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**COMBINING AND ANALYZING THE
TANKER AND AIRCREW SCHEDULING
HEURISTICS**

THESIS

Cem BOKE, Second Lieutenant, TUAF

AFIT/GOR/ENS/03-04

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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AFIT/GOR/ENS/03-04

COMBINING AND ANALYZING THE TANKER AND AIRCREW SCHEDULING
HEURISTICS

THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the
Degree of Master of Science in Operations Research

Cem BOKE, B.S.

Second Lieutenant, TAAF

March 2003

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AFIT/GOR/ENS/03-04

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HEURISTICS

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Abstract

Air refueling is an integral part of U.S. air power across a wide range of military operations. It is an essential capability in the conduct of air operations worldwide and is especially important when overseas basing is limited or not available. The planning, tasking, and scheduling of aerial refueling require solution of two major problems: assigning and scheduling of tankers to refueling points and efficiently assigning crews to each tanker.

To address the scheduling of tankers, Wiley (2001) developed an efficient tabu search approach. Combs (2002) developed another tabu search approach to assign crews to tankers. This research combines the two scheduling heuristics so that the tanker schedules generated by the tanker scheduling heuristic can feed the crew scheduling heuristic.

COMBINING AND ANALYZING THE TANKER AND AIRCREW SCHEDULING HEURISTICS

CHAPTER I. INTRODUCTION

1.1 GENERAL DISCUSSION

“No single innovation of recent times has contributed more to air power flexibility than the aerial tanker....”

Major General Perry B. Griffith (The Airman, No.8, 1960).

Air refueling is an integral part of U.S. air power across the range of military operations. It significantly expands the employment options available to a commander by increasing the range, payload, and flexibility of air forces. Therefore, aerial refueling is an essential capability in the conduct of air operations worldwide and is especially important when overseas basing is limited or not available. (Air Force Doctrine Document 1-3.2,1997)

The Air Mobility Command (AMC), of the United States Air Force (USAF), is the single organization in the U.S. structured to provide America’s “Global Reach” capability which is a key element of U.S. military strategy in both war and peace time. AMC coordinates the planning, tasking, and scheduling of aerial refueling to support intertheater and intratheater air operations for the Air Force, Army, Navy, Marines, and allied forces. These challenging tasks have two major aspects:

1. Assigning and scheduling of tankers to refueling points during intertheater and intratheater deployment of forces – addressed by the Aerial Fleet Refueling Problem (AFRP).
2. Once the flight schedule is determined, assigning crews efficiently to each tanker to fulfill the mission – addressed by the Tanker Crew Scheduling Problem (TCSP).

1.2 MOTIVATION

The importance of aerial refueling was emphasized during the Gulf War. Getting the warplanes and their support equipment and personnel as well as ground combat troops, equipment, and supplies to the Middle East required an extraordinary aerial refueling effort on short notice. The first group of deployed F-15s required seven refuelings during their fifteen-hour flight direct to Saudi Arabia from Langley AFB, Virginia. (Ritter, 1993)

During the Air War Over Serbia (AWOS), tanker forces directly contributed to the US/NATO victory. American airlift and tanker aircraft flew over 18,701 sorties, and transferred over 355,800,000 pounds of fuel during inflight refuelings to receiver groups (AWOS Fact Sheet, 1999).

Aerial refueling also played a key role in the operations in Afghanistan. The average range of U.S. in-theater air bases to Afghanistan is more than 1,000 miles. B-2 bombers have carried out 30 hour-long bombing missions from bases 10,000 miles away. Even the humanitarian airdrops have been performed by C-17s flying out of Ramstein,

Germany, nearly a distance of 3,000 miles. As the range between available air bases and battlefields increases, so does the need for aerial refueling (Goure, 2002).

These past experiences emphasize the importance of aerial refueling and reveal how large a war time problem might be. Complexity of the problems, scale and the specific constraints make both the AFRP and the TCSP difficult problems to solve with conventional optimization methods.

To solve the AFRP, Wiley (2001) developed a model utilizing group theoretic tabu search. His approach finds very good, detailed solutions to the AFRP within a planning horizon to answer the following questions:

- How many tankers are required to meet the air refueling requirements?
- How quickly can all the receivers be deployed to their final destinations?
- How far do the tankers and receiver aircraft have to travel?
- How much fuel do both tankers and receiver aircraft burn?

Given a deployment scenario, Wiley's model develops a tanker schedule, using the assumption that there is an unlimited number of tanker crews available. However, General Walter Kross said, "We never broke the tanker crew ratio out of the Cold War formula — we must if we are to survive."(Anaheim, Calif. Oct. 25, 1997). Most often, the limiting factor in mission planning is aircrew availability rather than aircraft availability (AFDD 2-6.2,1999).

For today's airlines, crew costs are the second highest component of the direct operating costs (fuel cost is the highest) (Gershkoff, 1989). This is also true today for the flying units in the Air Force in terms of costs such as temporary duty (TDY) per diem.

More important than cost is the effective scheduling of the aircrews. This is essential. Combs (2002) developed an analytical model that schedules the crews in an efficient manner to minimize cost, cover each flight, and satisfy AF crew utilization regulations.

He utilized an adaptive tabu search approach to solve the TCSP, a difficult combinatorial optimization problem. The model yields very good solutions in a short amount of time.

This research aims to link the approaches of Wiley and Combs so that any schedule generated by Wiley's AFRP model can feed Combs' TCSP model.

1.3 PROBLEM STATEMENT

Currently AMC utilizes CMARPS (Combined Mating and Ranging Planning System) for scheduling the tankers. CMARPS is a computer simulation that helps analyze, plan, and schedule the deployment of tankers in support of immediate and anticipated military operations. Unfortunately, this tool can take up to two weeks to produce meaningful results (Wiley, 2001).

For tanker crew scheduling, AMC analysts use a simulation program, "Crew Dog", to determine the number of crews needed to fly a given aerial refueling schedule (Ryer, 2000). Crew Dog embodies a simple greedy heuristic. This type of greedy heuristic tends to converge to local optimal solutions, thus ignoring large portions of the solution space (Combs, 2002).

AMC needs a tool that links the capabilities of Wiley's AFRP and Comb's TCSP tools to work interactively providing efficient and practical solutions. Introducing a heuristic approach to determine if a flight schedule is feasible in terms of crew

availability will provide an interactive approach that will open the door for creation of solutions that are feasible both in terms of tankers and crews while minimizing cost, waiting time for crews, and meeting other key objectives. A procedure for generating sample deployment scenarios is developed and 18 scenarios with various sizes are generated. A response surface is created to probe the mathematical relationship between the key factors and the number of tankers and crews required.

CHAPTER II. LITERATURE REVIEW

This chapter reviews selected topics in tabu search (TS) and explains how Harder's OpenTS engine works, which provides the baseline for TS in both models. It also discusses the tanker scheduling tools developed to address the AFRP. A detailed explanation of Wiley's AFRP model and Combs' TCSP model and the implementation of TS in both models are provided. Finally, general principles in experimental design are discussed.

2.1 TABU SEARCH

"Tabu Search is a meta-heuristic that guides a local heuristic search procedure to explore the solution space beyond local optimality." (Glover and Laguna, 1997:2)

"A heuristic is a technique which seeks good (i.e. near optimal) solutions at a reasonable computational cost without being able to guarantee either feasibility or optimality, or even in many cases to state how close to optimality a particular feasible solution is." (Reeves, 1995:6) A meta-heuristic is the master strategy that guides and modifies other heuristics in order to avoid local optimality and reach better solutions.

"The philosophy of tabu search (TS) is to derive and exploit a collection of principles of intelligent problem solving. In order to qualify as intelligent, TS must incorporate adaptive memory and responsive exploration. Adaptive memory allows the implementation of procedures that are capable of searching the solution space economically and effectively. Responsive exploration integrates the basic principles of intelligent search exploiting good solution features while exploring new promising regions." (Glover and Laguna, 1997:1-4).

The move definition is a key element of the tabu search meta-heuristic. All possible moves define the neighborhood of the current solution. A neighborhood $N(x, \sigma)$ of a

solution x is a set of solutions that can be reached from x by a simple move operation σ . Such an operation σ might be the removal of an object from, or addition of an object to, a solution. The interchange of two objects in a solution is particularly common in sequencing problems (Glover and Laguna, 1997:5). After the initial solution is constructed, the tabu search algorithm iterates through the solution space by means of the defined “move” structure in search of better solutions.

The tabu list is another key element of tabu search. At each iteration, a move is made to some “best” solution in the neighborhood of the current solution (not necessarily an improving solution). TS forbids, or makes tabu, solutions with certain attributes in order to prevent cycling and to direct the search to other regions of the solution space not yet explored. These attributes remain on the tabu list for a defined number of iterations called the tabu tenure. Short term and long term memory functions prevent solutions possessing these attributes from occurring, primarily through measures of recency and frequency. Tabu list structures, which contain the attributes associated with recent moves, are the most common form of short-term recency-based memory structures (Capehart, 2000:14). An alternative to attribute-based tabu lists is a solution-based tabu list. Since storing complete solutions might consume a lot of time and space, and the computational effort associated with keeping and searching a list of integers is negligible compared with the evaluation of the neighborhood, *hash functions* have the role of mapping a solution vector to an integer, and a *hash list* contains the function values for recent solutions (Glover and Laguna, 1997:246).

2.1.1 Aspiration Criteria

“Aspiration criteria are introduced in tabu search to determine when tabu activation rules can be overridden, thus removing a tabu classification otherwise applied to a move.” (Glover and Laguna, 1997:50). If a move which is currently tabu satisfies some specific aspiration criterion, the move is considered among the other candidate solutions. The primary reason for an aspiration criterion is to avoid passing on superior solutions. A widely used aspiration criterion consists of removing a tabu classification from a trial move when the move yields a solution better than the best obtained so far.

2.1.2 Intensification

Intensification strategies help drive the search to thoroughly search a promising region of the search space. “Intensification strategies are based on modifying choice rules to encourage move combinations and solution features historically found good. They may also initiate a return to attractive regions to search them more thoroughly.” (Glover and Laguna, 1997:96) Move combinations and solution attributes are identified for the good solutions and the use of these moves and attributes is encouraged. This can be accomplished by locking these attributes in the solution by increasing tabu tenure until pre-specified condition is reached.

2.1.3 Diversification

TS diversification strategies help to drive the search into unexplored regions of the solution space. Often they are based on modifying choice rules to bring attributes into the solution that are infrequently used. Alternatively, they may introduce such attributes by

periodically applying methods that assemble subsets of these attributes into candidate solutions for continuing the search, or by partially or fully restarting the solution process. In tabu search, diversification is created to some extent by short-term memory functions but is particularly reinforced by certain forms of longer-term memory. (Glover and Laguna, 1997:98-99)

2.1.4 Candidate List Strategy

For combinatorial optimization problems, as the problem size increases, the neighborhood built with the possible moves gets extremely large. The computational cost of evaluating each solution can restrict the examination of every move within the neighborhood. To reduce the neighborhood to a reasonable size, a candidate list strategy is utilized. Candidate lists can be constructed from context related rules and from general strategies (Glover and Laguna, 1997:61).

2.1.5 Strategic Oscillation

Temporarily relaxing problem constraints in some strategic fashion is referred to as strategic oscillation.” Strategic Oscillation is closely linked to the origins of tabu search and provides a means to achieve an effective interplay between intensification and diversification over the intermediate to long term. Strategic oscillation operates by orienting moves in relation to a critical level, as identified by a stage of construction or a chosen interval of functional values.” (Glover and Laguna, 1997:102) The critical level might be feasibility and infeasibility, certain function values, switch between particular evaluation functions, periodically relaxing certain constraints.

The binary multidimensional knapsack problem was first used to introduce strategic oscillation and provides a simple example. Items are added until the infeasible region is explored for a certain number of iterations, and the direction is reversed toward the feasible region by changing the variables from 1 to 0 (Glover, 1977).

2.1.6 Vocabulary Building

Vocabulary building is based on viewing a chosen set S of solutions as a text to be analyzed, capturing attribute combinations shared in common by various solutions x in X , and generating new solutions by combining the attribute combinations that emerge as significant or incorporating the new attribute combinations into tabu restrictions and aspiration conditions (Reeves, 1995:122). Different heuristic approaches can be applied to identify the attributes to combine and generating the new ones or to take the newly created solution back to feasibility. In a nutshell, there are two major objectives in vocabulary building (Glover and Laguna, 1997:253):

1. to identify a good collection of reference points (i.e., partial solutions); and
2. to identify paths in one or more neighborhood spaces that will unite components of these partial solutions, with suitable attendant modifications, to produce complete solutions.

2.2 OpenTS

OpenTS, developed by Robert Harder in 2001, has a JavaTM based environment, and was inspired by Harder et al. (2002). This research used tabu search for vehicle routing, analysis of force mixtures, and assignment of weapons to targets. Open TS

enables rapid development of tabu searches, emphasizing efficiency in design and execution.

OpenTS asks you to define the basic elements common to all tabu searches and then performs iterations based on these elements. The following elements are defined as separate Java classes:

- Solution structure – how the solution is represented
- Objective function – how the solution is evaluated
- Tabu list – the memory mechanism for tabu search
- Move – how a move is represented
- Move manager – how neighborhoods are determined

2.2.1 An Iteration in OpenTS

OpenTS uses java classes to search the solution space. Given a starting, or current, solution, the move manager is asked to generate a list of moves for the iteration. OpenTS uses the objective function to determine the value of the solution that would result from each of these moves. With the help of the tabu list, OpenTS determines which move is the best, and that move operates on the starting, or current solution, which results in a new current solution. Figure 1 shows this cycle graphically.

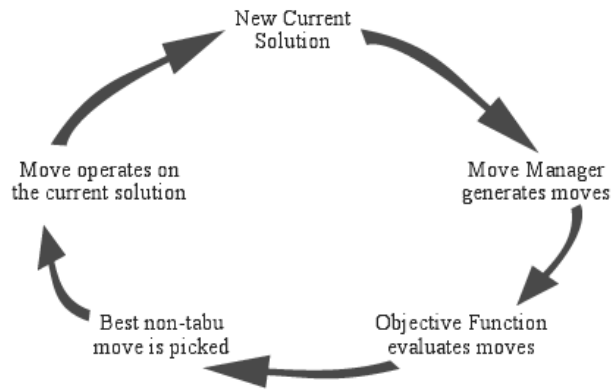


Figure 1. An iteration in OpenTS (Harder, 2002)

2.2.2 Hierarchical Objective Function

The objective function is structured as an array which allows handling problems with a single objective function using an array of dimension 1, or with multiple objective functions using an array of dimension longer than 1. Thanks to that array structure, solutions in more than one dimension can be evaluated and compared first by comparing the most important value, then the second, the third and so on. Two example objective functions are presented in Figure 2 for a minimization problem (Harder, 2001):

	Example 1		Example 2	
	Sol 1	Sol 2	Sol 1	Sol 2
Goal	1.3	1.5	1.3	1.3
1: Goal	3.5	2.1	3.5	2.1
2: Goal 3:	0.6	0.5	0.6	0.5
	Better		Better	

Figure 2. Implementation of Hierarchical Objective Function

In the examples of Figure 2, each column represents a solution, and each row corresponds to a goal, which is to be minimized. In the first example, comparing the values for the first goal is adequate to determine that the first solution (sol 1) is better than solution 2 (sol 2). In example 2, there is a tie in the values of the first goal. Therefore the proceeding goal is compared and it is determined that the second solution is better.

2.3 TANKER SCHEDULING TOOLS

The tools developed to address AFRP are the previously mentioned Combined Mating and Ranging Planning System (CMARPS), Quick Look Tool (QLT) (Russina & Ruthsatz, 1999), and Tanker Assignment Planning (TAP) Tool (Capehart, 2000).

QLT is a spreadsheet model that provides a means to schedule the tanker aircraft to receiver groups. It does not model multiple locations for these tankers.

The TAP Tool uses tabu search to solve the primary tanker scheduling problem of assigning tankers, which are based at multiple locations, to different refueling points and at the same time making sure that each receiver group arrives before its required delivery date. The tool allows AMC to input several receiver groups consisting of various aircraft types and numbers. Each receiver group contains a point of origin and destination, with the option of providing one waypoint along the path. The user is also able to specify the locations of tanker aircraft. (Capehart, 2000) The critical drawbacks of this tool are as follows:

- The waypoints (WPT) generated do not guarantee that all aircraft will complete their mission without running out of fuel.

- Receiver groups (RG) that require escort are escorted from their first WPT to their destination base, regardless of whether or not the WPT is located over open water.
- A tanker cannot serve multiple WPT nodes. The tanker that serves a WPT has to go back to its beddown base.

The AFRP model developed by Wiley (2001) provides the detailed analysis of CMARPS, overcomes the drawbacks of the TAP Tool, and provides very good solutions within a reasonable time frame.

2.3.1 Group Theoretic Tabu Search

Wiley utilized Group Theoretic Tabu Search (GTTS) to solve the AFRP. GTTS makes use of adaptive tabu search to dynamically update memory structures as well as to promote diversification. Group theory provides group actions such as multiplication and conjugation, which helps to implement different types of moves and define move-based neighborhoods. (Wiley, 2001)

A symmetric group on n letters represented as S_n is used to define the solution for the AFRP. Assuming that G consists of n objects labeled $1,2,3\dots n$, S_n is the group of all the permutations of n objects and has the order $n!$ (Faasler and Stiefel, 1992)

The GTTS approach assumes that the following information is given for any deployment scenario:

- A known set of tankers and their associated original beddown (starting) bases,

- A known set of receiver aircraft, each with an initial departure base and a final arrival base, where one or more aircraft is aggregated to form Receiver Groups (RGs),
- A known set of bases capable of refueling tankers and RGs,
- A known set of flight characteristics for each aircraft including flight speed, altitude, take-off weight, fuel capacity, and fuel burn rates, and
- A known set of tanker specific characteristics including fuel-offload capacity and fuel-offload rates.

The assigning and scheduling of tankers to refueling points during the “deployment” of forces from one theater to another is known as the AFRP. For a given deployment, the following decisions compose the solution to the AFRP:

- The waypoints (WPTs), i.e., the physical locations and start times where the refueling of RGs takes place,
- The tanker(s) that serve each WPT,
- The amount of fuel the assigned tanker(s) should deliver to a WPT.

The objective function that drives the model to a solution is multicriteria and hierarchical in form. The hierarchical criteria are given in the following order that can be modified according to the specifications of the problem and priorities. Items 1-3, 5, and 6 represent the feasibility constraints that have been incorporated into the objective function. All five must be zero to have a feasible solution. Any nonzero values for these criteria either violate USAF policy, or one or more aircraft fail to complete their required flight, which is unacceptable.

Minimize

1. the number of unescorted RGs requiring escort between WPTs;
2. the number of WPTs not serviced by a tanker;
3. the number of misordered precedence pairs;
4. "bad" tanker assignments, i.e., a tanker servicing another tanker, a return to base node next to a return to base node, and so on;
5. tanker fuel in excess of the available fuel is used;
6. RG fuel in excess of the available fuel is used;
7. the amount of time spent by RGs and tankers in "orbit" at a WPT;
8. the amount of RG late arrival time, i.e., where one or more RGs arrive later than a desired "soft" arrival time;
9. the overflow amount of tankers at all active tanker bases;
10. the number of tankers used;
11. the amount of tanker flight time required;
12. the total distance flown by tankers;
13. the amount of fuel used by tankers;
14. the amount of fuel off-loaded by tankers; and
15. the amount of fuel used by RGs.

These criteria are interpreted in a strict hierarchical fashion as illustrated in Figure 2. While comparing two distinct solutions, first the values of criterion 1 are checked. The solution that has the lesser value is considered to be superior. The criteria are checked until either the first superiority is determined or all criteria turn out to be identical.

2.3.1.1 The Primary Constraints for AFRP

AFRP has inter-related constraints mainly based on timing and fuel use of the tankers and RGs. The primary constraints are as follows:

- All aircraft are refueled in a timely manner to guarantee that none of the receiving aircraft has its available fuel fall below a pre-specified “minimal reserve”;
- Tankers have limited fuel capacity;
- The flight duration restrictions that affect the crew-tanker availability to travel long distances and to provide fuel;
- Certain bases have limited capacity for resident tanker aircraft (maximum on ground (MOG));
- WPTs must be visited in the correct order along the RG’s flight path;
- If two WPTs are located over a large body of water and the associated RG contains one or more light aircraft, the flight “leg” between the two WPTs requires escort by a tanker;
- When a tanker returns to an active tanker base, it must remain at that base for a minimum amount of service time (4 hours for Wiley’s AFRP model).

2.3.1.2 Solution Methodology

Instantiation of the initial solution

For the initial solution, the AFRP assigns a tanker to all the WPT nodes of each RG. For nontrivial problems, this approach will most likely produce infeasible starting solutions. To overcome the infeasibility of the initial solution, an initial set of moves

using a Tanker Insert Move Neighborhood (TKI) is generated using the remaining available tankers and inserting them within the current employed tanker's WPT assignment. The insertion point is strongly influenced by the requirement that some RGs must be escorted over open waters. Placement of the tankers continues until there are no available tankers or until a feasible solution is obtained.

Dynamic neighborhood selection

Once the initial TKI has performed its function, additional move neighborhoods are invoked based on the current search status and solution. These neighborhoods are as follow:

- a Return To Base Insert Move Neighborhood;
- a Restricted Insert Move Neighborhood;
- an Escort Pair Insert Move Neighborhood;
- a Return To Base Delete Move Neighborhood;
- a Tanker Swap Move Neighborhood;
- a Restricted Swap Move Neighborhood;
- a Return To Base Swap Move Neighborhood.

2.3.1.3 Tabu Search

The tabu search structure used in Wiley's AFRP model applies adaptive tabu tenure. As the search progresses, the tabu tenure is adaptively modified based on the status of the current solution (Chambers and Barnes, 1996; Dell'Amico and Trubian, 1993). As moves are selected, the letter moved is recorded and put into tabu-active status for a specified number of iterations. If the current solution is the best solution found so

far, the tabu tenure is reset to the pre-specified default value. If the current solution is a better move than the previous one, but not the best solution so far, the tabu tenure remains at its current value. If the current solution is not better than the previous move, the tabu tenure is increased by one.

2.3.1.4 GTTS Preprocessor

“The GTTS described in the previous sections assumed that the WPTs were provided by an external source and were consistent, i.e., feasible (flyable) solutions could be found when those WPTs were used. But externally supplied WPTs are not necessarily consistent, i.e., Capehart’s Middle East Deployment Problem” (Capehart, 2001). “To account for this possibility, a modified form of the GTTS, the GTTS Preprocessor (GTTSP), has been developed to determine consistent WPTs for a single RG’s flight path. Hence, the GTTSP is also an adaptive tabu search method developed specifically to find consistent active WPT node sets for a single RG.” (Wiley, 2001)

2.4 ADAPTIVE TABU SEARCH APPROACH FOR TCSP

According to Air Force Defense Doctrine, the Air Force does not have enough tanker crews to properly perform the mission. Tanker units are currently manned at 1.17 – 1.36 crews per aircraft (AFDD 2-6.2, 1999). This level of manning makes crew scheduling an important issue.

AMC uses a simulation program, Crew Dog, to determine the number of crews needed to fly a given aerial refueling schedule. (Oneill, 2002) Crew Dog embodies a

simple greedy heuristic to assign the crews without an attempt to avoid getting trapped at local optimal solutions, so it ignores a large portion of the solution space.

The adaptive tabu search model developed by Combs (2002) solves the tanker crew-scheduling problem. The symmetric group on n letters S_n provides the solution structure for the TCSP. Combs' model is general enough to handle the Airline Crew Scheduling Problem (ACSP) which is an important problem for the commercial airlines. The ACSP and TCSP are similar. They have different constraint structures imposed by the Federal Aviation Administration and the Air Force, respectively.

2.4.1 Airline Crew Scheduling Problem

Gershkoff (1989) describes the ACSP as follows:

1. The objective is to minimize the cost of flying the published schedule, subject to the constraints in 2-5 below.
2. Each flight must be covered once and only once.
3. Each pairing (pairings are sequences of flights a crew flies) must begin at a crew base, fly around the system, and return to the same base.
4. Each pairing must conform to the limitations of FAA regulations and published work rules in force at the airline.
5. The number of jobs at each crew base must be within specific minimum-maximum limits, in accordance with the airline's manpower plan.

Constraint 2 requires a set-partitioning problem (SPP) with the general mathematical formulation as follows (Hoffman and Padberg, 1993):

Equation 1. Set Partitioning Problem (SPP) Formulation

$$\min \sum_{j=1}^n c_j x_j \quad (1)$$

Subject to

$$\begin{aligned} Ax &= e_m, \\ x_j &\in \{0,1\} \text{ for } j=1, \dots, n, \end{aligned} \quad (2)$$

where e_m is an m -dimensional vector of ones, and n is the number of rotations we consider. The first letter in a crew's rotation is the identification number of the crew, and each remaining letter represents the flights flown and the order in which they must be flown, i.e., (0,4,6,9) means crew 0 flies flight segments 4, 6, and 9. For the TCSP, each column of matrix A from (2) represents a flight rotation with a cost of c_j , and each row represents a flight segment.

$$\begin{aligned} x_j &= 1 && \text{if rotation } j \text{ is flown} \\ &0 && \text{otherwise} \end{aligned}$$

The A matrix is generated one column at a time with

$$\begin{aligned} a_{ij} &= 1 && \text{if flight segment } i \text{ is covered by rotation } j \\ &0 && \text{otherwise} \end{aligned}$$

The SPP defined above is an NP-complete problem (Nemhauser and Wolsey, 1999:134). As the size of the problem increases, the solution time increases exponentially. For a problem with 1000 flight segments, billions of feasible rotations exist. Therefore, it may be infeasible to enumerate and solve the problem optimally. In Combs' TCSP model, it was shown that a metaheuristic, when combined with a classical optimizer, provides an excellent column generation approach to SPP problems.

2.4.2 TCSP

The crew rotation difficulties, combined with the specific characteristics of USAF missions, create a problem similar to airline crew scheduling, but it is different in some aspects. The first objective is to minimize the number of tanker crews needed to fly the schedule and then maximize the efficiency of these crews by minimizing the number of hours the crews spend waiting to fly, both within the duty day and between duty days. The table below shows four main crew constraints dictated by the AF:

Table 1. Crew Constraints For the TCSP

Constraint	Limit
Flight Duty Day	16 hours (24 with augmented crew*) max
Crew Rest	12 hours min
30 Day Flying Limit	125 hours max
90 Day Flying Limit	330 hours max

*Augmented crew: Two operational crews are assigned to a particular flight, thus sharing the flying time.

With these constraints, the TCSP can be described as follows:

- 1) Minimize the number of crews required and maximize the efficiency of the crews, subject to constraints 2-7 below.
- 2) Each flight of the aerial refueling problem must be flown uniquely.
- 3) Crew duty days must not exceed 16 hours.
- 4) Once its duty day is over, a crew must rest for a minimum of 12 hours.
- 5) Crews can fly no more than 125 hours in 30 days and 330 hours in 90 days.
- 6) The user-defined minimum time between flights (MWBF) must be met.
- 7) Bases of arrival and departure must match for each crew and aircraft.

2.4.2.1 Solution Structure

The cyclic form of S_n provides a compact solution structure for the TCSP. A TCSP solution is written as the product of disjoint cyclic factors, where each disjoint cycle is a single crew's rotation. The first letter in each cycle is the identification number of the crew, and each remaining letter in a cycle represents flights to be flown and the order in which they must be flown. These solutions are characterized in terms of feasibility as follows:

- 1) **Feasible Solutions:** The solutions that meet all TCSP constraints.
- 2) **Near feasible Solutions:** The solutions violate some of the constraints, but the amount of constraint violation is within an allowable tolerance. The size of each constraint deviation is user-defined and pre-set prior to starting the solver.
- 3) **Poor Infeasible Solutions:** The solutions exceed the allowable constraint violation on one or more of the TCSP constraints.

Initial Solution Heuristic

To start the tabu search, we need an initial solution. The heuristic used to find the initial solution in Combs' TCSP model is very similar to the Crew Dog tool used by AMC analysts. Tabu search for this problem runs in two modes, operational and analysis.

The assumptions for the operational mode heuristic:

- 1) AMC crews are physically mobilized for a deployment or other operation.
- 2) It is given a tanker flight schedule sorted in order of increasing flight departure, i.e. the first flight in the list departs the earliest.

- 3) Existence of a crewHistory.txt file that contains the 30 and 90 day flying histories of each mobilized crew to be able to check all previously defined crew constraints.

The heuristic immediately instantiates the given number of crews and reads their crew histories from the text file. It then begins iterating through the flights. For each flight, it checks all the TCSP constraints and determines if any of the existing crews can cover the flight. If so, the flight is assigned to the crew with the smallest identification number. If no crew can cover that flight, every constraint is ignored except matching the arrival and departure bases. The flight is assigned to the crew with the smallest identification number whose last arrival base matches the flight's departure base. In case of no available arrival-departure base matches, the flight is placed into the first crew's rotation.

The assumptions for the analysis mode heuristic:

- 1) It is given a tanker flight schedule sorted in order of increasing flight departure, i.e. the first flight in the list departs the earliest.
- 2) Existence of user-supplied input parameter $prob_{fly}$, to determine whether or not a crew flew on any of its previous 90 days.
- 3) Existence of a cumulative flying time distribution file created by AMC.

The heuristic creates an initial crew and populates its 30 and 90 day flying histories in a JavaTM array list. The flying histories are populated using two Monte Carlo draws. For the first one, $prob_{fly}$ is used and if a crew did fly, then another draw is made and

compared to the cumulative flying time distribution crewProbabilities.txt file to determine the flight duration.

Once the first crew is instantiated, the heuristic begins to iterate through each flight in the schedule. For each flight, each crew is examined by order of creation. If a crew can feasibly cover a flight, then the flight is assigned to the available crew with the smallest identification number. Otherwise, the heuristic creates a new crew, populates 30 and 90 day flying histories and determines whether or not the crew can cover the flight. New crews are created until all flights are covered, ensuring an initial feasible solution. A graphical representation of both the operational and analysis mode initial solution heuristic is presented in Figure 3.

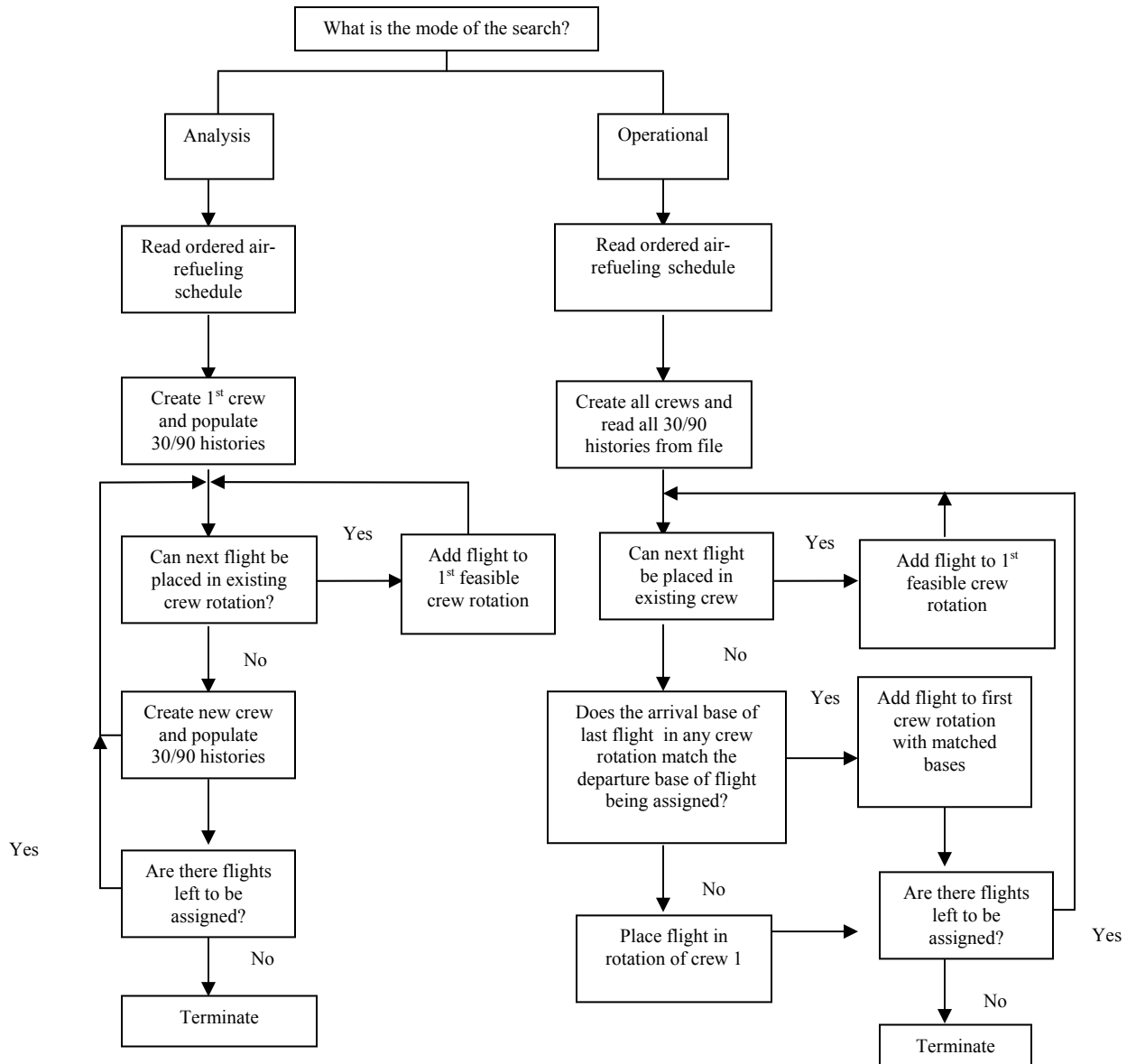


Figure 3. Initial Solution Heuristic (Combs, 2002)

Moves Used for Local Search Process

Swap and insert moves enable an efficient neighborhood search for the tabu search algorithms developed for scheduling problems. Combs' TCSP model examines the swap and insert neighborhoods simultaneously. This is defined as the Combined Restricted

Swap/Insert Neighborhood (CRSIN). As the problem size increases, individual swap and insert neighborhoods can become extremely large, so a candidate list strategy is utilized to reduce the neighborhood size.

The ATS uses the following rules to create its Restricted Swap Neighborhood:

- Only swap flights between disjoint cycles or rotations,
- Only swap flights that maintain proper base of arrival-departure matching,
- Only swap flights that maintain increasing letter order within each affected rotation.

The Restricted Insert Neighborhood is created according to the following rules:

- Only insert a flight from one crew rotation to another,
- Only allow inserts that maintain proper base of arrival-departure matching,
- Only allow inserts that maintain increasing letter order within each affected rotation.

The ATS periodically is trapped in areas of poor infeasibility during the search process. When this happens, ATS adapts a new neighborhood strategy, Targeted Combined Restricted Swap/Insert Neighborhood (TCRSIN). TCRSIN escapes from the trap of poor infeasibility as follows:

- Allows mismatches between arrival and departure bases,
- The neighborhood targets the crews that are currently infeasible.

Solution and Move Evaluation

The solution evaluation function captures the objectives and constraints that compose the TCSP:

- A crew variable to capture the number of crews in the solution,

- A waiting time variable to capture a measure of the efficiency of the schedule,
- Penalty variables relating to violations of each TCSP constraint.

To evaluate the initial solution or a solution generated from a restart, Equation 2 is used:

Equation 2. TCSP Solution Evaluation

$$\begin{aligned} eval_{solution} = & \textit{waiting time} + \rho_{crews} * (\# \textit{crews}) + \rho_{rest} * (\textit{rest penalties}) + \\ & \rho_{duty} * (\textit{duty day penalties}) + \rho_{MTBF} * (\textit{MTBF}) + \rho_{30} * (\textit{thirty day penalties}) \\ & + \rho_{90} * (\textit{ninety day penalties}) + \rho_{bases} * (\textit{mismatched base penalties}) \end{aligned}$$

For the swap and insert moves, only two crews are affected at any iteration so there is no need to calculate the $eval_{solution}$ from scratch. Instead, incremental means of calculating are used to increase the efficiency of the code. The resulting move evaluation function is presented as Equation 3:

Equation 3. TCSP Move Evaluation

$$\begin{aligned} eval_{move} = & \Delta \textit{waiting time} + \rho_{crews} * \Delta(\# \textit{crews}) + \rho_{rest} * \Delta(\textit{rest penalties}) + \\ & \rho_{duty} * \Delta(\textit{duty day penalties}) + \rho_{MTBF} * \Delta(\textit{MTBF}) + \rho_{30} * \Delta(\textit{thirty day penalties}) \\ & + \rho_{90} * \Delta(\textit{ninety day penalties}) + \rho_{bases} * \Delta(\textit{mismatched base penalties}) \end{aligned}$$

Solution and move evaluation functions contain seven parameters that must be continuously adapted. By means of the parameters, strategic oscillation between the feasible, near feasible, and poor infeasible areas of the solution space is controlled.

Penalty refers either to the number of infeasible solutions found in the last ten iterations or to the linear penalty defined as $| \textit{actual value} - \textit{desired value} |$ depending on

the parameter type. *Actual value* is the value calculated by the algorithm, and *desired value* is the target value of the particular constraint.

2.4.2.2 Tabu List

To avoid getting trapped at a local optimum, tabu search uses the tabu list. The ATS uses the solution-based tabu list. The search records the hash value of each solution visited in the Java™ array list. There are two tabu tenure implementations for this problem:

1. Every solution visited is declared as tabu for the rest of the search
2. Adaptive tabu tenure is used implementing the following rules:
 - If the current solution is a revisited solution, the tabu tenure doubles.
 - If the current solution is unique, the tenure decreases by one.

2.5. EXPERIMENTAL DESIGN

Investigators in virtually all fields of inquiry usually perform experiments to make inferences about the systems or the processes under consideration. Experiments can be defined as a test or series of tests in which purposeful changes are made to the input variables of a process or system so that we may observe and identify the reasons for changes that may be observed in the output response. All of this is accomplished in such a fashion that allows for maximum information about the system being tested given a limited amount of resources (Montgomery, 1997).

Understanding the key relationships between input variables and the response variables enables us to do several things (Montgomery, 1997).

- Determine which inputs are most influential and least influential on the response,
- Determine the input variable settings such that the response will always be near the desired nominal value,
- Establish input variable settings that minimize response variance,
- Establish input variable settings that minimize the effect of the uncontrollable variables.

“Factorial designs are widely used in experiments involving several factors where it is necessary to investigate the joint effects of the factors on a response variable. By joint factor effects, we typically mean main effects and interactions. A very important special case of the factorial design is that where each of the k factors of interest has only two levels. Because each replicate of such a design has exactly 2^k experimental trials or runs, these designs are usually called 2^k factorial designs.” (Myers and Montgomery, 2002)

The 3^k factorial designs are also widely used where the system under consideration has factors with three levels. When these factors are quantitative, low, intermediate, and high levels are generally denoted as -1 , 0 , and 1 , respectively. This facilitates fitting a regression model relating the response to the factors (Myers and Montgomery, 2002).

2.6 CHAPTER SUMMARY

This chapter briefly discussed the basics of tabu search and explained the methodologies developed to address the AFRP and TCSP in detail. The next chapter describes the methodology developed to combine and analyze the tanker and crew scheduling models.

CHAPTER III. METHODOLOGY

This chapter details how the AFRP and TCSP models are combined and explains how the heuristic works to check the feasibility of a move-solution combination in terms of crews and how it is adapted to the AFRP model. The chapter finishes with a detailed look at the experimental design conducted in order to probe the mathematical relationship between key factors and the number of tankers and crews required to support a given deployment scenario.

3.1 ORDERED AIR REFUELING SCHEDULE

In order to combine the AFRP and TCSP models, we need a tanker schedule file that contains the following information for each tanker:

- Tanker Aircraft Identification Number;
- Departure Base;
- Departure Time;
- Flight Time;
- Arrival Base; and
- Arrival Time.

The characteristics required for this file are:

- If the tanker has multiple flights, these flights should be represented separately;
- The flights should be in an ascending order in terms of their departure time; and
- Departure time, flight time, and arrival time should be in minutes.

After the AFRP model finds a best tanker schedule, the tanker schedule file, with the aforementioned characteristics, is generated for use by Combs' TCSP model which assigns the crews to the tankers.

An example of the tanker schedule file is presented in Table 2.

Table 2. Ordered Air Refueling Schedule

AID	DBase	Dtime	FTime	ABase	ATime
21	15	0	337	59	337
15	9	0	768	60	768
14	9	0	768	62	768
13	9	0	530	55	530
6	37	20	12	37	32
2	36	53	231	36	284
0	36	137	107	36	244
1	36	207	78	36	285
3	12	528	146	12	674
5	12	541	13	12	554
20	15	597	664	15	1261
22	15	607	424	15	1031
8	37	652	310	37	962
19	38	730	744	65	1474
13	55	770	324	68	1094

In order to generate the ordered air-refueling schedule, each tanker route should be examined. These routes are stored in the solution representation for the Wiley's AFRP model. An example solution representation is presented as follows:

(0 18 55 29 51)**(1** 45 46 60)**(2** 27)**(3** 19 49 37 38 39)**(4** 23)**(5** 22 61 28)

In this example solution, six tankers are used. The first bold italic letter in each parenthesis represents the tanker identity number whereas the rest of the letters represent either a waypoint or another tanker base.

The ordered air-refueling schedule file is generated depending on the following cases (different possible flight segments are represented symbolically in Figure 4). In all cases, a tanker services all waypoints between bases visited.

- **Case 1:** The tanker takes off from its original beddown base, services WPTs, and lands at another tanker base to be refueled and serviced. After refueling and service, it leaves that base to service additional WPTs.
- **Case 2:** The tanker takes off from its original beddown base, services WPTs and then returns to its beddown base.
- **Case 3:** The tanker takes off from a tanker base, at which it has landed to be refueled and serviced, and then lands at another tanker base to be refueled or serviced before continuing its mission.
- **Case 4:** The tanker takes off from a base which is not its original beddown base, and after servicing the rest of the waypoints on its route, it returns to its beddown base.
- **Case 5:** The tanker takes off from its original beddown base, services all WPTs and lands at another tanker base and stays there.
- **Case 6:** The tanker takes off from a base which is not its beddown base and after servicing the rest of the waypoints, it lands at another tanker base and stays there.

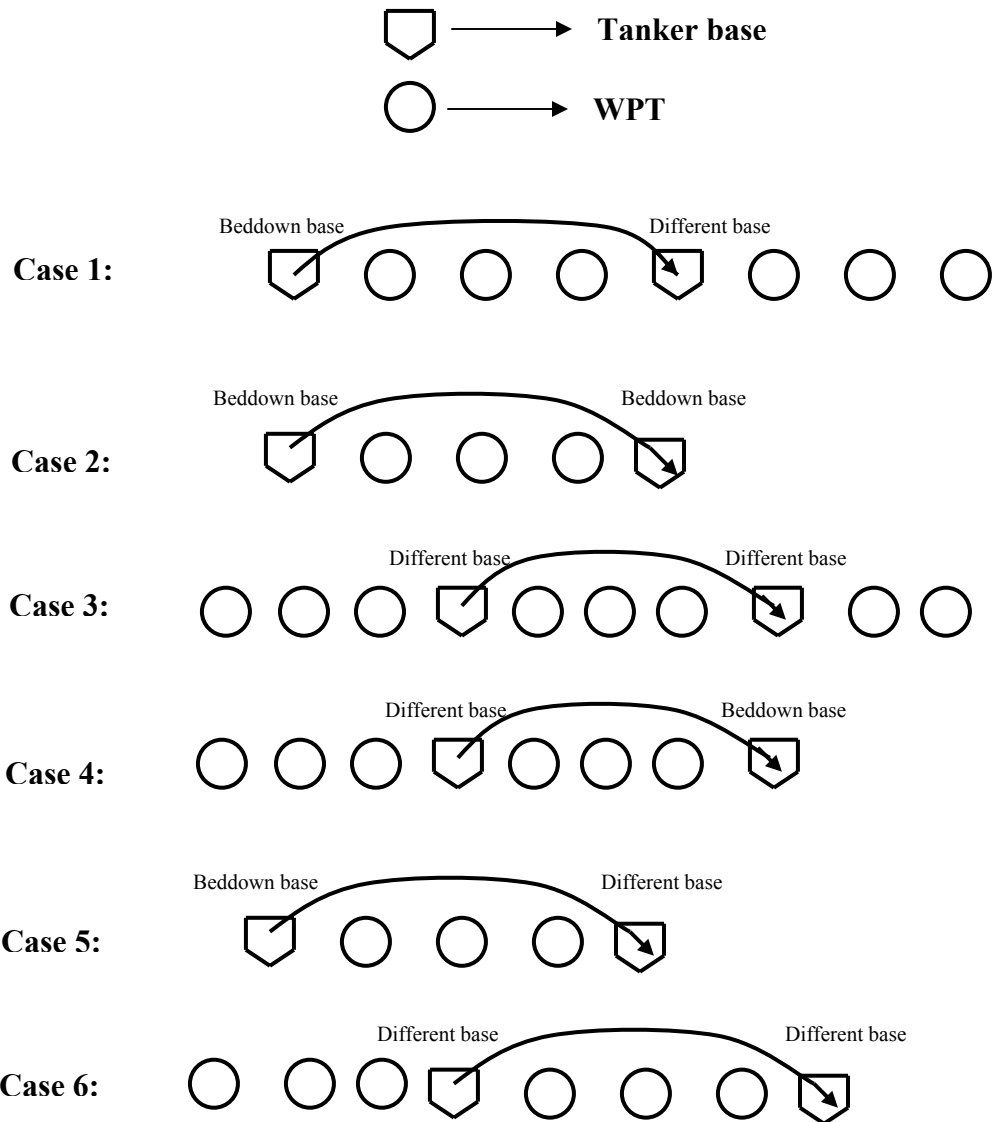


Figure 4. Symbolic Representations of the Possible Tanker Route Segments

The tanker schedule generated by Wiley's AFRP model is used as an input for Combs' model to determine crew assignments. In case of large deployments, the number of available crews may not be able to feasibly service the complete tanker schedule. In order to overcome, or at least ease, this problem a new heuristic is introduced. This

heuristic will determine the feasibility of a tanker schedule and will be introduced as a new goal within the current hierarchical objective function of the AFRP.

3.2 HEURISTIC APPROACH TO CHECK THE CREW FEASIBILITY

At each tabu search iteration for Wiley's AFRP model, the hierarchical objective function is strictly implemented when evaluating solutions. The AFRP model does not include crew availability within its hierarchical objective function. Given a deployment scenario, Wiley's model develops a tanker schedule and assumes that there is an unlimited number of tanker crews available. However, according to AFDD (1999), in general, the limiting factor in mission planning is aircrew availability rather than aircraft availability. Therefore, we need to take into consideration the crew availability while generating the tanker schedule so that at least no grossly infeasible (in terms of crew availability) tanker schedules are passed to Combs' crew scheduling model.

Wiley's model has 15 goals that are minimized. The new heuristic approach developed to test the crew feasibility becomes the sixteenth goal in the AFRP model, and it is included in the hierarchical objective function. The heuristic yields the number of required crews for crew-feasible solutions and a default big number for crew infeasible solutions. Since the objective is to minimize the number of crews, crew feasible solutions are preferred over crew infeasible solutions.

The heuristic instantiates the given number of crews and reads their crew histories from the crew histories file. It then begins iterating through the flights. For each flight it checks all the TCSP constraints and determines if any of the existing crews can cover it. These constraints are as follows:

- Arrival base and next departure base should match;
- There must be a predetermined minimum time between departure time and arrival time;
- The rest limit constraint for the crew should be met; and
- The 30/90-day flying limits should not be exceeded.

If all constraints are met, the flight is assigned to the crew with the smallest identification number. This procedure is repeated until all flights are matched with a crew or there is no crew to cover a given flight. As soon as a flight fails to have a crew assigned, the heuristic yields a big number associated with infeasible solutions. If all the flights are assigned a crew, then the heuristic yields the feasible number of crews required. The graphical representation of the crew feasibility heuristic is presented in Figure 5.

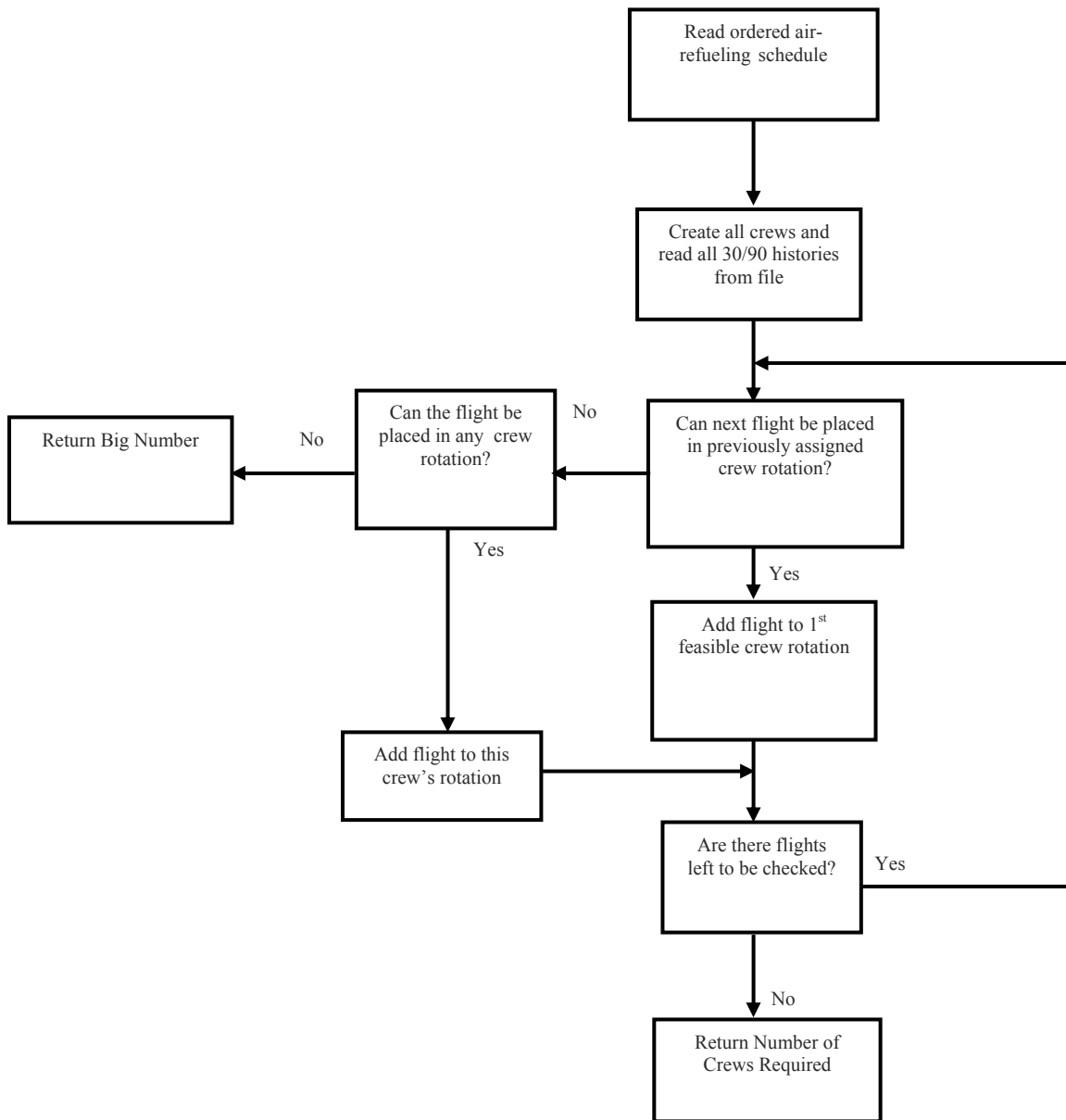


Figure 5. Crew Feasibility Heuristic

As a default, the crew feasibility goal is the sixteenth goal in the hierarchical objective function. However, a crew feasible solution that contains additional tankers is preferred over a crew infeasible solution with fewer tankers. Therefore, the crew feasibility objective is placed just above the number of tankers used objective in the

hierarchical objective function. In order to let the decision maker prioritize all these goals, including crew feasibility, a Graphical User Interface (GUI) is developed. With this GUI, the user can change the position of a goal in the hierarchical objective function, implying a change in the importance of that specific goal. The higher position of the goal, the more influence it gains on the solution. For instance, if the crew feasibility check constraint is placed in the first position, the first thing that is checked is crew feasibility, and if one of the solutions is infeasible in terms of crews, then that solution will be ruled out automatically without checking the rest of the goals (assuming a better solution has already been found). A screenshot of the GUI is presented in Figure 6.

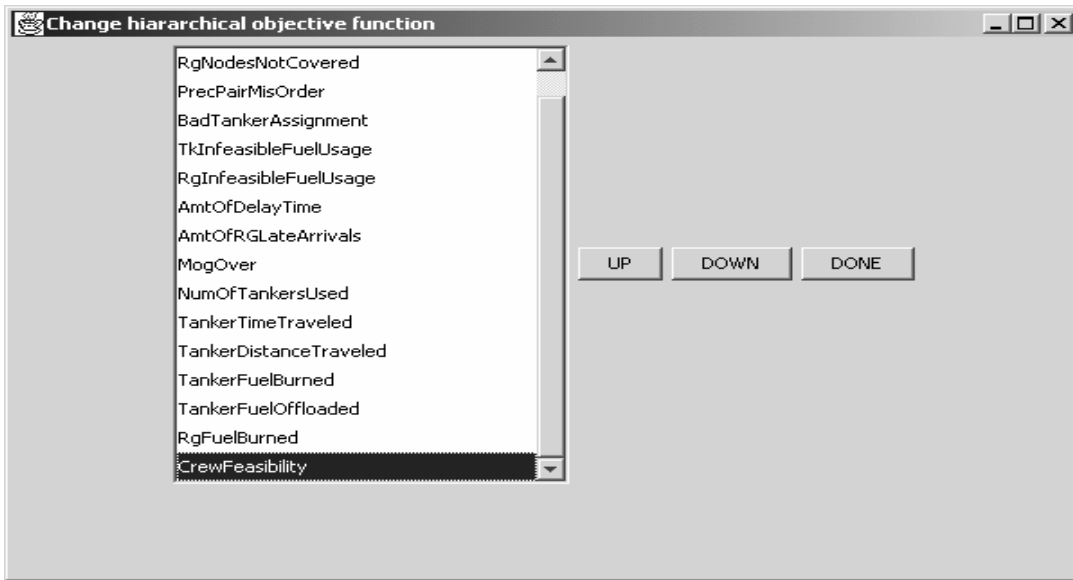


Figure 6. GUI for Modifying Hierarchical Objective Function

3.3 GENERATING DEPLOYMENT SCENARIOS

For experimental purposes, we needed instances of deployment scenarios with various sizes. In order to generate these scenarios, eight bases in the USA were chosen as

receiver group departure bases. Since these bases are usually home to homogeneous types of aircraft, choosing the departure base dictates the aircraft type or vice versa. In order to vary the arrival bases, three bases in Saudi Arabia, one base near England, and one base in Portugal are chosen. These bases are listed in Appendix B.

Wiley's original AFRP model assumes that all WPTs are consistent and feasible (flyable for RGs) solutions that can be obtained by using those WPTs. In order to generate consistent scenarios, all possible WPT spatial locations are generated from departure bases to arrival bases with a 100 NM great circle distance between consecutive waypoints. Figure 7 presents a screenshot of the GUI developed to determine these waypoints.

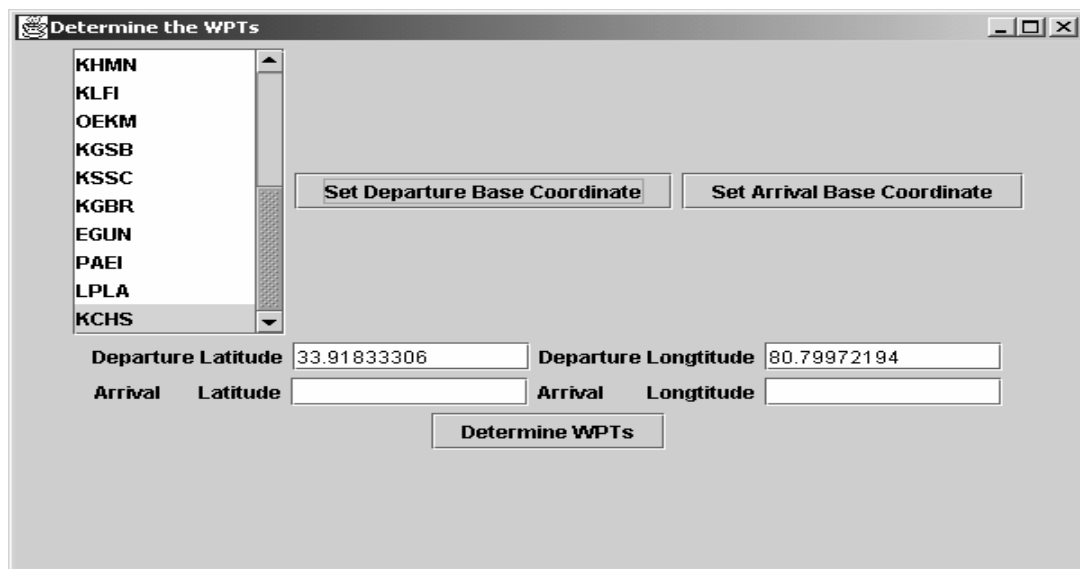


Figure 7. GUI for Determining the Spatial Locations of 100 NM Distanced WPTs Between two Bases

After generating the candidate WPTs for a flight path, the AFRP preprocessor model is run in order to determine the actual WPTs that are served by tankers. Since the amount of fuel demanded at a WPT is a function of the number of aircraft, along with the

aircraft type and distance flown since last being refueled, WPTs chosen along a flight path depend upon all these factors. Therefore, distinct and unique files for the selected WPTs are generated for each combination of type of aircraft, number of aircraft, departure base, and arrival base. For instance, the combinations presented in Table 3 might require refueling at different WPTs.

Table 3. Two Different Example RG Formation

Receiver Type	Number of Receiver Aircraft	Starting Base	Ending Base
F15	6	KLFI	OEDR
F15	3	KLFI	OEDR

Since there is a rule of thumb for the number of specific aircraft that fly in a formation, the light aircraft are flown in a formation of six aircraft and heavy aircraft are flown alone. As a result, forty routes with eight different departure and five different arrival bases were generated for use in the small, medium, and large size deployment scenarios. The routes generated are presented in Appendix A.

3.4 EXPERIMENTAL DESIGN

In order to probe the impact of the size of the deployment on the number of tankers and crews required to service that deployment, a 3x3x2 response surface design, depicted in Figure 8, is conducted.

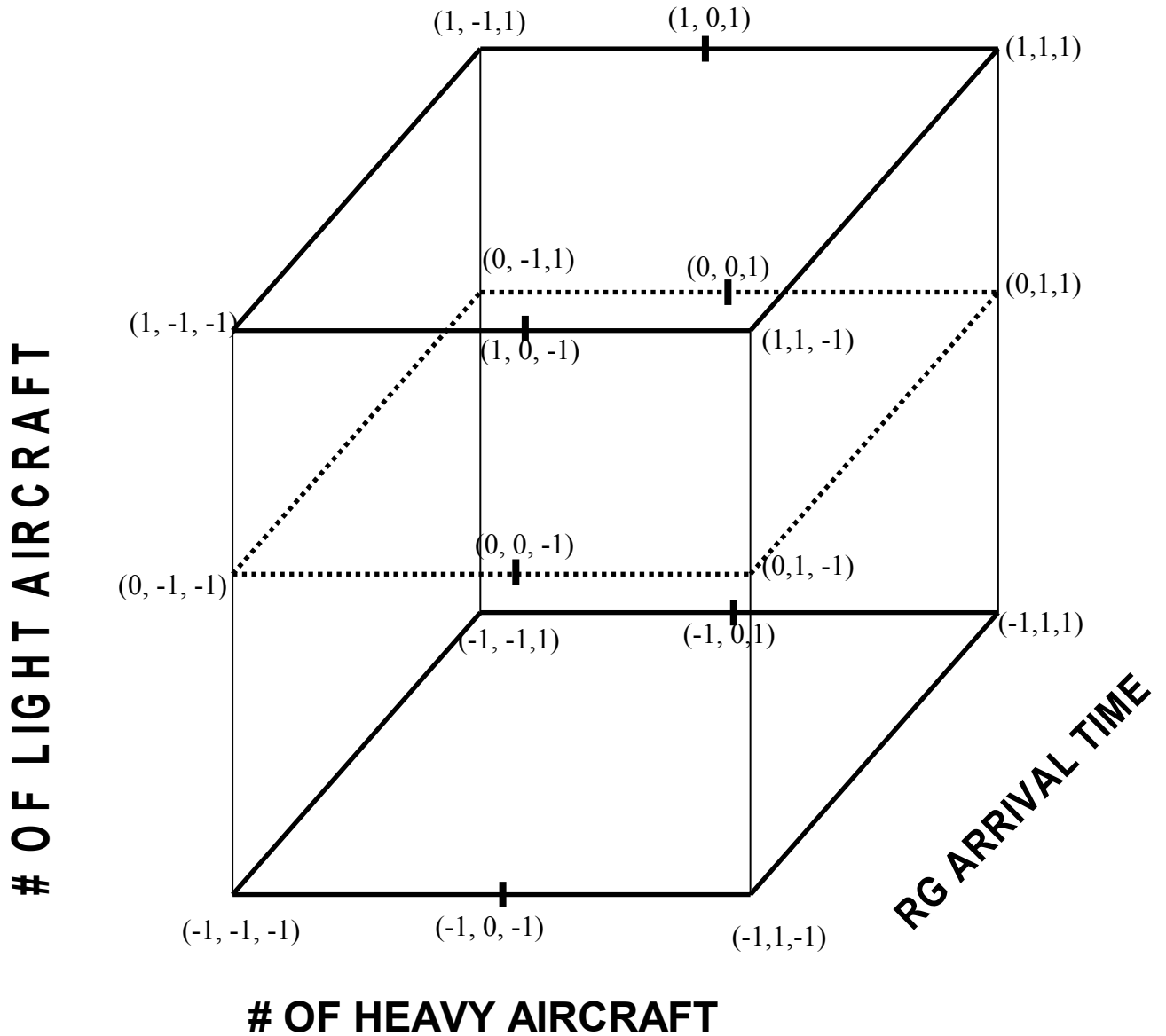


Figure 8. Response Surface Designs

Since a light aircraft has limited fuel storage capacity, it requires refueling more often than a heavy aircraft. Heavy aircraft usually require only one or two refuelings based on distance flown. Additionally, light aircraft must be escorted over oceans which further taxes tanker resources. For these reasons, rather than combining heavy and light aircraft under a common factor name such as total number of aircraft, we treated each as a distinct factor. The third factor considered was the time frame for the deployment. Three factors and two different responses are presented in Table 4.

Table 4. Factors and Responses Considered in Experimental Design

FACTORS	RESPONSES
1. # of Light Aircraft	1. # of Tankers Required
2. # of Heavy Aircraft	2. # of Crews Required
3. Arrival Time of Receiver Groups	

Intuitively, increasing the number of light and heavy aircraft involved in a deployment and reducing the latest allowable arrival time for RGs should increase the need for more tankers and crews. However, we cannot be sure about the form of the mathematical relationship between factors and responses. It may not necessarily be true that doubling the number of light and heavy aircraft will double the need for tankers and crews.

The number of light and heavy aircraft are quantitative factors whereas the latest arrival time is treated as a qualitative factor with two levels. The first level represents the earliest arrival possible for each RG assuming no delays. This arrival time is calculated by dividing distance flown by rate of travel for each RG. The second level for the arrival

time is set at 120 hours (5 days) as suggested by AMC. So, we want the last RG to arrive at its destination no later than 120 hours after the start of the deployment.

Three levels for the number of light and heavy aircraft are presented in the Table 5.

Table 5. Quantitative Factor Levels

Levels	Number of Light Aircraft	Number of Heavy Aircraft
Low	30	20
Intermediate	108	40
High	186	60

The number of available tankers is another key issue. The AFRP model assumes that enough tankers are available to produce a feasible solution. However, the AFRP seeks to reduce the number of required tankers while maintaining feasibility. Therefore, it is assumed that tankers are evenly distributed among seven different locations in the USA, Europe, and the Middle East. For all problems instances, there were 196 tankers available.

CHAPTER IV. RESULTS AND CONCLUSIONS

This chapter presents the results of solving 18 deployment scenarios with Wiley's AFRP model and Combs' TCSP model. The analysis and validation of two prediction functions is shown for two different responses: the number of tankers and the number of crews required. In addition, the results obtained from the crew feasibility heuristic, used to test the crew availability for a given move-solution combination for the AFRP model, and the effectiveness of the heuristic are discussed. This chapter finalizes with the conclusions reached.

4.1 RESULTS AND ANALYSIS OF DESIGNED EXPERIMENT

The 3x3x2 response surface design described in Chapter 3 was used to capture information about the deployment scenarios. The first factor considered is the number of light aircraft involved in the deployment and it has three levels: 38, 108, 186. The second factor is the number of heavy aircraft involved in deployment with three levels: 20, 40, and 60. The third factor is the arrival time for the RGs which is a qualitative factor with two levels. The first level requires all RGs to depart at time zero, so that flying at their tactical air speed, they can arrive at their destination on time. They are allowed to depart later than time zero, but if they do so, it is certain that the RG will bust the latest allowed arrival time. The second level relaxes the arrival time and requires the RGs to arrive at their destination at most 120 hours after the deployment has started.

For each deployment, the AFRP model was run and the number of tankers required to refuel all of the RGs in the scenario was determined. The AFRP model also generated

the tanker schedule which is used by the TCSP to assign the crews to the tankers. The second response variable, the number of crews required to accomplish the schedule, is determined by the TCSP model.

Since the AFRP model, modified to include the code related to the crew feasibility heuristic and the generation of the tanker schedule needed by TCSP, was run on seven different computers with various capabilities, it is hard to compare the solution times for the various scenario sizes. It took almost 2 hours to complete the smallest sized scenarios and almost 71 hours for one of the largest scenario to finish 500 TS iterations using a Pentium IV processor and 1 GB of memory. Three scenarios were solved with and without the crew feasibility heuristic (CFH) and the solution times presented in Table 6 are compared.

Table 6. Solution Times with and without Crew Feasibility Heuristic

	# of LAC	# of HAC	RG Arr Time	With CFH	W/O CFH	Difference
Scenario 1	30	20	120 hours	134 minutes	105 minutes	27%
Scenario 3	30	40	120 hours	875	570	53%
Scenario 8	186	60	120 hours	4267	4602	-0.07%

For scenario 1 and scenario 3, Wiley’s original model (without CFH) ran remarkably faster. The run time was almost the same for scenario 8; on the other hand ,the model with CFH yielded a solution that requires 191 tankers while the original model without CFH yielded a solution that requires 132 tankers. The major reason the modified model runs slower is the fact that the crew feasibility heuristic is evaluated almost 48,000 times for the smallest scenario. Other reasons may be related to the implementation of the heuristic in the code.

In the modified model, the crew feasibility heuristic is placed before the “number of tankers required” goal. For scenario 8, the number of tankers required were different with and without CFH. The difference stems from the fact that CFH and its position in the hierarchy affects the regions to be searched in the solution space.

The TCSP model was run on a computer that has a Pentium IV processor and 1 GB of memory and the solution times for the smallest and largest scenarios were around 2 minutes and 8 minutes, respectively, for 10,000 TS iterations.

The results obtained from these two models are presented in Table 7. The two response variables, the number of tankers required and the number of crews required, were analyzed separately depending on the number of light and heavy aircraft and the arrival time for RGs. All of the data analysis was conducted using JMP® statistical software.

Table 7. Experimental Results

Scenarios	Coded Factor Levels		Original Factor Levels		Latest Arival Time	Tankers Required	Crews Required
	Light AC	Heavy AC	Light AC	Heavy AC			
1	-1	-1	30	20	120 hours	38	36
2	-1	1	30	60	120 hours	85	81
3	-1	0	108	40	120 hours	57	50
4	0	-1	108	20	120 hours	123	107
5	0	1	108	60	120 hours	162	159
6	0	0	108	40	120 hours	148	121
7	1	-1	30	20	120 hours	164	127
8	1	1	186	60	120 hours	191	185
9	1	0	186	40	120 hours	190	180
10	-1	-1	30	20	Earliest	47	46
11	-1	1	30	60	Earliest	112	109
12	-1	0	30	40	Earliest	72	71
13	0	-1	108	20	Earliest	111	105
14	0	1	108	60	Earliest	163	152
15	0	0	108	40	Earliest	132	126
16	1	-1	186	20	Earliest	179	151
17	1	1	186	60	Earliest	194	191
18	1	0	186	40	Earliest	191	186

The analysis of second order response surface design involves three phases:

1. Estimation of response function;
2. Validation of the response function; and
3. Visualization and model interpretation.

Before the analysis of the design, a description of the basic statistics is presented in the following section.

4.1.1 Statistics Used throughout the Experiment

Throughout the experiment, an α value of 0.05 was used. The value of α is called the level of the test and denotes the probability of a type I error, which occurs if H_0 is rejected when H_0 is true (Wackerly, Mendenhall, and Scheaffer, 2002:463).

When testing a hypothesis, the smaller the p-value becomes, the more compelling is the evidence that the null hypothesis should be rejected. The conclusion at any particular level of α results from comparing the p-value to α (Wackerly, Mendenhall, and Scheaffer, 2002:483):

- If the specified value of α is greater than or equal to the p-value, the null hypothesis is rejected for that value of α .
- If the specified value of α is less than the p-value, the null hypothesis is **not** rejected for that value of α .

4.1.2 Estimation of Response Functions

Conducting the response surface design yielded a response function for the number of tankers required and a response function for the number of crews required for the deployment.

4.1.2.1 Estimation of Response Function for the Number of Tankers Required

Initially, all of the terms presented in Table 8 are included in the response surface design. The response function obtained from this design is called the full model.

Table 8. Terms Included in the Full Model

Main Factors	Interaction Terms	Quadratic Terms
# of Light Aircraft	# of Light Aircraft x # of Heavy Aircraft	# of Light Aircraft x # of Light Aircraft
# of Heavy Aircraft	# of Light Aircraft x RG Arrival Times	# of Heavy Aircraft x # of Heavy Aircraft
RG Arrival Times	# of Heavy Aircraft x RG Arrival Times	

The full model obtained from this analysis and the statistics related to each term is presented in Table 9. LAC and HAC represent the number of light and heavy aircraft involved in the deployment, respectively, and ArrTime represents the arrival time for the RGs.

Table 9. Full Model for the Number of Tankers Required

$$Y(\text{LAC}, \text{HAC}, \text{ArrTime}) = -34.0673 + 1.4375 * \text{LAC} + 1.8099 * \text{HAC} - 2.9145 * \text{ArrTime} - 0.002164 * \text{LAC}^2 - 0.005609 * \text{LAC} * \text{HAC} - 0.002292 * \text{HAC}^2 + 0.03418 * \text{LAC} * \text{ArrTime} - 0.07916 * \text{HAC} * \text{ArrTime}$$

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-34.06739	20.2733	-1.68	0.1272
Light AC&RS	1.4375411	0.190068	7.56	<.0001
Heavy AC&RS	1.8099359	0.974656	1.86	0.0963
Arrival Time[120 hours]	-2.91453	6.944459	-0.42	0.6846
Light AC*Light AC	-0.002164	0.00077	-2.81	0.0204
Heavy AC*Light AC	-0.005609	0.002125	-2.64	0.0269
Heavy AC*Heavy AC	-0.002292	0.011719	-0.20	0.8493
Arrival Time[120 hours]*Light AC	0.034188	0.034698	0.99	0.3502
Arrival Time[120 hours]*Heavy AC	-0.079167	0.135322	-0.59	0.5729

Before we proceed to the analysis, we need to check whether or not any of the terms included in the full model has predictive capability for the response. For that purpose, the following hypothesis is tested:

- $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$ (None of the terms has predictive capability)
- H_a : not all β_k ($k=1,2\dots 8$) equal zero

The ANOVA table associated with the full model is:

Table 10. ANOVA Table for Number of Tankers Required

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	47129.861	5891.23	67.0234
Error	9	791.083	87.90	Prob > F
C. Total	17	47920.944		<.0001

The p-value indicated by an arrow in Table 10 is less than the α value of 0.05.

Therefore, H_0 hypothesis is rejected, meaning at least one of the terms has predictive capability on the response. At this point, the insignificant terms included in the full model are excluded to form the reduced model. The resultant reduced model and its statistics are presented in Table 11.

Table 11. Final Reduced Model for the Number of Tankers Required

$$Y(\text{LAC}, \text{HAC}) = -31.01183 + 1.43754 * \text{LAC} + 1.6266 * \text{HAC} - 0.002164 * \text{LAC}^2 - 0.005609 * \text{LAC} * \text{HAC}$$

Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-31.01183	12.15936	-2.55	0.0242
Light AC&RS	1.4375411	0.178921	8.03	<.0001
Heavy AC&RS	1.6266026	0.250784	6.49	<.0001
Light AC*Light AC	-0.002164	0.000725	-2.98	0.0106
Heavy AC*Light AC	-0.005609	0.002	-2.80	0.0149

4.1.2.2 Estimation of Response Function for the Number of Crews Required

Initially, all of the terms presented in Table 8 are included in the response surface design to specify the full model. The full model obtained from this analysis and the statistics are presented in Table 12.

Table 12. The Full Model for the Number of Crews Required

$$Y(\text{LAC}, \text{HAC}, \text{ArrTime}) = -23.87541 + 1.07766 * \text{LAC} + 1.67403 * \text{HAC} - 8.5427 * \text{ArrTime} - 0.00174 * \text{LAC}^2 - 0.000801 * \text{LAC} * \text{HAC} - 0.003958 * \text{HAC}^2 + 0.024572 * \text{LAC} * \text{ArrTime} - 0.02083 * \text{HAC} * \text{ArrTime}$$

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-23.87541	24.59177	-0.97	0.3570
Light AC&RS	1.0776627	0.230554	4.67	0.0012
Heavy AC&RS	1.6740385	1.18227	1.42	0.1905
Arrival Time[120 hours]	-8.542735	8.423718	-1.01	0.3370
Light AC*Light AC	-0.00174	0.000935	-1.86	0.0956
Heavy AC*Light AC	-0.000801	0.002577	-0.31	0.7630
Heavy AC*Heavy AC	-0.003958	0.014216	-0.28	0.7870
Arrival Time[120 hours]*Light AC	0.0245726	0.042089	0.58	0.5737
Arrival Time[120 hours]*Heavy AC	0.0208333	0.164148	0.13	0.9018

The ANOVA table shown in Table 13 tests the significance of the full model.

Table 13. ANOVA Table for Number of Crews Required

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	41489.611	5186.20	40.0995
Error	9	1164.000	129.33	Prob > F
C. Total	17	42653.611		<.0001

Again since the p-value, indicated by an arrow, in Table 13 is less than the α value of 0.05, this indicates that at least one of the terms has predictive capability of the response.

Based on the full model, the three main factors and square term for number of light aircraft are deemed significant. Since the arrival time is significant, one response function for each level of the RG arrival time is obtained. The estimated β value for the 120 hours level is -5.055556 whereas it is $+5.055556$ for the second level which requires the earliest arrival time. Two response functions are obtained by simply adding the estimated β value of the qualitative factor to the estimated intercept β coefficient.

The reduced model obtained and the statistics related to each term is presented in Table 14.

Table 14. Final Reduced Model for Number of Crews Required

$$Y(\text{LAC}, \text{HAC}) = -15.13609 + 1.04561 * \text{LAC} + 1.2708 * \text{HAC} - 5.0555 * \text{ArrTime} - 0.00174 * \text{LAC}^2$$

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-15.13609	9.438961	-1.60	0.1328
Light AC&RS	1.0456114	0.176575	5.92	<.0001
Heavy AC&RS	1.2708333	0.140551	9.04	<.0001
Arrival Time[120 hours]	-5.055556	2.295196	-2.20	0.0463
Light AC*Light AC	-0.00174	0.0008	-2.17	0.0488

4.1.3 Validation of the Response Functions

Before inferring anything about the relationship between the factors and the responses by means of the response functions, the model needs to be validated. In order to validate the model, the assumptions regarding normality of the studentized residuals and constant variance of the residuals must be satisfied.

4.1.3.1 Normality Assumption of the Studentized Residuals

The first assumption that must be satisfied is the normality of the studentized residuals. This is tested by creating a histogram of the residuals and subjectively judging whether or not they look normally distributed. It is also confirmed by the Shapiro-Wilk test which is an objective measurement for the normality of the studentized residuals. The hypothesis tested is:

- H_0 : Studentized residuals are normally distributed
- H_a : Non-normality

4.1.3.1.1 Normality Assumption of the Studentized Residuals for the Number of Tankers

The histogram of the studentized residuals for the number of tankers required is presented in Figure 9.

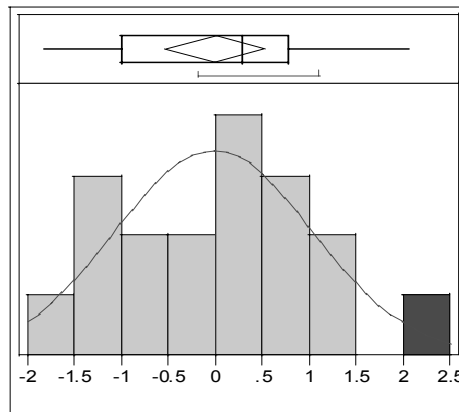


Figure 9. The Histogram of the Studentized Residuals for The Number of Tankers Required

The histogram appears to be normal; however, an objective measurement must be utilized to verify this assumption. The Shapiro-Wilk test is done to compute the goodness of fit of the normal distribution to these residuals. The results of the Shapiro-Wilk test are presented in Table 15.

Table 15. Shapiro-Wilk Test Results for Number of Tankers Required

Goodness-of-Fit Test	
Shapiro-Wilk W Test	
W	Prob<W
0.963331	0.6558

The high p-value indicated by an arrow, in comparison to an alpha of 0.05, given by the Shapiro-Wilk test indicates that the assumption of normality is statistically satisfied.

4.1.3.1.2 Normality Assumption of the Studentized Residuals for the Number of Crews

In order to check the normality assumption of the studentized residuals for the number of crews required, the histogram of the studentized residuals is built and presented in Figure 10.

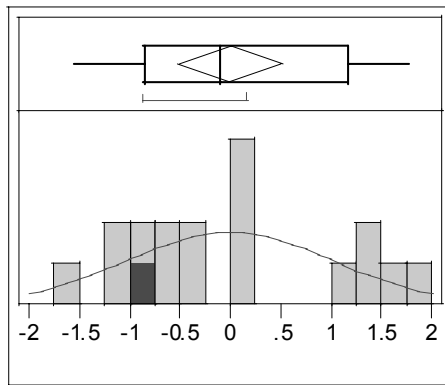


Figure 10. The Histogram of the Studentized Residuals for The Number of Crews Required

The Shapiro-Wilk test is done to compute the goodness of fit of the normal distribution to these residuals. The results of the Shapiro-Wilk test are presented in Table 16.

Table 16. Shapiro-Wilk Test Results for Number of Crews Required

Goodness-of-Fit Test	
Shapiro-Wilk W Test	
W	Prob<W
0.932652	0.2206

The Shapiro-Wilk test indicates that the assumption of normality is statistically satisfied.

4.1.3.2 Constant Variance Assumption of the Residuals

The next assumption that must be tested and satisfied is the constant variance of the residuals. This is subjectively tested by plotting the predicted response values against the residuals and affirmed by Breusch-Pagan test which is an objective measurement to test the constant variance assumption of residuals. The hypothesis tested is:

- H_0 : Constant variance of residuals
- H_a : Non-constant variance of residuals

4.1.3.2.1 Constant Variance Assumption of the Residuals for the Number of Tankers

The predicted number of tankers required versus the residuals plot is displayed in Figure 11.

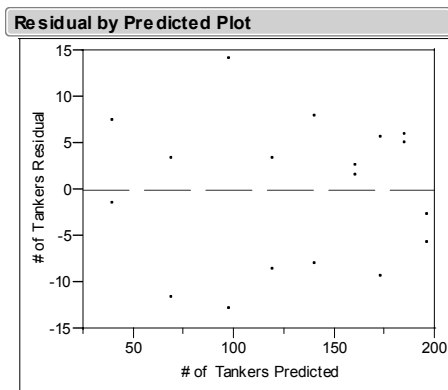


Figure 11. Residual by Predicted Plot for The Number of Tankers Required

The desired plot would display no trends in the data. The profile of a mega-phone is not visible in the data suggesting that constant variance is satisfied. The objective test to verify this is the Breusch-Pagan test which calculates a p-value. A summary of the Breusch-Pagan test is presented in Table 17.

Table 17. Breusch-Pagan Test Results for Number of Tankers Required

Chi-Squared Breusch-Pagan = $(SSR^*/\# \text{ of columns in X matrix})/(SSE/n)^2$	
SSR*	34225.103
SSE	1012.583
n	18
# of columns in the X matrix	5
Degrees of freedom for model	4
Chi-Squared Breusch-Pagan =	2.163009894
Converted to a p-value =	0.705806767

The results of the Breusch-Pagan test affirms the visible evidence in the plot. Therefore, H_0 , constant variance of the residuals, statistically cannot be rejected. The computations for the Breusch-Pagan test were accomplished by taking data from the original regression model and obtaining data from a separate regression using the residuals squared as the response variable. The CHIDIST function of Excel was used to convert the test statistic into a p-value. The p-value was tested at $\alpha = 0.05$ significance level.

The validity of the model cannot be statistically rejected by checking normality and constant variance assumptions and is supported by the adjusted R^2 value. The value of R^2_{adj} is 0.9723 and it indicates that the model explains about 97.23% of the variability

observed in the number of tankers required. Since adding a variable to the model will always increase R^2 , regardless of whether the additional variable is statistically significant or not, the R^2_{adj} statistic is preferred. The R^2_{adj} statistic will not always increase as variables are added to the model. In fact, if unnecessary terms are added the value of R^2_{adj} will often decrease (Myers and Montgomery, 2002:32). Since the difference between ordinary R^2 and R^2_{adj} is relatively small, illustrated in Table 18, it can be concluded that insignificant terms were not included in the model.

Table 18. Summary of Fit for Number of Tankers Required

Summary of Fit	
RSquare	0.97887
RSquare Adj	0.972368
Root Mean Square Error	8.825589
Mean of Response	131.0556
Observations (or Sum Wgts)	18

4.1.3.2.2 Constant Variance Assumption of the Residuals for the Number of Crews

The predicted number of tankers required versus the residuals plot is displayed in Figure 12.

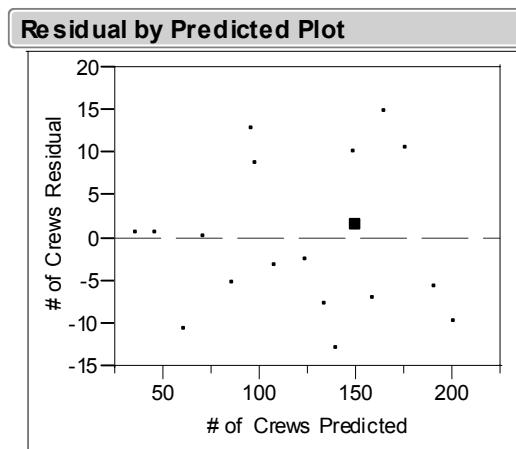


Figure 12. Residual by Predicted Plot for The Number of Crews Required

The plot suggests that the constant variance assumption is satisfied. The Breusch-Pagan test is conducted to objectively verify this. A summary of the Breusch-Pagan test is presented in Table 19.

Table 19. Breusch-Pagan Test Results for Number of Crews Required

Chi-Squared Breusch-Pagan = $(SSR^*/\# \text{ of columns in X matrix})/(SSE/n)^2$	
SSR*	18499.346
SSE	1232.694
n	18
# of columns in the X matrix	5
Degrees of freedom for model	4
Chi-Squared Breusch-Pagan =	0.788897931
Converted to a p-value =	0.939930226

The fact that the p-value obtained by Breusch-Pagan tested at an $\alpha=0.05$ significance level states that the constant variance assumption cannot be statistically rejected.

The validity of the model cannot be statistically rejected by checking normality and constant variance assumptions and is supported by the adjusted R^2 value which is presented in Table 20.

Table 20. Summary of Fit for Number of Crews Required

Summary of Fit	
RSquare	0.9711
RSquare Adj	0.962208
Root Mean Square Error	9.737692
Mean of Response	121.2778
Observations (or Sum Wgts)	18

4.1.4 Visualization and Interpretation of Response Functions

Visualization facilitates making inferences about the response surface model and makes it more understandable for the ones who do not have detailed knowledge about the system.

4.1.4.1 Visualization and Interpretation of the Number of Tankers Required Function

The final reduced model and associated surface and contour plots are presented in Figure 13.

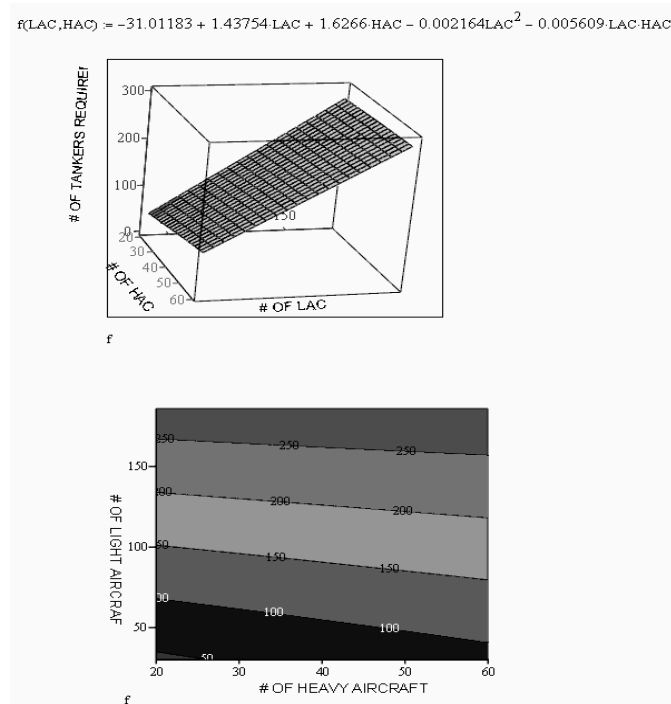


Figure 13. The Final Reduced Model and Associated Surface and Contour Plots for The Number Of Tankers Required

When both of the plots are examined, it can be seen that the number of tankers required increases as the number of light and heavy aircraft increases which is intuitive. However, looking at the mathematical relationship reveals more information about the impact of the variables on response. As seen in Table 21, comparing the standardized estimated β value for the number of light aircraft shows it is virtually three times more significant than the number of heavy aircraft involved in the deployment.

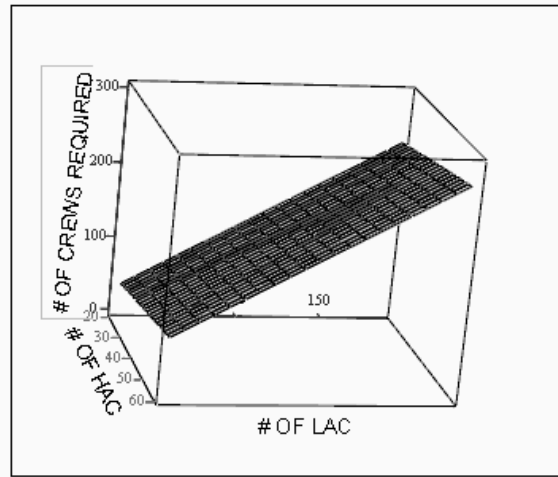
Table 21. Standardized Beta Values for Number of Tankers Required

Parameter Estimates					
Term	Estimate	Std Error	t Ratio	Prob> t	Std Beta
Intercept	-31.01183	12.15936	-2.55	0.0242	0
Light AC&RS	1.4375411	0.178921	8.03	<.0001	1.774364
Heavy AC&RS	1.6266026	0.250784	6.49	<.0001	0.514801
Light AC*Light AC	-0.002164	0.000725	-2.98	0.0106	-0.58939
Heavy AC*Light AC	-0.005609	0.002	-2.80	0.0149	-0.35528

4.1.4.2 Visualization and Interpretation of the Number of Crews Function

The two response models and their associated response surfaces are presented in Figure 14 and Figure 15, respectively.

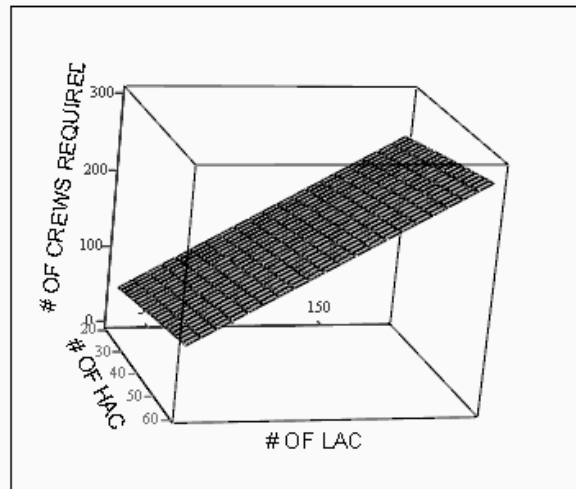
$$f(\text{LAC}, \text{HAC}) := -20.1016 + 1.04561 \cdot \text{LAC} + 1.2708 \cdot \text{HAC} - 0.00174 \cdot \text{LAC}^2$$



f

Figure 14. The Final Reduced Model and Associated Response Surface for The Number Of Crews Required (Relaxed Arrival Time of RGs (120 Hours))

$$f(\text{LAC}, \text{HAC}) := -10.0805 + 1.04561 \cdot \text{LAC} + 1.2708 \cdot \text{HAC} - 0.00174 \cdot \text{LAC}^2$$



f

Figure 15. The Final Reduced Model and Associated Response Surface for The Number Of Crews Required (Early arrival time for RGs)

For both early arrival and relaxed arrival of RGs, the number of crews required increases as the number of light and heavy aircraft increases, which is again intuitive. However, looking at the mathematical relationship reveals more information about the impact of variables on response. As presented below in Table 22, the number of light aircraft is virtually three times more significant than the number of heavy aircraft involved in the deployment.

Table 22. Standard Beta Values for Number of Crews Required

Parameter Estimates					
Term	Estimate	Std Error	t Ratio	Prob> t	Std Beta
Intercept	-15.13609	9.438961	-1.60	0.1328	0
Light AC&RS	1.0456114	0.176575	5.92	<.0001	1.367973
Heavy AC&RS	1.2708333	0.140551	9.04	<.0001	0.426316
Arrival Time[120 hours]	-5.055556	2.295196	-2.20	0.0463	-0.10385
Light AC*Light AC	-0.00174	0.0008	-2.17	0.0488	-0.50215

4.2 EFFECTIVENESS OF CREW FEASIBILITY HEURISTIC

The purpose of introducing the crew feasibility heuristic into Wiley’s AFRP model was to reduce the possibility of generating tanker schedules which are infeasible in terms of available crews. As mentioned before, the heuristic is implemented for each move-solution combination and either yields the number of crews required or an infeasibility flag. Therefore, the best solution found by the AFRP model might either be infeasible or feasible in terms of crews required. For all 18 scenarios tested in this research, the number of crews available was 275. This number ensures the heuristic would not return “infesible” due to insufficient crews to service the given tanker schedule.

The results obtained from both the crew feasibility heuristic and Combs’ TCSP model are presented in Table 23.

Table 23. Comparison between the heuristic and Combs' TCSP model results

Scenarios	Light AC	Heavy AC	Latest Arrival Time	Crews Used(CFH)	Crew used(Combs)
1	30	20	120 hours	38	36
2	30	60	120 hours	85	81
3	30	40	120 hours	57	50
4	108	20	120 hours	Infeasible	107
5	108	60	120 hours	Infeasible	159
6	108	40	120 hours	Infeasible	121
7	186	20	120 hours	Infeasible	127
8	186	60	120 hours	Infeasible	185
9	186	40	120 hours	Infeasible	180
10	30	20	Earliest	47	46
11	30	60	Earliest	112	109
12	30	40	Earliest	72	71
13	108	20	Earliest	111	105
14	108	60	Earliest	Infeasible	152
15	108	40	Earliest	Infeasible	126
16	186	20	Earliest	Infeasible	151
17	186	60	Earliest	Infeasible	191
18	186	40	Earliest	Infeasible	186

Having the crew feasibility heuristic in Wiley's AFRP model as the tenth objective just before "the number of tankers required" objective, only seven out of 18 tanker schedules generated for the scenarios were feasible in terms of crews. The crew histories might have played a significant role to make the heuristic come up with the current solutions. However Combs' TCSP model found feasible solutions for all of the schedules. For the tanker schedules which were identified as feasible by the crew feasibility heuristic, the number of crews required was equal to the number of tankers required which indicates that for each tanker, a distinct crew was assigned. A crew could not be assigned more than one flight segment because one of the following constraints has failed at each attempt:

- Minimum time between departure time of the next flight and arrival time of the previous flight should be satisfied

- Arrival base of the previous flight and next departure base must match
- Rest limit constraint for the crews must be satisfied
- 30/90 day flying limits for the crews should not be busted.

4.3 CONCLUSIONS

The aerial fleet refueling problem and tanker crew scheduling problem were successfully combined during this research. Having compared the solutions of the proposed heuristic to test the crew availability for a given move-solution combination with Combs' model, it was determined that there is no need to incorporate the crew feasibility heuristic into the AFRP model because all of the schedules generated by this model are flyable for crews and the heuristic slows down the model.

Analyzing the results of the experimental design conducted for the number of tankers required, the number of light aircraft is almost 3 times more significant than the number of heavy aircraft involved in the deployment and the arrival time of the receiver groups does not affect the number of tankers required. For the number of crews required, the number of light aircraft is almost 3 times more significant than the number of heavy aircraft involved in the deployment and the arrival time of the RGs is statistically significant and there is almost 10 crews difference for any scenario with the same number of light and heavy aircraft but one with relaxed (120 hours) RG arrival time and the other with the earliest RG arrival time.

CHAPTER V. CONTRIBUTIONS AND RECOMMENDATIONS

This chapter discusses the contributions produced by this research and future avenues of research.

5.1 RESEARCH

The research conducted for this thesis was pursued along three primary lines of investigation. First, combining Wiley's AFRP model with Combs' TCSP model so that the tanker schedule generated by the AFRP model can be used as input for the TCSP model. Second, the research investigated how a heuristic that tests the feasibility of each move-solution combination generated by the AFRP model in terms of crew availability would affect the tanker schedule generated. The third line of investigation probed the impact of several factors that are presumed to significantly affect the number of tankers and crews required.

5.2 CONTRIBUTIONS

This research has yielded the following major contributions:

- This research efficiently combines Wiley's AFRP model and Combs' TCSP model by introducing a sequential approach where the aerial fleet refueling problem is solved and feeds the resulting schedule to the crew scheduler.
- A procedure to generate different scenarios is developed and eighteen scenarios with various sizes were generated and solved in both models.

- A GUI is incorporated into AFRP model so the user can move any goal in the objective function up and down thus changing the significance of the goal.
- An analysis of the sensitivity of the AFRP and TCSP models to changes in the number of light aircraft, number of heavy aircraft, and arrival times for RGs with respect to the number of tankers and crews required.
- This research also revealed that the TCSP model finds feasible crew schedules for all of the tanker flight schedules provided by Wiley's AFRP model.

5.3 SUGGESTIONS FOR FUTURE RESEARCH

This section provides a description of the future avenues of research that appeared while completing this research.

This research follows a sequential approach where the solution for Wiley's model becomes input for Combs' model. An alternative approach is to solve aerial fleet refueling problem and TCSP simultaneously. The objectives and constraints of each problem could be combined and that combined problem may yield solutions better than the sequential approach.

While solving various sized scenarios the time was an important issue for AFRP model and even though the maximum number of iterations was 500, the best solution was mostly found at early stages of iterations. A visual display that shows the progress of solution might be helpful for the user to make the decision to stop the model during the solution process and the best solution found up to that point can be recorded and used to

generate the tanker schedule. VisAD, which is a visualization tool package for java, might be useful for that purpose. It is compatible with java and source files and API documents are available on the web for free.

Appendix A

Number of Receivers	Starting Base	Ending Base	Earliest Start Time	Latest Finish Time(Late)	Number of Hops	Latest Finish Time(Early)
6	KPOB	OEDR	0	120	0	20.785
6	KPOB	OERY	0	120	0	20.604
6	KPOB	OEKM	0	120	0	21.021
6	KPOB	EGUN	0	120	0	11.586
6	KPOB	LPLA	0	120	0	8.375
1	KSZL	OEDR	0	120	0	17.377
1	KSZL	OERY	0	120	0	17.342
1	KSZL	OEKM	0	120	0	17.887
1	KSZL	EGUN	0	120	0	10.187
1	KSZL	LPLA	0	120	0	8.247
1	KBAD	OEDR	0	120	0	15.637
1	KBAD	OERY	0	120	0	15.576
1	KBAD	OEKM	0	120	0	15.973
1	KBAD	EGUN	0	120	0	9.392
1	KBAD	LPLA	0	120	0	7.45
1	KTIK	OEDR	0	120	0	15.247
1	KTIK	OERY	0	120	0	15.224
1	KTIK	OEKM	0	120	0	15.687
1	KTIK	EGUN	0	120	0	9.201
1	KTIK	LPLA	0	120	0	7.517
1	KRCA	OEDR	0	120	0	14.742
1	KRCA	OERY	0	120	0	14.79
1	KRCA	OEKM	0	120	0	15.401
1	KRCA	EGUN	0	120	0	8.865
1	KRCA	LPLA	0	120	0	7.716
6	KLFI	OEDR	0	120	0	13.422
6	KLFI	OERY	0	120	0	13.301
6	KLFI	OEKM	0	120	0	13.582
6	KLFI	EGUN	0	120	0	7.31
6	KLFI	LPLA	0	120	0	5.204
6	KSSC	OEDR	0	120	0	13.945
6	KSSC	OERY	0	120	0	13.825
6	KSSC	OEKM	0	120	0	14.097
6	KSSC	EGUN	0	120	0	7.874
6	KSSC	LPLA	0	120	0	5.736
1	KCHS	OEDR	0	120	0	13.821
1	KCHS	OERY	0	120	0	13.704
1	KCHS	OEKM	0	120	0	13.974
1	KCHS	EGUN	0	120	0	7.818
1	KCHS	LPLA	0	120	0	5.709

Appendix B

EGUN	MILDENHALL AFB
KBAD	BARKSDALE AFB
KCHS	CHARLESTON AFB
KLFI	LANGLEY AFB
KPOB	POPE AFB
KRCA	ELLSWORTH AFB
KSSC	Shaw AFB
KSZL	WHITEMAN AFB
KTIK	TINKER AFB
LPLA	LAJES AB
OERY	RIYADH AIR BASE
OEKM	KING KHALID AIR BASE
OEDR	DHAHRAN/KING ABDULAZIZ AIR BASE

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Vita

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