular	Heat Produced	Heat Tolerable	Power Required	Vibration Tolerable Fixed	Vibration Tolerable Modular
Radar A	30	33	5	5.5	8	10	18	15	12
Radar B	20	22	4	4.4	5	10	12	10	8
EO/IR A	60	66	10	11	7	10	16	20	16
EO/IR B	30	33	8	8.8	3	10	12	15	12
Missile A	300	330	60	66	1	1	1	30	24
Missile B	200	220	40	44	1	1	1	25	20
Torpedo A	200	220	40	44	1	1	1	25	20
Torpedo B	150	165	30	33	1	1	1	20	16
Comm A	10	11	4	4.4	4	10	10	12	9.6
Comm B	5	5.5	3	3.3	2	10	6	10	8
Computer A	20	22	10	11	10	10	20	12	9.6
Computer B	10	11	5	5.5	7	10	16	10	8
GPS A	15	16.5	8	8.8	6	10	8	12	9.6
GPS B	10	11	4	4.4	2	10	4	10	8
Fuel Pod A	100	110	30	33	1	1	1	25	20
Fuel Pod B	150	165	45	49.5	1	1	1	25	20
Sonobuoy A	60	66	25	27.5	1	1	1	20	16
Sonobuoy B	40	44	20	22	1	1	1	15	12

This table displays the attributes of each payload in our data set.

4.1.2 Slots

Each slot on the Tern has characteristics that limit which payloads can be attached. Table 4.2 lays out the values we chose for these characteristics. The Outermost and Outerleast slots on either side of the Tern can hold significantly more weight and volume than the Innermost and Innerleast slots. We assume that the majority of the Tern's power supply will be centralized, so the Innermost and Innerleast slots have much more power supply available. We assume that the vibration present increases with the distance from the centerline of the UAS. We also assume that it is more difficult to prepare payloads attached closer to the center than farther away and it takes twice as long to prepare payloads which are modular. We do not differentiate among payloads' preparation time.

Table 4.2. Slot Data

Slot	Distance From Center	Weight Capacity	Volume Capacity	Heat Tolerable	Power Available	Vibration Present	Time to Prepare Fixed	Time to Prepare Modular
Outermost Left	-6	700	200	20	5	20	1	2
Outerleast Left	-4	400	100	20	15	15	2	4
Innerleast Left	-2	100	15	20	30	10	3	6
Innermost Left	-1	50	5	20	50	5	4	8
Innermost Right	1	50	5	20	50	5	4	8
Innerleast Right	2	100	15	20	30	10	3	6
Outerleast Right	4	400	100	20	15	15	2	4
Outermost Right	6	700	200	20	5	20	1	2

This table displays the attributes of each slot in our data set.

4.1.3 Sorties and Tasks

We explore three different scenarios in our experimentation. We begin by investigating two sorties, then four, and finally six. Table 4.3 details the frequency of each sortie within every scenario. Comm Node is a sortie in which the Tern acts as a message relay between various ships and aircraft. Intelligence, Surveillance, and Reconnaissance (ISR) is a sortie where the Tern is sent to investigate an area and gather intelligence or monitor a situation. Anti-Submarine Warfare (ASW) is a versatile sortie which can range from locating a submarine, to tracking, to even engaging the target. Search is a sortie in which the Tern is sent to find an object believed to be located in a certain area. Strike is a sortie where the Tern is sent to engage an enemy target. Finally, Deterrence is a sortie in which the Tern is merely sent as a show of force in an area to display combat power to the enemy.

Table 4.3. Sortie Frequency by Scenario

Sortie	Scenario 1	Scenario 2	Scenario 3
Comm Node	0.67	0.60	0.50
ISR	0.33	0.30	0.25
ASW	-	0.06	0.05
Search	-	0.04	0.03
Strike	-	-	0.02
Deterrence	-	-	0.15

This table displays the frequency of each sortie within each scenario for our data set.

Table 4.4 details the values we use for each sortie's requirements in our test runs. We assume that the Comm Node Sortie should be the lightest total weight to allow for more endurance. In accordance with this thinking, the Comm Node and ISR sorties require the most amount of fuel while the Strike Sortie needs the least as it is expected to be quick. Although not listed in any table, we set the maximum allowable net torque value (τ) to be 2000 for every sortie.

Table 4.4. Sortie Data

Sortie	Proportion of Total Weight Allowed	Preparation Time Allowed	Volume of Fuel Required
Comm Node	0.2	15	200
ISR	0.5	25	150
ASW	0.4	35	120
Search	0.5	30	100
Strike	0.4	35	50
Deterrence	0.3	30	80

This table displays the data for each sortie in our data set. The proportion of total weight allowed means if the Tern can hold W pounds of weight, we restrict the total weight to 0.2W for the Comm Node Sortie.

Table 4.5 provides the conditional probabilities for each task the Tern will conduct given the sortie it is currently on. Some of these tasks are known to be executed with certainty ahead of time, but others have uncertainty. For example, we know the Tern needs to Navigate on an ASW sortie, but there is a 0.05 probability that the Tern needs to Launch a Torpedo as well.

Table 4.5. Task Probabilities

		Sorties					
		Comm Node	ISR	ASW	Search	Strike	Deterrence
Tasks	Fly	1.00	1.00	1.00	1.00	1.00	1.00
	Navigate	1.00	1.00	1.00	1.00	1.00	1.00
	Communicate	1.00	1.00	1.00	1.00	1.00	1.00
	OTH Detection	0.00	0.00	0.00	0.80	0.00	0.00
	LOS Detection	0.00	1.00	0.00	1.00	1.00	0.00
	Drop Sonobuoy	0.00	0.00	1.00	0.00	0.00	0.00
	Launch Torpedo	0.00	0.00	0.05	0.00	0.00	0.00
	Launch Missile	0.00	0.00	0.00	0.00	1.00	0.05
	Target	0.00	0.00	0.05	0.80	1.00	0.05

This table displays the probability of each task given a sortie in our data set. OTH stands for Over the Horizon and LOS stands for Line of Sight.

Table 4.6 entails the value of every payload for each possible task on a scale of zero to one. A zero means that the payload provides no value for the task in question (such as a fuel pod for launching a missile) whereas a one means there is no payload which could do the task better. Fractional values are interpreted to be how well a payload does a task compared to one that has a value of one. For example, Missile B has a value of 0.5 for Launch Missile and Missile A has a value of 1. If possible, we would like the Tern to have Missile A when this task is required, but maybe because of weight restriction we can only take Missile B which does only 50% as well as Missile A.

Table 4.6. Payload Values

	Tasks								
Payloads	Fly	Navigate	Communicate	OTH Detection	LOS Detection	Drop Sonobuoy	Launch Torpedo	Launch Missile	Target
Radar A	0.0	0.0	0.0	1.0	0.2	0.0	0.0	0.0	0.0
Radar B	0.0	0.0	0.0	0.5	0.3	0.0	0.0	0.0	0.0
EO/IR A	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
EO/IR B	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0
Missile A	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
Missile B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0
Torpedo A	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
Torpedo B	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0
Comm A	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
Comm B	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0
Computer A	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5
Computer B	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
GPS A	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
GPS B	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fuel Pod A	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fuel Pod B	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Sonobuoy A	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Sonobuoy B	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0

This table displays the value of a payload for each task in our data set. Values are on a scale from 0 to 1 with at least one payload with the value of 1 in each column.

All scenarios were solved by implementing the mathematical formulation described in Section 3.4, coded in Pyomo (Hart et al., 2017; Hart, Watson, & Woodruff, 2011) and solved with the CPLEX solver (Studio, 2015). Every scenario took less than a second of computer runtime to solve.

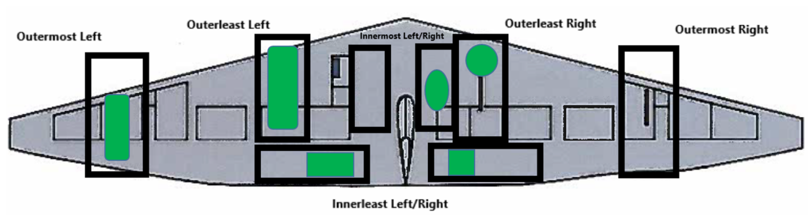
4.2 Scenario 1: Two Sorties

For the first scenario, we consider a deployment in which the Tern will only be conducting the sorties Comm Node and ISR with the frequencies detailed in Table 4.3. Consequently, we are only using task probabilities from Table 4.5 that are in the corresponding sortie columns of interest. In summary, this example consists of 5 generic payload categories (10 total specific payloads), 2 sorties, and 4 tasks.

The model produced a solution with the total expected value of the Tern being 95.8% of its potential value. A 100% value means that the best payloads are onboard the Tern for the sorties they are needed. In the following subsections, we provide the exact results and give explanations for the decisions made by the solver.

4.2.1 Fixed Design

The fixed configuration of the Tern (Figure 4.1) depicts the payloads that are chosen to always be on the UAS for both sorties. Since there are only two sorties, we expect most payloads to be fixed since the benefit of modularity is the ability to remove unnecessary payloads for sorties and add necessary ones. In fact, we find that for this data, all payloads are fixed.



This figure displays the fixed configuration of payloads when there are two sorties. From left to right: Fuel Pod A, Fuel Pod B, Computer A, Comm A, GPS A, and EO/IR B.

Figure 4.1. Fixed Configuration for Scenario 1

We see in Figure 4.1 that Fuel Pods A and B are fixed so that the Tern will have sufficient fuel for either sortie. The model chose to fix all the beneficial payloads for both sorties because it was feasible to do so. This behavior of choosing fixed designs when possible while still maintaining a high level of mission effectiveness is accomplishing both **Goal 1 and 2** stated in Chapter 2.

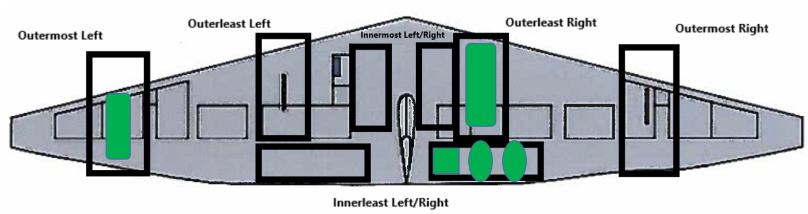
The only shortcoming of the design in this scenario is that EO/IR B is chosen over EO/IR A, even though the A model is twice as effective as the B model. The reasoning for this is that only the four inner slots have enough power to support the installation of EO/IR A and the payload is too large for the innermost two slots. Consequently, the only option is either the innerleast left or innerleast right slots. However, there is not enough power to support both Computer A and EO/IR A in one slot and there is not enough volume for both GPS

A and EO/IR A to fit in one slot. As such, our model maximizes the expected value of the Tern by keeping Computer A and GPS A and substituting EO/IR B for EO/IR A.

It is apparent from this small example, consisting of only two sorties and a limited number of payloads and tasks, that choosing the optimal payload configuration is no trivial feat. As such, it is not something that can be done by hand and requires the use of an optimization model.

4.2.2 Alternate Approach Results

In Chapter 3 we mention an alternate approach for counting the value of each payload with respect to tasks. In this alternate approach we suggest that instead of considering the value of only one payload for each task within a sortie, we could count every payload. This approach allows for the idea of synergy, where multiple payloads act in concert to perform better. Figure 4.2 displays the resulting configuration of payloads using this alternative approach.



This figure displays the configuration of payloads when we use the alternate approach. From left to right: Fuel Pod A, GPS B, Comm A, Comm B, and Fuel Pod B.

Figure 4.2. Configuration for Scenario 1 Using Alternate Approach

We see from this result that two Comm payloads are attached which is unnecessary in the way we define the problem. Furthermore, there are no payloads onboard that offer any detection or tracking capabilities. Even more worrying though is that no computer is attached, which is the payload required for the task of flying. Therefore, while there exist flaws in the assumptions we make using the approach of considering only one payload for each task in a sortie, the results in even the simplest case show the method is superior to counting every payload attached to the Tern.

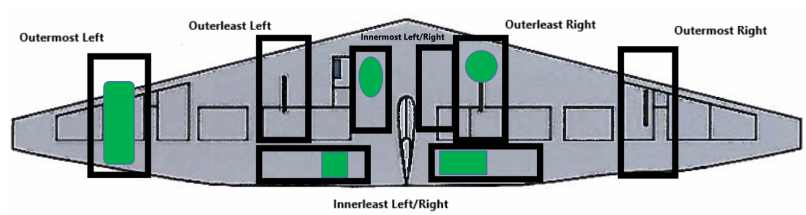
4.3 Scenario 2: Four Sorties

For the second scenario, we now consider a deployment in which the Tern is conducting the sorties ASW and Search in addition to those from Scenario 1. The frequencies of the sorties are detailed in Table 4.3. We now use all task probabilities from Table 4.5 except for the Launch Missile task since all other tasks are represented in these four sorties. In summary, this example consists of 8 generic payload categories (16 total specific payloads), 4 sorties, and 8 tasks.

The model produces a solution with the total expected value of the Tern being 95.9% of its potential value, almost the same value as in Scenario 1. In the following subsections, we provide the exact results and give explanations for the decisions made by the solver.

4.3.1 Fixed Design

The fixed configuration of the Tern (Figure 4.3) depicts the payloads that are chosen to always be on the UAS for all four sorties. Now that the number of sorties has doubled, we expect more payloads to be modular to accommodate the need for versatility.



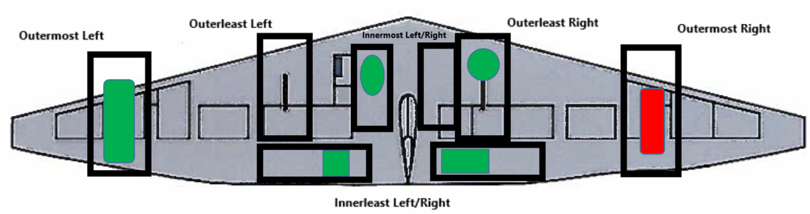
This figure displays the fixed configuration of payloads when there are four sorties. From left to right: Fuel Pod B, GPS A, Comm A, Computer A, and EO/IR B.

Figure 4.3. Fixed Configuration for Scenario 2

The only notable difference in the fixed configuration in this scenario as compared to that in Scenario 1 is that only Fuel Pod B is now fixed. The reason for this is that Fuel Pod B provides sufficient fuel for every sortie except for the Comm Node Sortie. In addition, the ASW Sortie requires six different payloads as well as its fuel supply. The only way for this to be feasible is to make the smaller fuel pod modular so it can be removed when it is unnecessary.

4.3.2 Comm Node Sortie

For the Comm Node Sortie, the only payload needed to be attached is Fuel Pod A in order to meet the minimum fuel requirements (Figure 4.4). Otherwise, the fixed payloads already provide 100% of the potential value for the sortie. Since this sortie's tasks are common to all sorties, this is an expected and favorable result since we see the frequency of this sortie is 60% in this scenario. In other words, since this is the main job the Tern is anticipated for, we want as many of the necessary payloads to already be fixed to the UAS and as few unnecessary payloads fixed as possible. Here, the only unnecessary payload is the EO/IR sensor and it is the only other payload needed by more than one sortie.



This figure displays the configuration of payloads for the Comm Node Sortie in Scenario 2. Fuel Pod A added (shown in red).

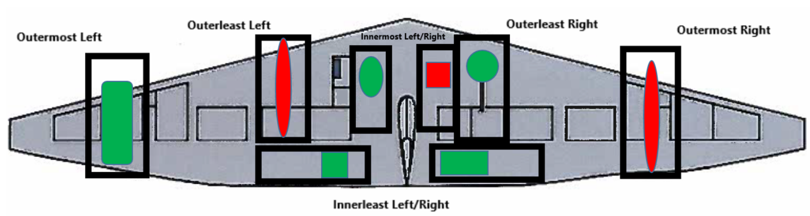
Figure 4.4. Comm Node Configuration for Scenario 2

4.3.3 ISR Sortie

In this scenario, the ISR Sortie does not require any additional payloads beyond the fixed design in Figure 4.3, but only obtains an expected value of 87.5%. Just as in Scenario 1, it is not feasible to attach EO/IR A for the same reasons of power and space limitations. However, if we change the power required by EO/IR A from 16 to 15, the results change drastically. In fact, every sortie could have the best payloads for every task. The fixed configuration changes to be the two fuel pods and the computer, GPS, and comm device. Then, every sortie simply attaches the modular payloads needed. This is just one example of how a simple physical limitation can cause a big change in the configuration. It also serves to demonstrate the usefulness of our model to highlight weak points in the design and areas where simple improvements to the design of the Tern would be beneficial. This kind of sensitivity analysis has larger implications for component construction and purchasing payloads since it informs decision makers on the key areas to focus on. Furthermore, since the model can be solved in a timely manner, sensitivity analysis is a feasible task.

4.3.4 ASW Sortie

Figure 4.5 represents the configuration of the Tern for the ASW Sortie in this scenario. Each payload added contributes to a task not required by the Comm Node or ISR Sortie. In fact, this configuration provides a 100% expected value for the sortie. The ability to remove Fuel Pod A allows for the addition of Torpedo A in its place. This demonstrates exactly the purpose of making payloads modular: to allow for substitutions of unnecessary payloads for necessary ones to achieve a higher level of effectiveness.



This figure displays the configuration of payloads for the ASW Sortie in Scenario 2. From left to right: Sonobuoy A, Computer B, and Torpedo A added (shown in red).

Figure 4.5. ASW Configuration for Scenario 2

4.3.5 Search Sortie

The only change made from the fixed design for the Search Sortie is to add Radar A for its over the horizon (OTH) detection capability. In the Search Sortie, it remains infeasible to have the EO/IR A payload for the same reasons previously discussed. As such, this sortie achieves only 89.6% of its potential value.

The results from Scenario 2 demonstrate that as the number of sorties with unique sets of tasks increases, one fixed design cannot meet all demands. However, our approach of using modular payloads allows for swaps to be made between sorties so that the necessary payloads may take the place of unnecessary ones. From both scenarios thus far we see that with payloads such as EO/IR A that there are a multitude of factors to consider when deciding where payloads should go and when. These factors are not clear to see with the human mind or even with the aid of an algorithm. Our proposed optimization model is well equipped to handle many physical limitations and operational considerations when choosing the configuration of the Tern for each sortie.

4.4 Scenario 3: Six Sorties

For the third scenario, we now consider a deployment in which the Tern conducts the sorties Strike and Deterrence in addition to those from Scenario 2. The frequencies of the sorties are detailed in Table 4.3. In summary, this example consists of 9 generic payload categories (18 total specific payloads), 6 sorties, and 9 tasks.

The model produces a solution with the total expected value of the Tern being 96.4% of its potential value (the best value of all scenarios). This is because the new sorties achieve high values which raise the overall average. Even though there were more sorties for this scenario with more tasks and payloads for consideration, the results remain almost the same as those in Scenario 2. The fixed design consists of the three payloads required for all six sorties as well as a fuel pod. Then, as expected, modular payloads are swapped in for the sorties they provide value (see Appendix for full details).

In this scenario, we again see that the EO/IR payload is the only reason the maximum value is not achieved. When the power requirement is modified to be 15 instead of 16, all sorties reach an expected value of 100%.

This example demonstrates the intuitive choices made by our model for the configuration of fixed and modular payloads. Frequently needed payloads are made fixed up to the point where room must be made to swap in more sortie-specific payloads such as torpedoes.

4.5 Fixed Only or Modular Only

One way to analyze the benefits of deciding whether each payload should be fixed or modular is to compare the expected values of the sorties from Scenario 3 with those when only fixed payloads are allowed and again when only modular payloads are allowed. Table 4.7 details the performance of each policy for the individual sorties and the deployment as a whole. Notice in the table that the Modular Only policy actually performs significantly worse than the Fixed Only policy. This is due to the many assumed disadvantages of making a payload modular. The most influential of these is that modular payloads can only tolerate 80% of the vibration they would if they were fixed. This among other assumed disadvantages leads to many limitations in where payloads can be placed.

Table 4.7. Sortie Value Comparison

		Payload Attachment Policy		
		Fixed Only	Modular Only	Fixed and Modular
Sortie	Comm Node	100%	33%	100%
	ISR	88%	63%	88%
	ASW	98%	63%	100%
	Search	73%	69%	90%
	Strike	60%	80%	92%
	Deterrence	97%	48%	100%
	Total	95%	46%	96%

This table displays the expected value of each sortie for the policy of only fixed payloads, only modular payloads, and lastly a mix of fixed and modular.

We conclude from this test that while the total value of the Tern does not increase compared to Fixed Only when both fixed and modular payloads are used, an individual sortie (see Search and Strike in Table 4.7) can experience a significant increase in value. This increase is due to the ability to remove some unnecessary payloads for a sortie in order to make room for those of value.

4.6 Summary

From studying the three scenarios in this chapter, we find that our model performs as expected. The optimization model seeks to maximize the value of the Tern and does so by trying to fit the best payloads for each task on the UAS with consideration for the multitude of constraining factors. The model is implemented in Pyomo and solved using the CPLEX solver in less than one second in every scenario.

Some of the best qualities of the model are that it strives for balance, prioritizes based on both frequency of the sortie and probability of the tasks within the sortie, and only uses modularity when it is needed. There are certainly shortcomings to the model, but it remains a useful tool for suggesting payload configurations under complex constraints to maximize performance.

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CHAPTER 5: Application for Multiple Terns

Consider now that perhaps it is possible to construct multiple models of the Tern, each designed to meet a subset of sorties for the ship or SAG it is stationed with. In order to demonstrate this, we continue to use the data for Scenario 3 in Chapter 4 in which there are six sorties.

5.1 Two Terns

To begin, we investigate the benefit of two models of the Tern. Tern-A designates the first model and Tern-B the second with sorties of responsibility detailed in Table 5.1.

Table 5.1. Sortie Distribution for Two Terns

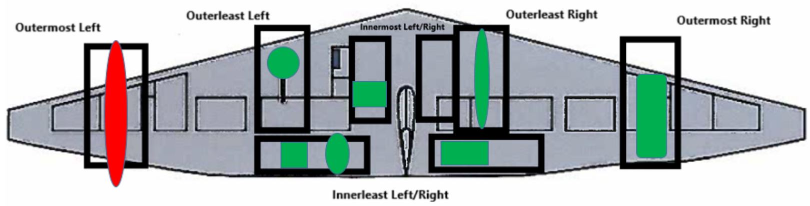
Tern-A	Tern-B
ASW	Comm Node
Strike	ISR
Deterrence	Search

This table provides the distribution of sorties each model of the Tern is responsible.

The sorties are split up in such a way that each model of the Tern has the fewest number of differing tasks between each of the sorties it is responsible for.

5.1.1 Tern-A

The fixed design for Tern-A consists of Fuel Pod B, Comm A, GPS A, both computers, Sonobuoy A, and EO/IR B. The reasons for these choices are sensible. The fuel pod provides enough fuel for all three sorties. The comm device, GPS, and both computers are needed for all sorties so it makes sense they are fixed. The design of Tern-A is shown in Figure 5.1.



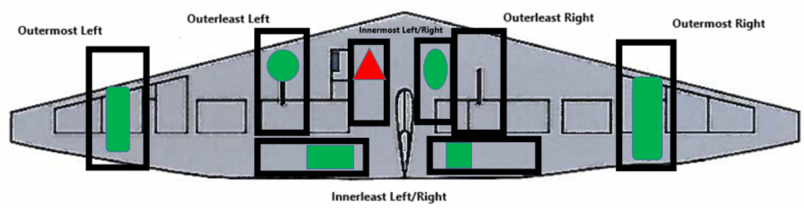
This figure displays the configuration of payloads for Tern-A when there are two models of the Tern. The fixed payloads are shown in green and the modular payload in red.

Figure 5.1. Configuration of Tern-A with Two Terns

The modular payloads consist only of Missile A and Torpedo A. The missile is attached for the Strike and Deterrence sorties while the torpedo is used for the ASW Sortie. In Figure 5.1, the red payload represents either Missile A or Torpedo A depending on the sortie. Both the Deterrence and ASW sorties have expected values of 100% while the Strike Sortie has an expected value of 91.7%. The only task without the best payload is the line of sight (LOS) detection task for the Strike Sortie since the EO/IR A payload is still not able to be attached.

5.1.2 Tern-B

The fixed configuration of Tern-B is comprised of both fuel pods, Computer A, Comm A, GPS A, and EO/IR B (Figure 5.2). The larger fuel pod is necessary for the ISR and Comm Node sorties, but the Comm Node Sortie requires both fuel pods and the smaller fuel pod is not enough for the ISR Sortie. Consequently, the model chooses to fix both since space is available. Computer A, Comm A, and GPS A are the best payloads for flying, communicating, and navigating so they are logically fixed to Tern-B just as on Tern-A. EO/IR B is fixed because it is needed for both the ISR and Search sorties while Radar A (the only modular payload, shown in red in Figure 5.2) is only needed for the Search Sortie. The Comm Node Sortie achieves an expected value of 100% while the Search Sortie has an expected value of 89.6% and the ISR Sortie has an expected value of 87.5%. The only task with a sub-optimal value is due to the use of the EO/IR B payload for the LOS detection task in both the ISR and Search sorties.



This figure displays the configuration of payloads for Tern-B when there are two models of the Tern. The fixed payloads are shown in green and the modular payload in red.

Figure 5.2. Configuration of Tern-B with Two Terns

While the expected values for each sortie are the same with the use of two Tern models (see the Fixed and Modular column from Table 4.7), reducing the number of sorties for each Tern allows for a greater number of payloads to be fixed. Specifically, with one Tern, seven payloads are made modular to achieve the same result where only three payloads are modular for two models of the Tern. This increase in the proportion of payloads fixed reduces the preparation time, total weight, and likelihood of payload failure while also increasing the fuel supply.

5.2 Three Terns

In this section we analyze how the results are affected when the sorties are distributed amongst three different models of the Tern: Tern-A, Tern-B, and Tern-C. Table 5.2 shows the two sorties each of the models of the Tern are responsible for in this example.

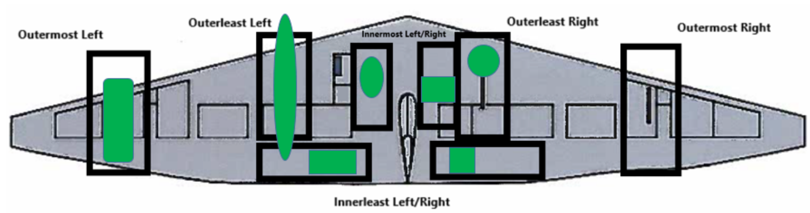
Table 5.2. Sortie Distribution for Three Terns

Tern-A	Tern-B	Tern-C
Strike	ISR	Comm Node
Deterrence	Search	ASW

This table provides the distribution of sorties each model of the Tern is responsible.

5.2.1 Tern-A

The configuration for Tern-A is all fixed payloads (Figure 5.3). The larger fuel pod provides sufficient fuel for both the Strike and Deterrence sorties. The only payload which does not provide full value is once again the EO/IR B payload for the LOS detection task, but this is also the only payload not needed by both sorties.



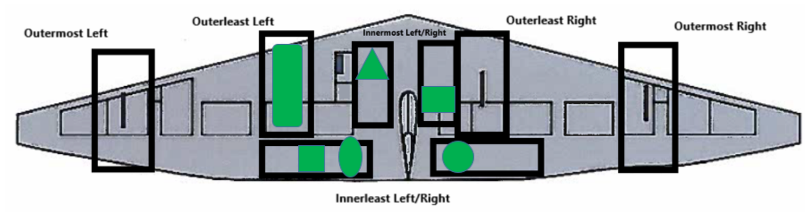
This figure displays the configuration of payloads for Tern-A when there are three models of the Tern.

Figure 5.3. Configuration of Tern-A with Three Terns

An interesting note with this design is that the smaller fuel pod could supply enough fuel for either sortie. The reason the larger one is chosen is because it provides a counter-weight to the missile also fixed to Tern-A. The Deterrence Sortie achieves an expected value of 100% while the Strike Sortie has an expected value of 91.7%.

5.2.2 Tern-B

Tern-B's configuration in this example is also comprised entirely of fixed payloads (Figure 5.4). The only payload not needed by one of the sorties is Radar A. However, the configuration does not achieve 100% effectiveness for either sortie due to the fact that Computer B is attached instead of A for the task of flying. On the other hand, EO/IR A is onboard Tern-B for the LOS detection task which is part of both sorties. It is arbitrary that EO/IR A is chosen over Computer A because the expected value of the Tern is the same either way, but this does show that there is a feasible way to have EO/IR A on the Tern. The Search Sortie has an expected value of 89.6% while the ISR Sortie has an expected value of 87.5%.

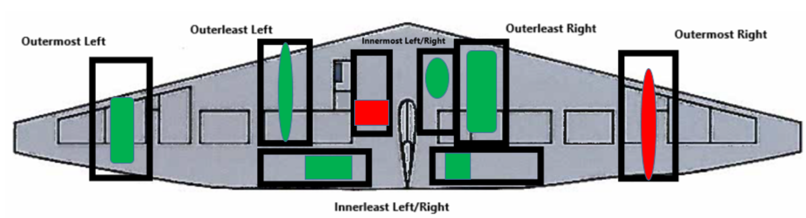


This figure displays the configuration of payloads for Tern-B when there are three models of the Tern.

Figure 5.4. Configuration of Tern-B with Three Terns

5.2.3 Tern-C

Tern-C has a fixed configuration (Figure 5.5) which entails both fuel pods, Computer A, GPS A, Comm A, and Sonobuoy A. The modular portion consists of Torpedo A and Computer B for the ASW Sortie. The reason that the torpedo and second computer are not simply fixed is because their added weight exceeds the maximum weight requirement of 500 for the Comm Node Sortie. Both the Comm Node and ASW Sortie achieve 100% expected values in this example.



This figure displays the configuration of payloads for Tern-C when there are three models of the Tern. The payloads in green are fixed while those in red are modular for the ASW Sortie.

Figure 5.5. Configuration of Tern-C with Three Terns

From examining the ability to divide sorties amongst three different models of the Tern, we see that now only two payloads are made modular and the same expected value for each sortie is maintained. There is definitely a benefit for Tern-A and Tern-B since they do not require any exchanging of payloads.

5.3 Summary

This chapter serves to demonstrate the potential benefits of creating multiple models of the Tern. Clearly having less sorties allows for more of the Tern's payloads to be fixed. The benefits of an increased fixed portion of the payload configuration are that the Tern is lighter, requires less preparation time, and is more robust.

Although it was not the case in our example, one can imagine that multiple models of the Tern could increase the effectiveness with which individual sorties are completed. However, in this example, we see that one Tern is able to meet the same expected values for each sortie as three Terns are. This is an effective demonstration of the power of modularity to handle a variety of sortie requirements.

In our example we focus on each model of the Tern having a disjoint set of sorties it is responsible for, but there could also be overlap. For instance, each of the models of the Tern we discuss is capable of the Comm Node Sortie since it requires only fuel, a computer, GPS, and a comm device. This overlap in responsibility could provide a redundancy in case of system failure on one model.

CHAPTER 6:
Perturbation of Data

In this chapter we examine the effects of varying certain data parameters used in the example in Chapter 4 for Scenario 3 where a single Tern is responsible for six different sorties: ASW, Comm Node, Deterrence, ISR, Search, and Strike.

6.1 Description of Randomization

In order to test whether solutions change by varying the data, we first set the frequency of each sortie to be a uniform random number between zero and one and then normalized so that the sum of all frequencies equals one. Furthermore, the probability of each task from Table 4.5 that is not zero or one is set to be a uniform random variable between zero and one.

Since power is a significant issue for our Scenario 3 example, we randomize the power available in each of the slots. Table 6.1 details the parameters of the random variable for each slot type.

Table 6.1. Randomization of Power Available

Slot	Minimum	Maximum
Outermost	2	7
Outerleast	10	20
Innerleast	20	40
Innermost	40	60

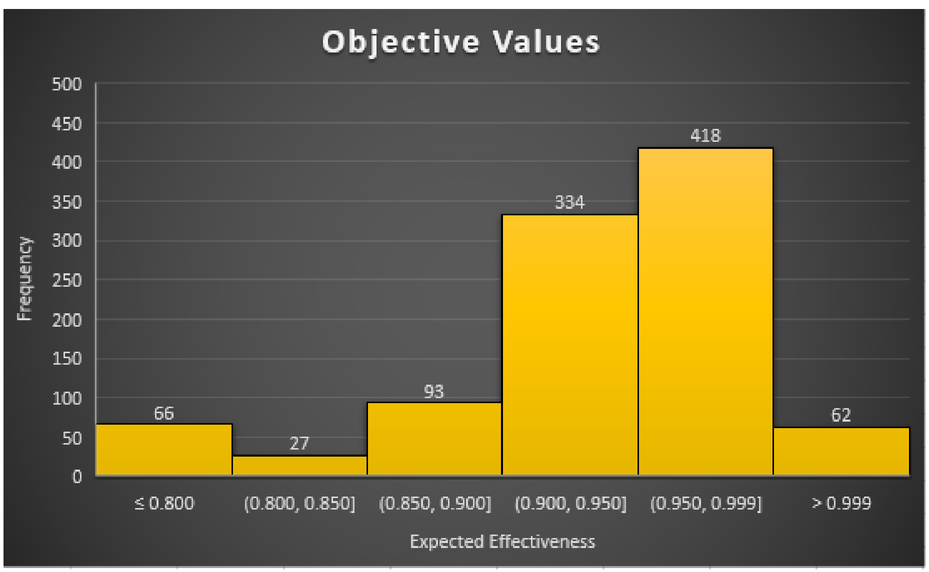
This table provides the parameters for the uniform random variable representing the power available in each slot.

In order to strain the decisions made by the solver, we also vary the proportion of total weight allowed, preparation time allowed, and volume of fuel required first presented in Table 4.4. The proportion of weight allowed is an independent uniform random variable between 0.1 and 0.5 for each sortie. Furthermore, the net torque allowed is uniform random variable between 1000 and 3000. The preparation time allowed is an independent uniform random variable between 15 and 45 for each sortie. The volume of fuel required is an independent uniform random variable between 50 and 200. Finally, we vary the capacity of the ship to house modular payloads as a uniform random variable between 100 and 300.

We expect that these perturbations of the data will result in different solutions for some runs. To test this, we run 1000 instances of the example problem and collect the results.

6.2 Results

The CPLEX solver solved our model in all 1000 instances to optimality within one second of computer runtime. The optimal value for each instance ranges from 0.2992 to 1.000. Figure 6.1 provides the distribution of all 1000 objective values.

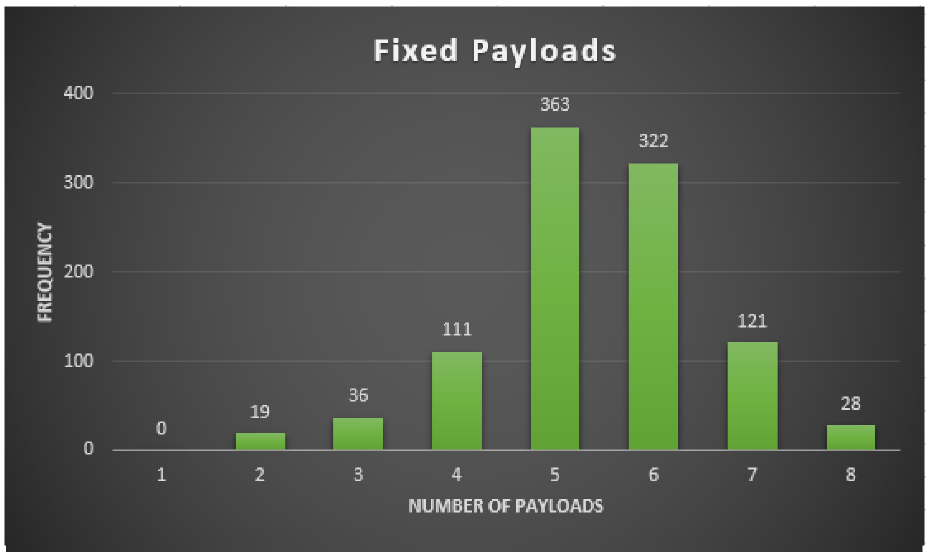


This figure displays the distribution of objective values for the 1000 problem instances.

Figure 6.1. Distribution of Objective Values

We see from these results that most of the time (81.6%), the objective value is at least 90%, despite variations. In fact, the model is able to achieve 100% expected effectiveness in 6.2% of the problem instances.

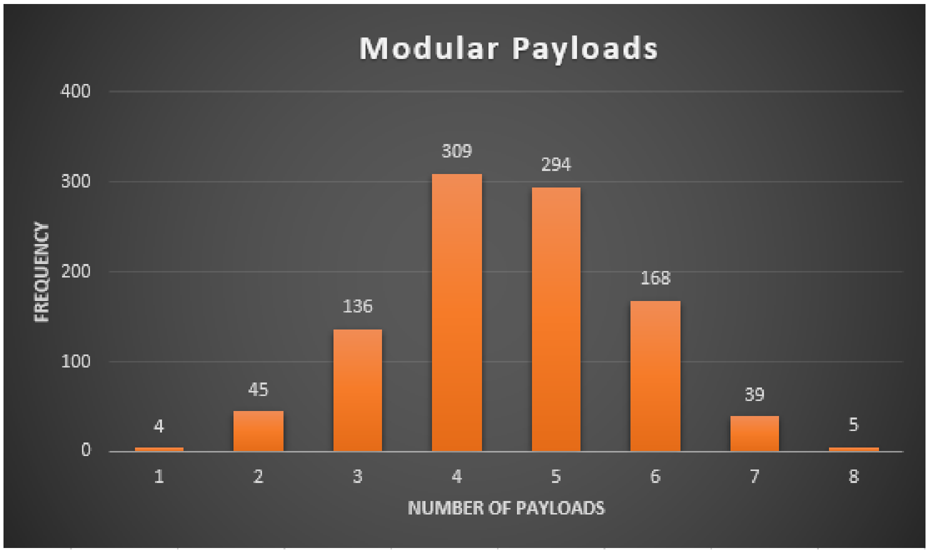
The number of fixed payloads ranges from two to eight across the 1000 perturbations of the data. Figure 6.2 shows the tendency for the number of fixed payloads to be about five or six (68.5% of the time) as we saw in Chapter 4 where there are five payloads fixed to the Tern. Notice that there are never more than 8 payloads fixed. This correlates to the number of slots on the Tern. While it is feasible to have more than two payloads in a single slot, we find it rare that this is ever implemented due to various reasons, but most notably cumulative heat and power limitations.



This figure displays the distribution of the number of fixed payloads for the 1000 problem instances.

Figure 6.2. Number of Fixed Payloads

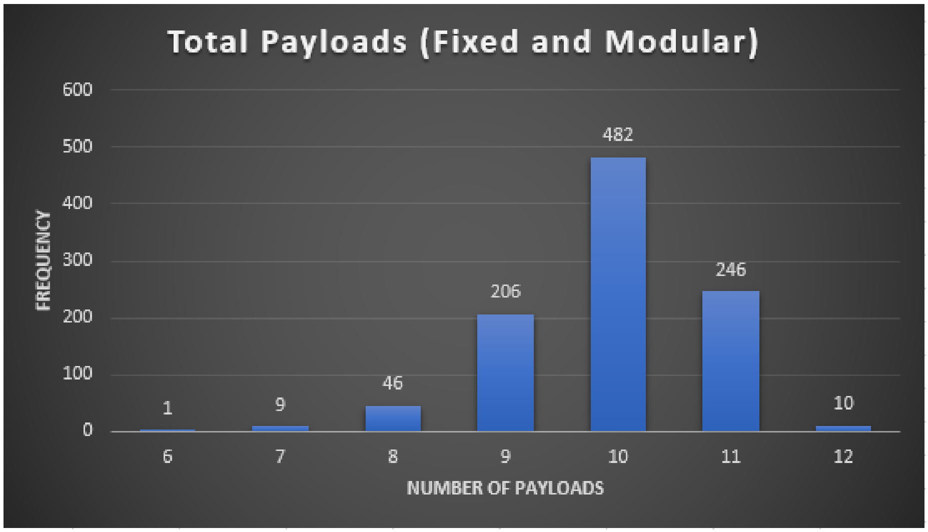
Figure 6.3 shows the number of modular payloads total. Note that this does not mean if there are four modular payloads that each one is always on the Tern. Recall for this example there are 9 generic payload categories, each with two models of a specific payload, for a total of 18 total payloads under consideration. From the example in Scenario 3 (Chapter 4), six payloads were chosen to be modular, which is actually one of the less frequent results when perturbing the data. Most of the time (60.3%), just four or five payloads are made modular to supplement the fixed configuration. Notice that the number of modular payloads is slightly more variable than the number of fixed payloads. This is substantiated by the relative standard deviations of 1.148 for fixed payloads and 1.212 for modular payloads. The latter is 5.6% larger than the former. This is not a significant result, but it does make sense as the number of modular payloads depends on how many payloads are fixed. If few payloads are fixed, many can be modular and if many payloads are fixed, few can be modular.



This figure displays the distribution of the number of modular payloads for the 1000 problem instances.

Figure 6.3. Number of Modular Payloads

Figure 6.4 represents the total number of payloads brought on deployment across the 1000 test instances. Note that this number is the sum of the payloads fixed to the Tern and the number made modular. It is also worthwhile to point out that there are nine generic payload categories. In an ideal situation, the Tern could attach the best payload for the seven generic categories where one specific model outperforms the other, both computers, and both fuel pods. Therefore, the Tern should need exactly 11 payloads on deployment for this example (as it does in Scenario 3). The cases where there are 12 payloads are due to bringing two models of the same generic payload because one is feasibly attached for one sortie and only the other is feasible for a different sortie. When there are less than 11 payloads total, this is most likely due to an infeasibility in that neither model of a generic payload can feasibly be attached for any of the sorties that need it. The cases where there are fewer than 10 total payloads are the ones that correspond to the lower objective values in Figure 6.1.



This figure displays the distribution of the number of total payloads (the sum of those fixed and modular) for the 1000 problem instances.

Figure 6.4. Number of Total Payloads

While no payload is fixed in all 1000 instances, the four most frequently fixed payloads are no surprise: Computer A, Comm A, GPS A, and Fuel Pod B. These are the four payloads all six sorties need for flying, communicating, navigating, and meeting minimum fuel requirements. The only payload never fixed is GPS B which is only even made modular in 13 of the 1000 instances. This makes sense because the GPS payload has low power requirements and is lightweight and small.

There is also no payload which is made to be modular in all 1000 instances. The payloads most frequently chosen to be modular are Sonobuoy A, Missile A, Radar A, Computer B, EO/IR A, Fuel Pod A, and Torpedo A. This makes sense because these are the payloads which provide the most value and enough fuel, but are only used in a limited number of sorties. It is of note that the troublesome EO/IR B payload is only modular in 3 out of 1000 instances and fixed in 200 out of 1000. When varying the parameters discussed earlier in this chapter, EO/IR A is often able to be attached either as a fixed or modular payload.

This chapter has shown that even when varying several parameters, the model is often able to achieve high levels of success. Furthermore, the choices made by the model continue to favor fixed payloads as much as possible. Reaching this balance of operational effectiveness through flexibility while maintaining a high degree of robustness is exactly our intent with the use of this model.

CHAPTER 7:
Conclusions

The purpose of this thesis is to provide a tool which can be used to better understand the intricacies of fitting a diverse set of objects in spaces with many physical limitations which must adhere also to the constraining factors of the system as a whole and meet a variety of demands. While our work focuses on the application of the model to the Tern, it could easily be used for many similar problems such as the payload configuration of other air platforms, personnel manning, or construction design.

We find in this thesis that the solutions produced by our model are sensible, but not simple. The results favor fixed payloads when possible while still striving for the best total value through the use of modular design. Often, we see results where the model makes trade-offs between various payloads that would take a great deal of analysis and enumeration by hand to arrive at the same solution.

In this work, we also provide an example of extending the application past a single configuration of the Tern to two and three unique models. By doing this, we find a method to increase the proportion of fixed payloads for any one Tern and possibly increase its effectiveness.

Finally, we study the effects caused by perturbing several data parameters in the input. We conclude that variations can sometimes cause significant drops in the objective value due to infeasibilities, but high levels of success are more often achieved.

7.1 Future Work

There are several opportunities for continuing research on both the formulation and application of our model. We discuss two different methods to calculate the objective value in our formulation. One way is to sum the value of every payload onboard the Tern for every possible task. The second approach, the one we use, is to count each payload which provides the most value for each task. There are shortcomings and advantages to each of these methods, but neither is perfect. Consequently, it would be beneficial to construct and analyze several different objective functions with respect to performance.

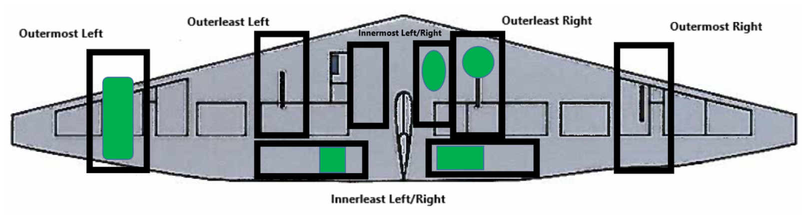
Both methods for defining the objective function focus on sortie importance, weighted by probabilities, and task effectiveness. The latter is captured by three categories. The first is that no payload onboard the Tern for a particular sortie has capability for the task and thus no value is added. The second is that one payload meets the optimum target and provides a value of one. The third and final category is a payload that meets a certain threshold at conducting the task, but is only partially as effective as the best payload and so only a fractional value is added.

There is potential for the objective value to be defined by other metrics. One such is maximizing the area of the distribution of the SAG. Another option is to penalize the objective value for creating a configuration which depends on beyond line of sight (BLOS) communication. This option originates from a concern that the Tern could be cut off from satellite capability and thus cut off from the rest of the SAG if using only BLOS.

Further study could also be done on consequences of integrating the Tern with a ship. One must consider the need for spare parts, training sailors to maintain and repair the Tern, and if the Tern will increase the warfighting capability of the ship by replacing the helicopter(s) currently in use.

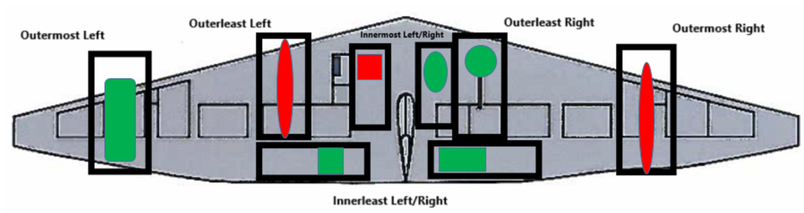
Finally, as previously mentioned, the model presented in this thesis can be adapted and applied to a multitude of other problems where the problem is assigning items to places with respect to constraints and the ability to make those items fixed or modular.

APPENDIX: Scenario 3 Figures



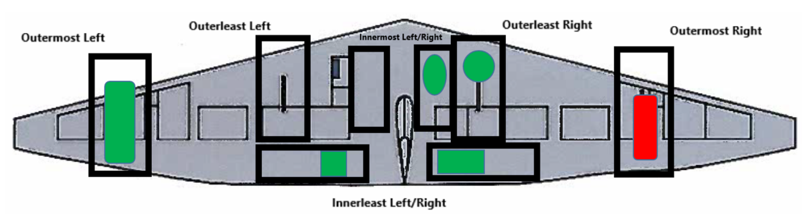
This figure displays the fixed configuration of payloads for Scenario 3. From left to right: Fuel Pod B, GPS A, Comm A, Computer A, and EO/IR B.

Figure A.1. Fixed Configuration for Scenario 3



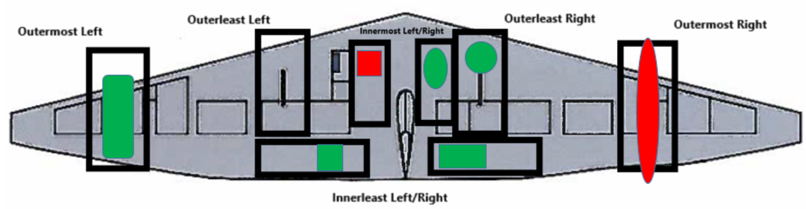
This figure displays the ASW configuration of payloads for Scenario 3. From left to right: Sonobuoy A, Computer B, and Torpedo A added (shown in red).

Figure A.2. ASW Configuration for Scenario 3



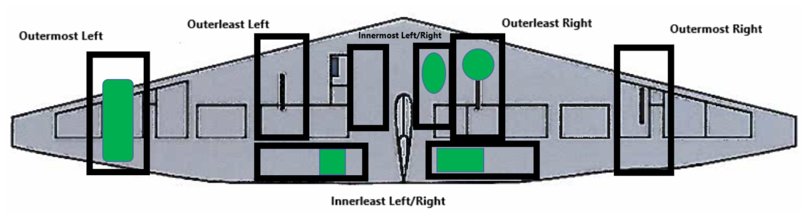
This figure displays the Comm Node configuration of payloads for Scenario 3. Fuel Pod A added (shown in red).

Figure A.3. Comm Node Configuration for Scenario 3



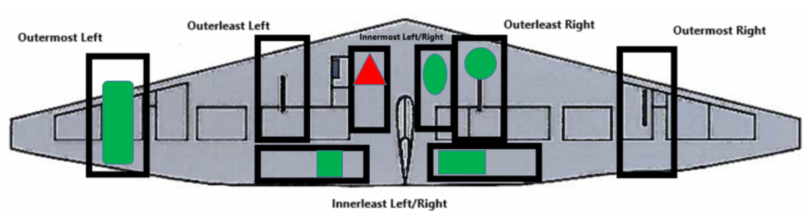
This figure displays the Deterrence configuration of payloads for Scenario 3. From left to right: Computer B and Missile A added (shown in red).

Figure A.4. Deterrence Configuration for Scenario 3



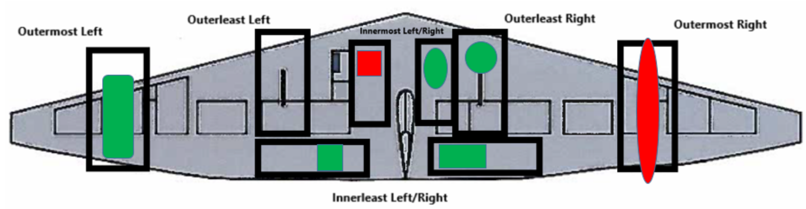
This figure displays the ISR configuration of payloads for Scenario 3. Note: this is the same configuration as Figure A.1.

Figure A.5. ISR Configuration for Scenario 3



This figure displays the Search configuration of payloads for Scenario 3. Radar A added (shown in red).

Figure A.6. Search Configuration for Scenario 3



This figure displays the Strike configuration of payloads for Scenario 3. From left to right: Computer B and Missile A added (shown in red). Note: this is the same configuration as Figure A.4.

Figure A.7. Strike Configuration for Scenario 3

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