An Optimization Modeling Approach to Awarding Large Fire Support Wildfire Helicopter Contracts from the US Forest Service

Stephanie A. Snyder, Keith D. Stockmann, and Gaylord E. Morris

Abstract: The US Forest Service used contracted helicopter services as part of its wildfire suppression strategy. An optimization decision-modeling system was developed to assist in the contract selection process. Three contract award selection criteria were considered: cost per pound of delivered water, total contract cost, and quality ratings of the aircraft and vendors. Discrete optimization decision models were developed and solved to optimize each of these objectives or contract selection criteria independently. These solutions provided the basis for a weighted goal programming model that minimized the percent deviation from each of the three, incorporating relative preference or priority weights on deviations from the goals. Managers chose to assign a greater relative importance to the quality rating than the two cost measures, resulting in a solution with higher quality aircraft, but at a cost of $55 million more than if total cost had been the only contract selection criteria. These optimization models show promise as a means of supporting agency decisionmaking regarding firefighting helicopter contracts. FOR. SCI. 58(2):130–138.

Keywords: wildfire resource allocation, goal programming, assignment model, government contracting

Wildfire suppression is a critical mission of the US Forest Service (FS), and one that has become more costly and difficult to accomplish over the past decade because of a buildup of flammable material on public lands, climate and weather issues (Flannigan et al. 2000), an increased occurrence of large wildfires (National Interagency Fire Center 2008), and expanding development within the wildland-urban interface (Radeloff et al. 2005, Reams et al. 2005, Stein et al. 2007).

Wildfire suppression is accomplished through a combination of aerial and ground-based activities. Aerial support is an essential component of both initial attack fire suppression and large fire support for incident management teams and is largely accomplished through the use of fixed-wing airtankers and two types of helicopters. Large fire support (LFS) helicopters spend the majority of their time retrieving and delivering water to support large fire suppression efforts, whereas type II helicopters perform a wider array of assignments, including transportation of fire crews. The primary way in which the FS obtains the necessary aerial equipment and crews is through multiyear, exclusive-use contract arrangements with private vendors.

Although vendor cost is an important consideration in FS contract awards, it is not the only criterion. The loss of firefighter life in recent years has largely been concentrated in transportation accidents. This fact has sharpened the focus on technical capabilities and safety operations for contracted aviation equipment, resulting in an emphasis on "quality" assessments of aircraft vendors in contract solicitations (National Interagency Fire Center 2011).

Before 2007, helicopter contracting decisions were made independently by each region within the FS on a yearly basis. For the 2007 season, however, a more coordinated approach was taken in which all of the national contracts were awarded by a single contracting officer based out of the National Interagency Fire Center in Boise, Idaho. The move toward national contracting solicitations was done to remove the artificial perception that wildfire suppression resources were the purview of FS regions rather than shared, national resources and to improve process standardization and operational efficiency within the Agency. The contracts during this initial year of national solicitations were awarded on the basis of a source selection plan that considered the cost to the government and expected service quality of the aircraft [1]. A spreadsheet ranking method was used to assist in the contract award decisions [2]. With several dozen bases and companies bidding aircraft with multiple configurations, this proved to be a difficult task to accomplish without a decision support tool.

Given the need for a more structured approach to awarding contracts, a decision was made by aviation managers after the first season of national contracting to develop a decision support system. The nature of the contract award process lent itself well to an optimization decision-modeling framework, so a suite of optimization models was developed to address this problem. The utilization of optimization models to support decisionmaking regarding firefighting equipment contract awards is a new approach for the FS, and one that shows promise for helping with this difficult resource allocation problem. The models are discussed in this article, along with experiences associated with developing and using them to support contracting decisions.

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Background

Optimization models have been developed to address two major types of problems related to wildfire equipment location and allocation: deployment and dispatching. Deployment decisions involve the assignment of equipment and crews to bases to minimize operating cost while meeting expected demand for fire suppression over a specified time frame (e.g., Greulich and O'Regan 1982, MacLellan and Martell 1996). Demand is typically incorporated through either historical or probabilistic information on fire locations. Dispatching models are typically built for a single fire and determine the number and type of resources to dispatch from their home bases to minimize suppression cost plus damage subject to resource availability constraints (e.g., Parks 1964, Greulich and O'Regan 1975, Bookbinder and Martell 1979, Mees et al. 1994, Donovan and Rideout 2003, Fried et al. 2006, Rachaniotis and Pappis 2006). Deployment and dispatching have largely been treated as separate problems in the optimization literature. The exception is the model of Haight and Fried (2007), which optimized deployment and dispatching decisions simultaneously. In addition, a rich body of literature exists on the use of optimization models for urban emergency vehicle and station location and deployment (for a review, see Goldberg 2003).

We are aware of only one other study that used an optimization approach to address contracts for wildfire suppression resources. Donovan (2006) developed a model to determine the optimal mix of federal and contract fire crews to hire for a fire season to minimize the expected cost of suppression. This problem was modeled as a transportation problem and determined the number of crews to use during each period in a fire season. It did not determine where to base these crews. To our knowledge, optimization models have not previously been used to assist in the contract award process for firefighting aircraft by the FS or any other US firefighting agency.

The focus of our study was to award contracts to helicopter vendors and assign firefighting helicopters to FS home bases over a 4-year contract period. Decisions about dispatching of aircraft once fires have ignited or daily transfer rules from home bases to air bases were not considered by managers as part of this contract award process. The problem we solved, then, had a different focus than the models in the deployment literature. In our application, each line item, composed of one or more home bases, had a predetermined demand for a single helicopter. These home bases serve as designated bases from which aircraft are dispatched to other airbases or fire locales once fires ignite [3]. Our models focused on minimizing the cost of assignment of aircraft to line items while maximizing the quality of the selected aircraft and vendors.

Data

Solicitation for the bids was made through FedBizOps following standard government contracting procedures (General Services Administration 2011). Vendors bid to receive contracts to station their aircraft at the 34 FS line items that require LFS helicopters. Bidders were required to submit the following information: bid prices (i.e., daily availability rate), aircraft type and characteristics, crew qualification and capabilities, and vendor safety record and safety program information.

Aircraft and line items were differentiated in a number of ways. First, aircraft could be bid for bucketed, tanked, or both configurations, although only one configuration of a given aircraft could be awarded a contract. Tanked aircraft have sealed tanks for water or retardants, which offer superior safety and protection for people and property below the aircraft, but weigh more than helicopters operating with buckets. Bucketed aircraft have a long line and an external sling or bucket to carry water. Tanked aircraft tend to be more expensive per pound of payload than bucketed aircraft because they have heavier equipped weights but the same lift capacity. Twenty-one of the line items in this solicitation only allowed tanked aircraft to be bid, whereas the remainder allowed either tanked or bucketed operations. Tanked aircraft were required at specific line items because of safety concerns near the designated bases in the line item.

The solicitation returned bids from 27 companies and 66 aircraft for 34 line items. Of these aircraft, 22 were bid in both tanked and bucketed configurations, with different cost structures associated with each configuration. For the purposes of awarding contracts, each configuration was considered a unique aircraft, resulting in 88 helicopter configurations that could be selected to fill the 34 line items: 51 aircraft were bid as bucketed configurations and 37 as tanked configurations.

The aircraft and line items were also differentiated by performance criteria known as hover-out-of-ground effect (HOGE). Payload curves for each aircraft model were used to screen them into HOGE tiers I, II, and III. Tier I aircraft could carry 5,000 pounds at 8,000 ft above mean sea level at 25°C; tier II aircraft could carry 3,000 pounds at 7,000 ft at 20°C; and tier III aircraft could carry 2,300 pounds at 5,000 ft at 30°C. Line items were also classified as one of the three tiers on the basis of the elevation of the highest base in each line item. Of the 34 line items, 10 were designated tier I, 8 as tier II, and 16 as tier III. If a helicopter qualified as a HOGE tier I aircraft, then it could be used at tier I, II, or III line items. If an aircraft qualified as a tier II aircraft, then it could be used at tier II or III line items. A tier III aircraft could only be used at tier III line items. Of the bid aircraft, 17 qualified as tier I, 43 as tier II, and 28 and tier III. Eligibility for each of the aircraft-line item pairs was determined by whether the aircraft was bid on that line item, whether it met tank or bucket requirements, and whether it met specified HOGE performance and firefighting certification criteria for that line item. The number of eligible bids for any line item ranged from 8 to 77, with an average of 39.

A technical evaluation team (TET) of FS aviation managers computed costs, both variable and fixed, for each qualified aircraft-line item combination from the estimated payload and daily availability rate information provided by the bidders. The following standard formulas were used to calculate a cost per pound of delivered water and total fixed cost for each aircraft at each line item for each of the 4 years that were bid (2008–2011):

$$\textit{Cost Per Pound } (\$/lb) = ((\textit{Daily Availability Rate } (\$/day)) + (\textit{Hourly Flight Rate } (\$/hr) \times 2.5 \textit{ hours per day}))/(6 \textit{ Loads of Payload per hour } (lbs/hr) \times 2.5 \textit{ hours per day}) \quad (1)$$

$$\textit{Total Cost } (\$) = (\textit{Net Days } (days) \times \textit{Daily Availability Rate } (\$/day)) + (\textit{Established Flight Hours } (hrs) \times \textit{Hourly Flight Rate } (\$/hr)) \quad (2)$$

The hourly flight rate, net days, and operating hours were standard and were provided by the FS to bidders. The daily availability rate bid by each vendor was allowed to vary by year for each line item and the aircraft configuration bid. From these formulas, an average cost per pound for each eligible aircraft-line item pair was computed over the 4 years of the contract. The total contract cost for each eligible aircraft-line item pair was computed by summing over the 4 contract years. Of the bids received, the cost per pound for any aircraft-line item pair ranged from 14 to 53 cents. The total 4-year cost for the aircraft-line item pairs ranged from approximately \$3 to \$28 million.

An "adjectival score" was also computed for each aircraft from information provided by the vendors. The adjectival score was a weighted function of four technical evaluation criteria: aircraft technical capability, safety/risk management, past performance, and organizational experience. Values for the adjectival scores for the bid aircraft ranged from 1.6 to 3.8 with 1.0 representing the best possible score.

Methods

Four discrete integer programming models based on the classic assignment problem from the location science literature (Hillier and Liebermann 1967) were formulated and solved. The assignment problem is one of minimizing the costs or maximizing the benefits of assignments such that each demand or task is filled by exactly one supplier and each supplier assigns to exactly one demand node. In our application, demand nodes are FS line items (single or sequential designated bases) and suppliers are firefighting helicopters. The assignment model has been applied to a wide variety of resource allocation problems, although none were specific to wildfire suppression resources. Seminal publications on the assignment problem include the following: Von Neumann (1953), Dwyer (1954), and Kuhn (1955). The assignment formulation requires that the number of demand nodes equals the number of service providers. In our case, the number of line items must equal the number of aircraft for each aircraft to have a unique assignment. In this solicitation, more aircraft were bid than eligible line items. Given this, 54 dummy bases were created to create equality between the number of aircraft and the number of line items to satisfy the constructs of the assignment formulation.

First, three single-objective assignment problems, one for each of the contract selection criteria, were formulated and solved. The individual optima from these become the goals from which deviations were to be minimized in the fourth model, a multiobjective goal programming assignment model. We used a goal programming format to address the multiple objectives or selection criteria in the contract award process. Goal programming is an approach to solving multiobjective models in which deviations from prespecified goals are minimized (for example, see Schniederjans 1995). Although some examples of goal programming assignment models can be found in the optimization literature (e.g., Saatçioğlu 1987, Jahanshahloo and Afzalinejad 2008), they are not numerous. Moreover, there are none that we are aware of that address a resource allocation problem in the context of wildfire suppression. The models were defined as follows.

Model I: Minimizing Average Cost Per Pound of the Assignments

The first model minimizes the cost per pound of delivered water averaged over all line item-aircraft pairs and over all 4 contract years when aircraft are assigned to the 34 actual line items.

Notation
Indices

j, J = index and set of eligible aircraft
k, K = index and set of total line items (K = J)
p, P = index and set of "real" line items ($P \leq K$)

Subsets

M_k = the subset of aircraft, j, that are eligible to fill a particular line item, k, based on HOGE ratings
N_j = the subset of line items, k, which are eligible to be filled by a particular aircraft, j, based on HOGE ratings
R_j = subset of "real" line items, k, eligible to be filled by an aircraft j
S_{il} = pairs of aircraft (i and l) that have limitations on simultaneous assignment to any of their eligible "real" bases

Parameters

CPP_{jk} = cost per pound of delivered water when assigning an aircraft j to line item k averaged over all 4 contract years
$P\text{Total}$ = the total number of "real" line items

Variables

X_{jk} = a binary decision variable equal to 1 if aircraft j assigns to line item k and 0 otherwise

The model was formulated as follows:

$$Z1 = Minimize \sum_{j=1}^{J} \sum_{k=1}^{P} (CPP_{jk} X_{jk})/PTotal \quad (3)$$

subject to

$$\sum_{k \in N_j} X_{jk} = 1 \qquad \forall\, j \in J \quad (4)$$

$$\sum_{j \in M_k} X_{jk} = 1 \qquad \forall\, k \in K \quad (5)$$

$$\sum_{k \in R_i} X_{ik} + \sum_{k \in R_l} X_{lk} \leq 1 \qquad \forall (i,l) pair \in S_{il} \quad (6)$$

$$X_{jk} \in \{0,1\} \quad (7)$$

The objective (3) minimizes the average cost per pound of delivered water when aircraft are assigned to the set of real line items. The first set of equations (4) ensures that each aircraft assigns to exactly one of its eligible line items. The next set of equations (5) ensures that each line item is filled by exactly one aircraft. Equation set 6 ensures that for certain pairs of aircraft configurations, at most one will assign to one of their eligible real line items. These requirements were included in the model because some of the aircraft were bid in both tanked and bucketed configurations. Although they represented separate bids, they were in reality the same aircraft. Thus, both could not be selected for contracts at real line items. In addition, one of the S_{il} pairs was a set of aircraft bid from a vendor who only wanted one of the two to be awarded a contract. Equation 7 defines the integer restrictions for the decision variables.

The CPP_{jk} coefficients for the dummy assignments were set to a value 3 orders of magnitude larger than any of the real CPP_{jk} coefficients to prevent the dummy assignments from influencing any of the actual assignments. On solving model I, the set of assignments that minimized the average cost per pound of delivered water over the 34 real line items was generated, as was an optimal value for the average cost per pound objective function ($Z1$). The value of $Z1$ was used as one of the goals in model IV.

Model II: Minimize Total 4-Year Costs of the Assignments

We next specified a model to minimize the total costs of the assignments or contract awards over the 4-year contract period.

Additional Notation Parameters

TC_{jk} = total (4-year) contract cost of assigning an aircraft j to line item k

The model was formulated as follows:

$$Z2 = Minimize \sum_{j=1}^{J} \sum_{k=1}^{P} TC_{jk} X_{jk} \quad (8)$$

subject to Equations 4–7.

The objective (8) minimizes the total cost over the 4-year contract period of assigning aircraft to the real line items. The constraints are exactly the same interpretation and structure as for model I. On solving model II, an optimal value for the total cost objective function ($Z2$) was obtained and used to create the second goal in model IV.

Model III: Minimize the Average Adjectival Rating of the Assignments

A third single-objective model was developed to minimize the average adjectival rating of the selected aircraft assigned to real bases, where smaller ratings indicate more desirable aircraft.

Additional Notation Parameters

ADJ_{jk} = adjectival score associated with assigning an aircraft j to line item k

The model was formulated as follows:

$$Z3 = Minimize \sum_{j=1}^{J} \sum_{k=1}^{P} (ADJ_{jk} X_{jk})/PTotal \quad (9)$$

subject to Equations 4–7.

The objective (9) minimizes the average adjectival score of assigning aircraft to the real line items. The constraints are the same interpretation and structure as model I. On solving model III, an optimal value for the adjectival score objective function ($Z3$) was obtained and used to create the third goal in model IV.

Model IV: Multiobjective Goal Programming Model to Minimize Deviations from Selection Criteria Goals

After the three single objective models were solved, a fourth model was developed to simultaneously consider the three objective functions in assigning aircraft to line items. The model was developed as a goal program and minimized the weighted sum of percent deviations from the three goals derived from solution of models I–III [4].

Additional Notation Parameters

$Z1$ = optimal value of the average cost per pound objective derived from solution of model I

$Z2$ = optimal value of the total cost objective derived from solution of model II

$Z3$ = optimal value of the average adjectival score objective derived from solution of model III

$w1, w2, w3$ = objective function weights whose sum must equal 1

Variables

$V1$ = percent deviation from the model I goal objective
$V2$ = percent deviation from the model II goal objective
$V3$ = percent deviation from the model III goal objective
$Y1$ = absolute deviation from the average cost per pound objective function goal
$Y2$ = absolute deviation from the total cost objective function goal
$Y3$ = absolute deviation from the average adjectival score objective function goal

The model is formulated as follows:

$$Z4 = Minimize\ (w_1 \times V1) + (w_2 \times V2) + (w_3 \times V3) \tag{10}$$

subject to

$$\sum_{j=1}^{J} \sum_{k=1}^{P} \left(\frac{CPP_{jk} X_{jk}}{PTotal} \right) - Y1 = Z1 \tag{11}$$

$$\sum_{j=1}^{J} \sum_{k=1}^{P} (TC_{jk} X_{jk}) - Y2 = Z2 \tag{12}$$

$$\sum_{j=1}^{J} \sum_{k=1}^{P} \left(\frac{ADJ_{jk} X_{jk}}{PTotal} \right) - Y3 = Z3 \tag{13}$$

$$\left(\frac{Y1}{Z1} \right) \times 100 = V1 \tag{14}$$

$$\left(\frac{Y2}{Z2} \right) \times 100 = V2 \tag{15}$$

$$\left(\frac{Y3}{Z3} \right) \times 100 = V3 \tag{16}$$

$$\sum_{k \in N_j} X_{jk} = 1 \qquad \forall\, j \tag{17}$$

$$\sum_{j \in M_k} X_{jk} = 1 \qquad \forall\, k \tag{18}$$

$$\sum_{k \in R_i} X_{ik} + \sum_{k \in R_l} X_{lk} \leq 1 \qquad \forall\, (i,l) pair \in S_{il} \tag{19}$$

$$X_{jk} \in \{0,1\} \tag{20}$$

The objective (10) minimizes the total weighted sum of percent deviations from the three goals specified from solution of the three single objective models. Equations 11–13 are used to define the absolute value of the deviation from each of the three objective goals. Equations 14–16 define the percent deviation from each of the three goals. The remaining equations are identical to those from the three single objective models.

Because of contracting requirements, the relative priority on the selection criteria had to be stated in the contract solicitation. The aviation managers and contracting officer decided that adjectival score would receive higher priority than either of the two cost objectives and that total cost would be emphasized more than the variable cost objective. The contract language reflected these priorities. FS aviation management and contracting officials came to this decision on relative priorities after reviewing results and exploring tradeoffs between cost and quality under a range of different objective weight combinations using the previous year's contract bid data in the decision support system. This analysis with the previous year's bids allowed the managers to get a sense of the magnitude of the tradeoffs and values of the objectives, which in turn allowed them to articulate the relative priorities as required by the contracting process. After the bids were received, managers explored numerous weighting combinations within the relative ranges established for the solicitation and selected a preferred set of objective function weights used in the selection process. Figure 1 illustrates a representative set of the solutions derived from the suite of objective function weights that were evaluated. In Figure 1, in each successive solution, the adjectival score is weighted more relative to either cost objective, and the total cost objective is weighted more relative to the cost per pound objective. The weight set that was ultimately chosen was one that satisfied the TET both in terms of the relative distribution of the weights on the three goals as well as the resulting tradeoffs between the goals [5].

Solution Hardware and Software

All of the models were solved on an IBM Lenovo personal computer, using the integrated solution package GAMS IDE/CPLEX 9.0 (1998; GAMS Development Corporation, Washington, DC). Input files were converted from Excel to a CPLEX 9.0-compatible format using GAMS (general algebraic modeling system), a program designed to generate data files in a standard format that optimization programs can read and process. The models were solved using CPLEX, an optimization solver designed for linear and integer programs. The revised primal simplex algorithm, in conjunction with the branch and bound algorithm for integer-variable problems, was used to solve the models. For the goal-programming model (model IV), multiobjective weighting was used as the method of solution (Cohon 1978).

Results

Each of the three single objective models was solved independently. For comparison purposes, the value for the other two selection criteria was also calculated ex post for each of the single-objective models (Table 1). The optimal solution of each of these three models yielded a different set of assignments, which meant that it was not possible to simultaneously optimize all of the objectives. Given this fact, tradeoffs between the three objectives or selection criteria occurred in the goal programming solution. The results from the single-objective models underscore the fact that minimizing total cost is not synonymous with minimizing the variable cost (cost per pound) of operations. All four models solve very quickly, with solution times of less than a minute for any model run.

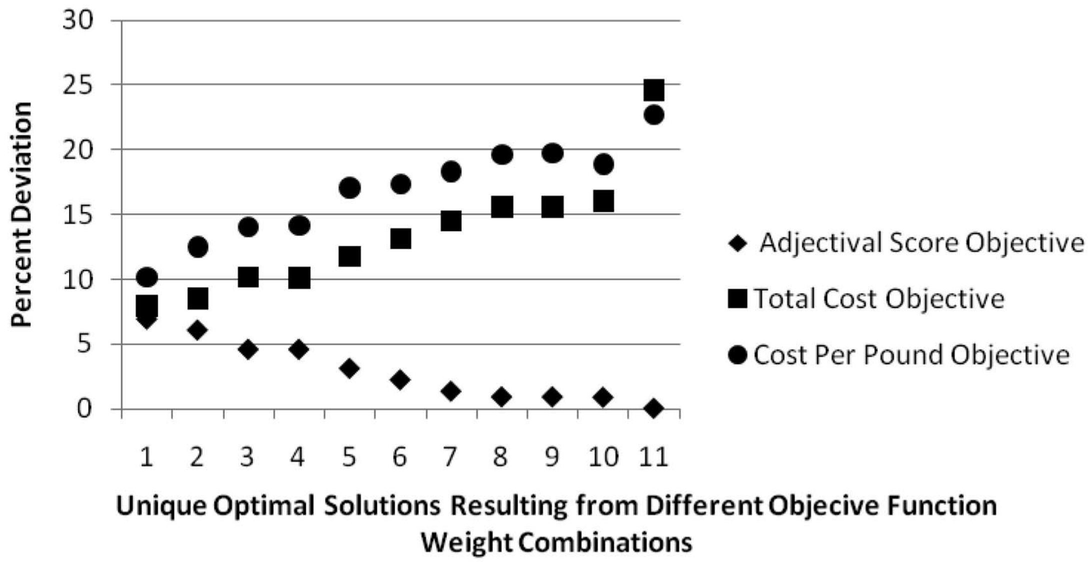

Figure 1. Tradeoff curve showing deviations from the three goals under different objective function weight sets within the bounds of the contract solicitation priorities. In each successive solution, the adjectival objective is weighted more relative to either cost objective, and the total cost objective is weighted more relative to the cost per pound objective.

Table 1. Results from solution of models I—III.

	Model I: average cost per pound ($/lb)*	Model II: total cost ($)*	Model III: average adjectival score
Average cost per pound objective	0.24575619	0.25713777	0.30736401
Total cost objective	434,121,912	375,539,258	480,127,991
Average adjectival score objective	2.42676471	2.38000000	1.93794118

* Costs are in 2008 dollars.

Table 2 shows results for model IV when solved with the set of priority weights specified by the TET. Results are reported in terms of the absolute and percent deviation from each goal, based on the optimal values for each individual objective from Table 1. In addition to the goal deviations, the actual values for each of the objectives are also reported. The solution from model IV resulted in a set of aircraft contracts that had a total 4-year cost 14.5% greater than if total cost had been the only consideration in awarding contracts (model I solution). The average 4-year cost per pound from the model IV solution was 18.3% higher than the solution that only considered cost per pound (model II solution), whereas the average adjectival score was 1.35% higher than the solution that only considered this score as the selection criteria (model III solution). Thus, the preferred solution only deviated slightly from the best possible adjectival or quality rating but had modest increases in both cost objectives. Conversely, if the optimal solution from model I had been selected as the overall best solution, the adjectival score would have been 25% worse than the solution that just optimized the adjectival score. Similarly, if the best solution from model II had been selected, the adjectival score would have been 23% worse than the solution that just optimized this score. These findings underscore the fact that the least cost solution, measured either in terms of total cost or cost per pound, would not have yielded the highest quality solution as measured by adjectival score. Thus, considering both cost and safety in the set of contract awards involves tradeoffs between these selection criteria. The use of optimization models allowed us to precisely quantify what those tradeoffs were.

Because some companies bid several like aircraft with similar costs and adjectival scores, seven alternate solutions (e.g., alternate optima) were generated when model IV was solved with the specified set of weights. Differences among the alternate optima were not great (Table 3). The same 34 aircraft were selected in each of the alternate optima; but their assignments among the line

Table 2. Results from solution of model IV.

	Average cost per pound ($/lb)*	Total cost ($)*	Average adjectival score
Objective function value	0.29078457	430,015,700	1.96411765
% deviation from goal (%)	18.322	14.506	1.351
Absolute value of the goal deviation	0.04502838	54,764,200	0.02617647

* Costs are in 2008 dollars.

Table 3. Comparison of alternate optima.

Aircraft	Config	Aircraft tier	Opt	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Alt 7
						Tier I line items				
A	T	1	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
B	T	1	*2*	*2*	*2*	*2*	*2*	*2*	*2*	*2*
C	T	1	3	8	3	8	3	7	8	8
D	T	1	*4*	*4*	*4*	*4*	*4*	*4*	*4*	*4*
E	T	1	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*
F	B	1	*6*	*6*	*6*	*6*	*6*	*6*	*6*	*6*
G	T	1	7	7	7	7	7	3	7	3
H	T	1	8	3	8	3	8	8	3	7
I	T	1	*9*	*9*	*9*	*9*	*9*	*9*	*9*	*9*
J	T	1	*10*	*10*	*10*	*10*	*10*	*10*	*10*	*10*
						Tier II line items				
K	T	2	11	13	12	11	16	16	12	14
L	T	2	12	11	13	12	12	14	13	11
M	T	2	13	12	11	14	11	13	14	12
N	T	2	14	16	14	16	14	12	11	13
O	B	2	*15*	*15*	*15*	*15*	*15*	*15*	*15*	*15*
P	T	2	16	14	16	13	13	11	16	16
Q	T	2	*17*	*17*	*17*	*17*	*17*	*17*	*17*	*17*
R	B	2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
						Tier III line items				
S	T	3	19	22	19	21	19	19	19	19
T	B	3	20	20	24	20	20	24	20	24
U	T	3	21	23	21	23	23	21	22	23
V	T	3	22	29	22	29	29	29	29	22
W	T	2	23	21	23	22	22	22	21	21
X	B	2	24	31	31	28	31	28	25	33
Y	B	2	25	28	25	24	24	31	26	26
Z	B	2	26	25	33	25	25	25	31	25
AA	B	2	*27*	*27*	*27*	*27*	*27*	*27*	*27*	*27*
BB	B	2	28	26	26	26	33	26	24	28
CC	T	3	29	19	29	19	21	23	23	29
DD	B	2	*30*	*30*	*30*	*30*	*30*	*30*	*30*	*30*
EE	B	2	31	33	28	33	28	20	28	20
FF	T	3	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
GG	B	3	33	24	20	31	26	33	33	31
HH	B	3	*34*	*34*	*34*	*34*	*34*	*34*	*34*	*34*

* Rows in italic type indicate that an aircraft was selected for the base in all of the alternate optima.

items differed in some cases. Fourteen of the 34 line items had the same aircraft assigned to them in all of the optima (e.g., the rows in italic type in Table 3). All of the optima contained 21 tanked and 13 bucketed configurations. Differences between the alternate optima largely involved similar types and rated aircraft swapping between bases with similar HOGE requirements. In many instances, it was the same make and model of aircraft swapping between bases or even the same make and model from the same company shifting between bases with like requirements. This occurred because in some cases the CPP and TC were the same for multiple aircraft at multiple line items.

Because the alternate optima all comprised the same 34 aircraft, the same 15 companies with the same number of awarded aircraft, and the same breakdown of selected bucketed versus tanked configurations, there was not much to distinguish between the optima. Given this, the alternate optima were reviewed and found to provide the same value per investment to the government, so the first solution was selected by the TET and used to award the contracts.

Discussion

Our models illustrated that tradeoffs between cost and quality of selected aircraft occurred with this set of bids and preferred weight structure. Of the selected aircraft, 21 were those bid in the tanked configuration. Although the remaining line items could have received tanked configurations, they all received buckets. The breakdown of average costs and adjectival scores by aircraft tier and configuration helps explain the selection of aircraft in the optimum solution. All the tier I line items were, by requirement, filled by tier I aircraft. Tier II bases could have been filled by tier I or II aircraft, although only tier II aircraft were selected in the optimum solution. The reasons that no remaining tier I aircraft were selected for these line items are both the higher average costs for both configurations of tier I aircraft and the better average adjectival score for tier II tanked aircraft compared with tier I tanked aircraft. Thus, given enough feasible bids by the tier II aircraft, it is unlikely that the model would select any remaining tier I aircraft to fill these demands. Most of the tier II line items required tanked

Table 4. Comparison of total cost and cost per pound among different helicopter makes and models.

Aircraft ID	Total cost ($)	Cost per pound ($/lb)
A	$9,333,150 (high)	$0.32 (high)
B	$14,303,100 (high)	$0.14 (low)
C	$7,942,350 (low)	$0.23 (high)
D	$5,275,230 (low)	$0.1 (low)

aircraft, allowing little option for bucketed configurations to be selected. The tier III line items could have been filled by any tier aircraft. However, the optimum solution was a combination of tier II and III aircraft for these line items. One reason that some tier II aircraft were selected for tier III line items is that the tier III aircraft on average have worse adjectival scores than either tier I or II aircraft, although considerably lower costs. Thus, with the priority emphasis on adjectival score, it became desirable to select the remaining tier II aircraft to fill tier III line items, driving total and variable costs up.

Two factors explain why multiple cost criteria were considered by aviation managers in this contract solicitation. First, the set of helicopters that minimizes total cost is not necessarily the same set that minimizes cost per pound over the set of contracts because different makes and models of aircraft can vary widely in their costs to operate versus their payload capacity. Some helicopters are very expensive to operate, but their performance or lift capability (i.e., the volume a helicopter can lift off of the ground and fly with) is not commensurate with their cost. Table 4 contains four examples of total cost and cost per pound from the bid aircraft, illustrating that there is not always a direct correspondence between cost per pound and total cost

The second reason that aviation managers were interested in optimizing two separate cost criteria has to do with the way funding streams are handled for helicopter contracts. Contracted helicopter costs to the government are, in general, the sum of availability for the contract period (e.g., fixed price per day multiplied by the number of days on contract) plus the sum of flight costs over the period of the contract (hourly flight rate multiplied by the number of hours flown). The availability costs must be obligated in advance from congressionally appropriated funds before awarding of the contract. However, flight costs are not paid until flown and are funded by the user, which may be one of a multitude of federal or state entities. Therefore, keeping the total cost low due to limited appropriated funds is one objective; keeping the cost per pound low to benefit the end user is another objective.

We developed a new approach to assist FS personnel in awarding firefighting helicopter contracts. This approach is based on a set of optimization decision models that minimize deviations from three objectives, which addressed the cost and technical quality (including a strong safety component) of aircraft vendors. Although the Agency has made use of optimization decision models for decades for other types of resource allocation decisions, this type of modeling framework represents a significantly different approach in the way in which the Agency evaluates and awards helicopter contracts. This decision framework improves on existing methods by adding more structure, consistency, and rigor to what is inherently a very messy and cumbersome combinatorial problem. The method allows decisionmakers to articulate and explicitly incorporate preferences or weights for selection criteria, which is an important strength. The method also provides decisionmakers the ability to allow clear and rapid evaluation of differences in contract awards and evaluate tradeoffs.

These model formulations could readily be adapted to include additional constraints relevant to the contracting selection process. For example, a budget constraint could be included. This would allow decisionmakers to determine whether or when it becomes too costly to meet the demand for a helicopter at each of the line items or when more cost-efficient aircraft need to be chosen to meet the budget. Constraints could also be developed to provide some parity among the bidders. That is, if relevant, constraints could be developed to ensure that no bidder is awarded more than a certain number of contracts. Given that an optimization modeling framework is well suited for conducting sensitivity analyses, a decisionmaker would readily be able to quantify the impact of such additional contracting requirements on the objective function values and optimal assignments.

This modeling framework offers improvements over previous methods used to award LFS helicopter contracts, but it is not without its challenges. Considerable effort is required in processing the data received from the bidding companies and formatting it in the structure required by the optimization software. The models require sophisticated optimization software, meaning that the aviation managers and the contract officer had to rely on analysts with specialized skills and software to develop and run the models for them. Improvements to the decision framework are being studied. These include the use of database software, rather than spreadsheets, for data preparation and management. In addition, bidders may be asked to provide their cost information in a format that will expedite cost calculation, qualification vetting, and data processing.

Although the models were successfully used to award the 2008 LFS contracts, a protest by one of the vendors was launched over the contract awards. This has been a common occurrence after the awarding of firefighting helicopter contracts. The protest, however, actually provided an opportunity to highlight a strength of the optimization approach. The models were able to be used in assisting in resolving the dispute by illustrating how the costs and adjectival scores would differ if select aircraft had been assigned to bases as the protestor desired.

Endnotes

[1] Refer to FSH 6309.32–Federal Acquisition Regulation (US Forest Service 2000) for more details on source selection plans.

[2] With this method, each qualified aircraft configuration bid was ranked for each eligible base (or "line item") by its average cost per pound, total 3-year contact cost, and a quality score (or adjectival rating). Next, the total cost and cost per pound ranks for each aircraft configuration at each line item were summed. This sum was then multiplied by the rank for adjectival score to produce the composite score for each aircraft at each line item. Aircraft selections were made by sequentially evaluating the line items and identifying the aircraft configuration with

the lowest composite score remaining after aircraft was selected for previous line items.

[3] Line items represent home bases for the aircraft and are needed for administrative purposes. However, the aircraft are constantly moving in the vicinity of these bases, spending most of the contract duration at fires and fire camp helibases.

[4] Percent deviations instead of the absolute value of deviations were used because there was such a disparity in the scale of the values of the three selection criteria.

[5] This set of weights is adaptable in the future and is not revealed to prevent bidders from gaming future bid requests, which protects the government's ability to contract the highest quality aircraft at the lowest possible cost.

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