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The University of Montana

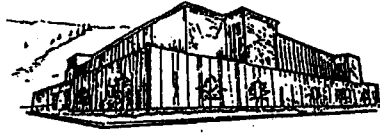
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**IMPROVING THE EFFICIENCY OF HELICOPTER OPERATIONS
ON LARGE WILDLAND FIRES BY INCLUDING HELICOPTER
PERFORMANCE INFORMATION IN THE DECISION PROCESS**

by

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B.S. University of Montana. 1983

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presented in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

The University of Montana

June 2004

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Improving the efficiency of helicopter operations on large wildland fires by including helicopter performance information in the decision process.

Chair: Dr. Tara Barrett *JmB*

Extreme fire seasons and rising fire suppression costs have made cost containment and suppression effectiveness a major concern. Fire suppression efforts must achieve their objectives at a minimum cost. This can be achieved by ensuring that the appropriate fire suppression resources are used. Since helicopter operations often account for a significant portion of the suppression costs on large wildland fires it is especially important that deployment decisions are made so the most efficient helicopters are deployed.

Helicopter performance, i.e., lifting capability, is a unique characteristic of individual helicopters because it depends not only on the make and model of the helicopter but also the weight of the equipped helicopter, fuel, and pilots. Helicopter performance changes with the altitude and temperature of operation. Hence it is not easy to include helicopter performance when deciding which helicopter will be most efficient at a fire.

A comparison index, which summarizes helicopter performance and cost information, is developed so the efficiency of individual helicopters can be compared at representative altitude and temperature conditions. By using the index to deploy helicopters to a fire significant savings can be achieved.

Finding the most efficient way to deploy helicopters to multiple fires requires a more sophisticated technique. The optimization problem is solved using mixed integer programming to assign helicopters to fires so the cost per pound delivered at each fire is minimized while the travel time to the fire is constrained. A genetic algorithm is also developed to solve the optimization problem with the multiple objectives of minimizing the cost and travel time and maximizing the amount delivered for each fire. The genetic algorithm finds a set of optimal solutions to the deployment problem that describes the tradeoffs between the competing objectives.

A comparison of the mixed integer programming and genetic algorithm shows that either method can be used to solve the problem, but their solutions provide different types of information. With mixed integer programming a single optimal solution is found, while the genetic algorithm describes the solution space and provides additional information that can be used in the decision making process.

ACKNOWLEDGEMENTS

I would like to thank J.P. Johnston, retired helicopter operations manager for the U.S. Forest Service, for educating me on helicopter performance and other issues that are important for improving the efficiency of helicopter operations. His relentless desire to improve the system in the face of institutional inertia has inspired me. I would like to thank Paul Markowitz for sharing his ideas on the inefficiencies of helicopter operations. A special thanks to my family for supporting me when it appeared that my desire to question tradition would cost me my job. And finally I would like to thank Bob Roth for his inspiration in the final hours when he asked for my assistance in developing a system to include helicopter performance information in deploying helicopters as J. P. Johnston and I had so enthusiastically promoted.

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INTRODUCTION

Extreme fire seasons and rising fire suppression costs have made suppression effectiveness and cost containment a major concern of the public, fire suppression organizations and politicians (National Association of State Foresters 2000, National Academy of Public Administration 2002, USDA Forest Service 2000a and 2000b). While the costs have risen dramatically the sensational large fires that have captured media attention show that wildland fire suppression efforts are not always effective. Public pressure is driving fire suppression organizations to make changes to control costs and improve effectiveness.

Although the importance of an effective initial attack organization cannot be overlooked, the majority of suppression costs and media hype can be attributed to large fires. The use of large helicopters for fire suppression on large fires has increased significantly in recent years (Stone 2002). These aircraft are versatile and contribute to the fire suppression effort in many different ways. They are also very expensive and often account for a large share of the total suppression costs on large fires, so it is important that they are used efficiently.

The effectiveness of wildland fire suppression using large helicopters is not well understood. The use of large helicopters for wildland fire suppression is relatively new so the knowledge gained through experience is limited. Helicopters can be used for many

different suppression activities from hauling personnel and cargo to dropping water (USDA Forest Service 2002). The water drops do not create a permanent barrier to fire as many other suppression resources do, so quantifying the effectiveness of water drops requires basic research into just how the fire is affected and how long the effect will last.

The water brought to the fire by a helicopter can be dropped onto the fire using a variety of tactics that will modify the effectiveness of the drop. The water can be dropped on the fire to reduce the fire intensity, on the unburned fuels to wet them or on the boundary between the fire and fuels for a combined effect (Blakely 1985). The airspeed of the helicopter can be used to control the concentration of water that is hitting the fuels, which relates directly to the effectiveness of the drop (Solarz and Jordan 2000a, 2000c, 2001; Johnson 2000). The load can also be split into several drops by some of the delivery systems (Solarz and Jordan 2000b). The variation caused by the use of different tactics complicates the quantification of the effectiveness of helicopter suppression activities. Without this quantification it is difficult to compare the effectiveness of helicopter drops to the effectiveness of other suppression resources, as is done in simulation models.

On large wildland fires the effectiveness of helicopter suppression operations are directly related to the amount that can be carried. When dropping suppressants payload determines the length of drop (Solarz and Jordan 2000a, 200b, 2000c, 2001; Johnson 2000). The effectiveness of delivering personnel and cargo is also related to the amount that can be carried. Thus helicopter payload can be used to measure effectiveness.

The U.S. Forest Service and other wildland fire management agencies currently categorize helicopters according to the payload capability of the make and model at sea level. Helicopters are requested for fire suppression by type. Cost and mobilization information is used to determine the least expensive available helicopter that is close enough for deployment (Roth 2004). This selection criterion allows for inefficient helicopters to be deployed because there is a wide range of performance within a helicopter type. Helicopter performance also depends on the altitude and temperature of operation so the amount a helicopter can carry depends on the location and conditions at the fire.

More efficient helicopter deployment decisions can be made by including helicopter performance in the decision criteria. The performance of individual helicopters depends on the make and model of the aircraft along with any modifications that change this performance. Performance charts developed for the helicopter make, model and modifications give the lifting capability for the engines at different altitude and temperature conditions (USDA Forest Service 2002). The maximum allowable payload is calculated by subtracting the weight of the helicopter, fuel and pilots from the chart values. This means that helicopters can be stripped of all nonessential equipment to increase their payload. Calculating helicopter performance for the conditions at a fire is impractical because the performance charts for the individual helicopters would have to be used.

My dissertation examines three methods for including helicopter performance information in the decision making process. An index is developed that summarizes

helicopter cost and performance information so the efficiency of individual helicopters can be compared. For deploying helicopters to multiple fires a genetic algorithm is developed that finds the Pareto-optimal solutions that maximize the effectiveness while minimizing the costs. Mixed-integer programming is also used to find the optimal solution by minimizing the cost per pound delivered at each fire while constraining the mobilization times for the deployed helicopters. I found that including helicopter performance information in the decision making process of deploying helicopters could improve the efficiency of helicopter operations substantially. The method used for including this information depends on the capabilities of the decision makers and the level of information they want to use in the decision process.

CHAPTER 1

LITERATURE REVIEW FOR FIRE PLANNING

Introduction

Wildland fire is a powerful natural occurrence that affects humans and the landscapes we live in. Every aspect of wildland fire is complex, from its benefits and uses to its amazing destructiveness and unpredictability. Wildland fire is so complex that it is not understood and modeled as a single entity. Rather the analysis and modeling of wildland fire deals with the specific areas that are currently viewed as important.

When wildland fire was destroying valuable timber in early 1900s fire suppression became important. The “10 a.m. Fire Control Policy” requiring a fast, energetic and thorough suppression effort on all fires was the answer to the problem (Silcox 1935, p.1, cited in Lundgren 1999). This policy recognized that fires are easier to stop when they are small, so that an early and aggressive suppression effort is most effective. By 1971 it became apparent that this rigid policy did not allow for differences in local conditions. The escalating costs of the aggressive fire suppression policy were noted by 1975, and in 1978 Congress directed the Forest Service to conduct a formal cost-benefit analysis to support future budget requests. (Lundgren 1999)

The need for cost-effective fire suppression planning that accounts for local variations spurred the development of systems to model and analyze fire suppression efforts.

Though cost-effectiveness is an underlying theme for most of these systems the focus of the fire suppression effort is constantly changing. New issues become important, such as the use of wildland fire for resource benefit, the growing wildland urban interface, and the exceedingly high cost of suppression on large fires (Snyder 1999). Because models are by necessity a simplification of the real world, there is a need to model and analyze details of wildland fire suppression in greater depth.

In the United States, Canada, and throughout the world, the need for cost efficient wildland fire suppression efforts have prompted the development of decision support systems. The National Fire Management Analysis System (NFMAS) (USDA Forest Service 1985) has been used for planning and budgeting in the Forest Service and several other federal and state agencies. NFMAS is used to evaluate alternate initial attack fire programs to find the most efficient level of protection based on the sum of the costs and the net value change (Lundgren 1999).

The National Parks System (NPS) manages critical habitat and special concern biological communities that are considered priceless and cannot be allowed to burn. It also manages sensitive species and biological communities that are dependent on the fire regime. To care for these special communities the NPS uses FIREPRO to determine the appropriate levels for staffing and funding which will achieve a 95 percent success rate for initial attack. (Botti 1999)

In California losses of non-market resources and the expanding wildland-urban interface contribute more to fire management decisions than timber losses that are easy to value (Gilless and Fried 1991). The California Fire Economics Simulator (CFES) does not include net value change in the decision criteria. Rather the expected annual frequency of escaped and contained fires, the total area burned by contained fires, the distribution of the burned area by fire size and dispatch level, and firefighting costs for contained fires are used to compare fire programs (Fried et al. 1987, Mitchell 1999, Gilless and Fried 1991).

In Canada where there are vast areas with low population and an extensive network of rivers and lakes, airtankers and helicopters are particularly important for the timely suppression of wildland fires. Operation research studies are used extensively to manage these resources and support decisions made by fire management (Martell 1982, 1997, and Martell et. al. 1999a, 1999b, Kourtz 1984).

The Level of Protection Analysis System (LEOPARDS), summarized by McAlpine and Hirsch (1999), is used to analyze fire management policies, budgets and suppression resource mixes for the province of Ontario. LEOPARDS simulates fire growth and suppression activities using historic fire ignitions and weather conditions. Regions are divided into areas with similar spatial characteristics. Specific initial attack dispatch rules tailored to each area are developed. Using the dispatch rules resource activities are modeled including the activities of up to four different types of aircraft.

Martell et al. (1999a,b) summarize how researchers working with the Ontario Ministry of Natural Resources (OMNR) have developed decision support tools that

address many aspects of fire management. Systems that predict natural and man caused fire ignitions provide information for the home-basing and daily movement of initial attack resources. Other systems have been developed to analyze dispatch rules for initial attack resources, but there has been little work developing systems for evaluating project fire management strategies (Martell 1982). Because of the lasting impact of capital expenditures such as aircraft, decision support systems have been developed to analyze and justify these expenditures.

As Canada moves towards centralized fire management Kourtz (1984) discusses how the development of decision support systems is essential to this process. Timely access to information on weather, lightning location, fuels, terrain, and suppression resources is important. Modeling capabilities are necessary for daily fire predictions, fire behavior, resource allocation, and fire effects to assist fire managers with decisions.

Rodríguez y Silva (1999) summarize the Arcar-Cardin simulation model used in Andalusia, Spain. The model simulates wildfire spread using GIS fuel and terrain information. Fire behavior along with the cell-by-cell growth of the fire is simulated. The efforts of suppression resources can also be included in the simulation. The model determines the economic value of a suppression effort by comparing the costs and consequences of the suppressed and unsuppressed simulations.

Pedernera and Julio (1999) describe the KITRAL (“fire” in indigenous Chilean language) system, which uses geographical databases and simulation models to model fire behavior and estimate probable losses and the workload required for containment. The model is used to review suppression efforts and determine where any inefficiencies exist.

Through the many systems that have been developed, multiple aspects of wildland fire suppression have been studied, analyzed, and modeled. There is much more work to do. This chapter is a discussion of the published works on decision support for fire suppression, followed by comments on the previous efforts regarding my area of expertise - fire suppression using airtankers and helicopters - and an introduction for my research project.

Modeling Fire Growth and Containment

Underlying the analysis of fire suppression is an understanding of wildland fire. Free burning fire growth and behavior is dependent on fuels, weather, and topography. These are distributed both spatially and temporally making wildland fire growth and behavior difficult to model. For initial attack suppression efforts, where fires are small and of short duration, the assumption of homogenous fuels, weather, and topography allow for fire growth and behavior to be modeled more easily.

A simple containment model for fire suppression resources determines containment when the length of fireline produced equals or exceeds the perimeter of the free burning fire (Mees 1985). NFMAS (USDA Forest Service 1985), FIREMANS (Van Gelder 1978), and the initial version of CFES (Fried and Gilless 1988a) use simple containment models to determine the effectiveness of initial attack resources.

The simple containment model fails to account for the way fire suppression resources modify fire growth and behavior. Including the suppression effort in fire modeling requires that the efforts of the individual resources be modeled. Resources that build a

continuous break between the fire and the unburned fuels, such as fire crews and bulldozers, are easily modeled while resources like engines, hotspotting crews, airtankers, and helicopters that use water, chemical retardants or produce discontinuous lines are more complex. (Bratten et. al. 1981; Martell 1982; Murphy et. al.1991)

Mathematical methods have been developed to analyze fire containment. A foundation paper by Albini et al. (1978) used simplifying assumptions: the free-burning fire boundary grows linearly with time, the suppression effort is divided into two equal crews that work on opposite flanks of the fire, and the rate of the suppression effort is constant. With these assumptions it is possible to write closed form expressions for the burned area and containment time. With the additional assumption that the free-burning fire boundary has an elliptical shape the problem simplifies to two integrals that can be solved using a programmable calculator (Albini and Chase 1980). These mathematical solutions agree exactly with Albini's theoretical model for circular fire shapes and are within five percent for ellipses with length to width ratios between 1.2 and 3.0. The work of Anderson (1989) extended the range of length to width ratios where accurate results could be obtained. Where Albini's theoretical model placed the origin at the focus of the ellipse, Anderson modeled fire growth as an ellipse with the x-axis aligned in the direction of maximum spread and the origin at the ignition point. The resulting model agrees with Albini's theoretical model to within a few percent for length to width ratios up to 7.0.

When the head of the fire is advancing too quickly indirect suppression tactics allow the fire to be contained where direct suppression tactics would fail. Both Albini et al.

(1978) and Anderson (1989) modeled indirect tactics mathematically. These models construct fireline in advance of the fire head, angle the fireline back to the fire perimeter, then use direct suppression tactics to complete containment of the fire.

Mees (1985) developed a complex containment model for comparison with the simple containment model. Free burning fire growth is modeled as an ellipse with the point of origin at one of the focal points. Using arrival times and fireline production rates for the available suppression resources (excluding airtankers because of complexity); fireline is constructed along the perimeter of the fire ellipse beginning at the head or rear of the fire. Suppression resources may be applied unequally. Fire growth and the fireline construction are calculated at the time the first resources arrive and at one-minute increments until the fire is contained. A comparison of the results produced by the simple and complex containment models shows that there are substantial differences in the cost estimates produced by the two methods. When the rate of perimeter growth is significantly less than the fireline production rate the two models produce similar results but when the two rates are similar the complex model produces much smaller containment areas. The cost of this improved prediction power is computing time; the complex model requires 100 times more computing time than the simple model. The complex model also shows how direct head attack can reduce containment areas.

Fried and Fried (1995) developed a fire containment model to update the CFES initial attack module (IAM) to include a more realistic representation of the effectiveness of suppression resources. The model is an extension and generalization of previous efforts. It assumes only that the free burning fire shape expands in a self-similar way as time

progresses, although in the paper it is derived using elliptical fire growth with the ignition point of the fire at the origin. Fireline construction proceeds at an uneven rate along each flank starting at either the head or rear of the fire. These production rates can fluctuate as resources come and go which allows for modeling of resources such as airtankers. As with Mees' (1985) complex model, the analysis of fire growth and fireline production is calculated at incremental times until the fireline surrounds the fire.

Simard (1978, 1979) developed the AIRPRO simulation model to evaluate airtanker productivity and effectiveness. The free burning fire is modeled as an ellipse with a variable length-to-width ratio. The effect of the suppression effort is modeled as point growth with parabolic segments connecting the points. To model placement of the suppression resources the perimeter of the fire is divided into four components: the head, two flanks and the rear. Ground suppression resources begin fireline construction at any of the four flank intersections and produce fireline at a rate inversely proportional to the fire intensity. Using an appropriate length for the retardant drop, the model simulates the arrival time and placement of retardant drops. Fireline production rates are increased when ground resources build line through an airtanker drop. In the model, airtanker operations may be simulated as any of 2184 different combinations of airtanker and tactic combinations.

Not all models assume elliptical fire growth. Parks (1964) modeled fire growth as linear with time, modeling just the time between the arrival of suppression resources and containment. The fire growth rate is highest when resources arrive and decreases at an effective deceleration rate, which is the difference between the natural acceleration of the

fires growth rate and the deceleration of the fire's growth rate caused by the suppression effort, until the growth rate is zero. The time of control and area burned can be solved directly. The model finds the level of suppression that minimizes the total fire costs.

The models discussed so far evaluate suppression efforts on individual fires. In order to measure the initial attack effectiveness of a set of fire suppression resources, the models must evaluate how effective they are for a sequence of fires that occur over a day or an entire fire season. Historical fires provide information about spatial and temporal fire occurrence patterns. Although it is very unlikely that future fire occurrences will be the same as they have been in the past, the historical model provides a realistic set of fires that can be used to compare the capabilities of suppression resources.

The Fire Operational Characteristics Using Simulation (FOCUS) program described by Bratten et al. (1981), was designed for what-if planning to compare two or more initial attack fire plans. FOCUS was envisioned as a probabilistic computer simulation that included prevention, fire start generation, detection, suppression and large fire modeling, but the task was too complex and had to be downsized to a deterministic simulation model analyzing historical fires. The simulation module simulates the elliptical growth of fires using start times, location, fuel type, terrain, and spread rate from historical fires. Suppression resources are deployed based on the threat posed by the fire or using a preplanned area dispatch. As the suppression resources using the appropriate transportation network (Mees 1978) arrive they hold portions of the fire ellipse. Three modes of attack can be specified: direct head attack, direct rear and flank attack, or indirect head attack. Fires that exceed predefined time or size limits are gamed by fire

experts to determine area burned, costs, and damages. Because a large portion of the costs and damages incurred are for escaped fires, the gaming of these fires must be conducted to avoid biasing the results.

FOCUS (Bratten et al. 1981) simulates the suppression actions of airtankers and helicopters with more detail than many other simulation models. Helicopters transport a crew from the base where they are located then pick up additional crews from either a base near the fire or a nearby road. They can also be used to transport a crew to the fire then switch to bucket operations refilling from a nearby water source. Placement of airtanker drops follows a complex logic. Retardant drops that are not reinforced by a fireline will hold the line for a maximum of 15 minutes, but the fire may spread around the ends of the drop before that time.

Martell et al. (1984) developed a simulation model to assist the Ontario Ministry of Natural Resources (OMNR) in evaluating airtanker use for initial attack. The deterministic simulation model evaluates the performance of a set of firefighters, transport aircraft and airtankers. Starting each day with all aircraft and firefighters available, the model simulates the daily suppression effort on historical fires. Eighty days are selected to represent a typical fire season. Dispatch rules based on fire location and weather conditions are used to determine initial attack requirements. Dispatched firefighters and aircraft are deployed from the base nearest the fire. The model independently builds fireline with airtankers and firefighters around the fire's perimeter. After every hour and after each airtanker drop the length of completed fireline is compared to the fire's perimeter. If there are firefighters on the fire, the fire is considered

contained when 40 percent of the fire's perimeter is contained. If airtankers are working alone then the airtanker drops must be twice the fire's perimeter to account for the times the fire is left unattended while the airtankers are reloading. Airtankers are sent back to their bases if their efforts are ineffective, if they run out of fuel, or before dark.

Airtankers do not return to a fire. Firefighters can only be deployed to one fire each day. The model processes each fire of the day independently in the order it occurred. Fires not contained by 10:00 am the following day are considered escaped. The model was used to evaluate alternate initial attack programs based on seasonal cost plus loss and found that airtanker support was not necessary if firefighters have adequate transportation.

Wiitala and Dammann (2003) developed an initial attack simulation model that models the complex movement of smokejumpers and their aircraft. Using historical fires to simulate fire occurrences, the model determines whether smokejumpers should be dispatched and from where they should be dispatched. The model simulates the movement of smokejumpers and aircraft to fires, between fires and bases, and between bases. Because the model simulates the details of smokejumper operations it can be used to evaluate the effects of changes to the smokejumper program.

Most of the previous research described in this section uses a simple geometric shape and relatively simple assumptions about fire growth, avoiding detailed assumptions about fuel or terrain. The emphasis is on decisions about suppression resources rather than fire behavior. With relatively simple assumptions about fire growth, these models use simulations that evaluate a small number of alternatives rather than finding the optimal

suppression option. The next section describes the variety of approaches to evaluating alternative fire management decisions.

Decision Criteria

Economic analysis provides a means for developing consistent and objective information by which alternate programs can be evaluated and compared. Timber production, water yield, recreation use, and air quality concerns; integrating the realities of social, political, environmental, and economic requirements into future fire management programs is necessary for their success and acceptance. The comparison of the costs and benefits provides a common denominator that can be used to compare uncommon programs (Chase 1987). Cost plus net value change (C+NVC) is a decision framework that is often used to compare the gains and losses associated with fire management programs.

Several research papers have noted that minimization of C+NVC is equivalent to profit maximization from traditional production economics (e.g., Rideout and Omi 1990). Restructuring of the fire management problem provides insights into such things as the substitution effects between reduction in acres burned and reduction in fire intensity.

The cornerstone of the Federal Wildland Fire Management Policy (USDI/USDA 1995) is the appropriate management response, which allows for suppression actions on wildland fires ranging from monitoring to aggressive suppression. Within this continuum of responses are those that require fires to be delayed, directed or contained within a defined area. Zimmerman (1999) discusses how the costs for the appropriate

management response will not necessarily be lower when viewed using a short-term perspective.

The measure of economic efficiency used most widely for fire management, C+NVC, is extended to cover the temporal nature of presuppression and suppression actions using control theory (Hesseln et. al. 1999). Future expenditures for presuppression and suppression activities are affected by current expenditures, thus optimizations should be over an extended period to account for future benefits of the current activities.

The costs involved in wildland fire suppression can be estimated along with the market value of the losses. Quantifying non-market values such as recreation is more difficult and costly. Rideout et al. (1999) suggests the use of cost effectiveness analysis (CEA) as a means for fire managers to evaluate the tradeoffs between fire management costs and the protection of non-market values. By comparing the effectiveness, or physical progress toward accomplishment, of the non-market values to the cost plus change in market value, the cost effective frontier can be located. These points denote cost-efficient alternatives and allow fire managers to conceptually include non-monetized values in the decision process.

Adding Stochastic Components

Fire suppression efforts are often modeled deterministically eliminating all the variability that exists in real wildland fire situations. Using the expected values for variables that are more accurately represented by a distribution of values simplifies the model and produces the expected result (Fried and Gilless 1988a). This masks one of the

problems with wildland fire and wildland fire suppression, namely uncertainty. This uncertainty is why even with the best planning, fire seasons are rarely as expected. A distribution of possible outcomes that gives the expected result and the level of risk better describes the effectiveness of a fire organization. This can be achieved by adding stochastic components to the fire suppression models.

Risk is an inherent factor in wildland fire operations. The values at risk and the degree of risk depend on the fire management scenario. Hesseln and Rideout (1999) discuss how work is needed to objectively characterize and institutionalize risk so it can be integrated into the decision-making framework.

Mills and Bratten (1982) summarize the Fire Economics Evaluation System (FEES) that uses economic efficiency and the probability of success as criteria for selection among fire suppression programs. A low-resolution model, FEES analyzes fire programs for areas of one to three million acres. A general description of the characteristics of the region that influence fire program performance is required. C+NVC is used to measure the economic efficiency of a fire program but other effects on resource outputs, which cannot be readily measured in dollars, must also be considered. Risk, the variability in performance that can result from the application of a single fire program, is treated as a separate decision criterion. For a given program level, fire management mix as described by González-Cabán et al. (1986), and suppression strategy, fire containment is simulated using a simplified version of the FOCUS containment model. Because most of the costs and net value change are due to escaped fires, the primary objective of the initial attack module of FEES is to estimate the number of fires that will escape under a given fire

management program. Fire scenarios developed from random draws of fire behavior, arrival times, and fireline production rate distributions are processed until distributions for C+NVC and physical change in resource output have been adequately defined. From these the level of risk associated with a fire management program can be determined. Bratten (1982) describes the mathematical framework for the probability model.

The CFES-IAM Version 2 (Fried and Gilless 1988a) adds several stochastic components to more closely represent real-world variability in wildland fire occurrences, fire behavior, and initial attack suppression effectiveness. Calculations of the expected values and confidence intervals for annual fire losses and control costs are achieved through multiple runs of the simulation.

Fried and Gilless (1988a, 1988b) use distributions derived from historical fire data to model local fire occurrences. A next-event clock-driven simulator realistically represents the chronological and spatial distribution of fire occurrences. The year is divided according to the level of fire occurrence; low, transitional and high. The fires at each level are described using three random variables. A binomial distribution is used to determine if any fires occurred on a given day. If there are fires then a geometric distribution gives the number of fires that occur that day. These fires are distributed over the day using random draws from a time of day distribution that describes the likelihood of fires occurring throughout the day.

Fried and Gilless (1989) conducted a survey of engine captains, hand crew bosses, and dozer operators to develop hand crew fireline production distributions for CFES-IAM Version 2. The survey design which was based on the probabilistic PERT/CPM technique

(Moder et. al. 1983, cited in Fried and Gilless 1989) obtained the expert opinions of fire personnel for worst case, best case, most likely, and 90th percent construction times for a specified length of fireline. Assuming that construction rates are distributed according to a beta distribution, the analyzed data showed that published production rates are overly optimistic.

Hirsch and Martell (1996) published a review of the research on initial attack fire crew productivity and effectiveness. They concluded that even though the productivity and effectiveness of initial attack fire crews is an integral part of most fire management applications these values have not been adequately quantified. They also note that the interdependencies of suppression resources, such as helicopter buckets and fire crews, are often misrepresented when the resources are considered individually. Beyond the rates of fireline production is the question of when the resources are no longer productive. For airtankers dropping retardant the limits on effective control have been estimated to be around 2000 kW/m (578 Btu/ft/sec) (Luke and McArthur 1978; Gould 1987; Buckley 1994; and Newman 1974, cited in Hirsch and Martell 1996). In comparison, the limits for hand crews are around 346 kW/m (100 Btu/ft/sec) (Albini 1976).

Hirsch et al. (1998) collected expert opinions regarding the effectiveness of initial attack fire crews. Fires escape initial attack when suppression resources are unable to construct enough fireline or when the fire or embers from the fire breach the fireline. Initial attack crew leaders were asked to estimate the probability of containment for 35 fire scenarios that varied by fire size and intensity. Beyond the development of prediction equations, additional information collected from the experts indicated that bucketing

helicopters are capable of building extensive fireline on larger, low intensity fires and that they can reduce the head fire intensity on small crown fires.

The production rates for continuous fireline depend on the relative difficulty of constructing and holding fireline due to fuel type characteristics and fire behavior. With hot-spotting the fire is contained by slowing or stopping the spread of a fire by reducing the heat energy output (Murphy et al. 1991). Priority is given to the most intense areas of the fire. Hot-spotting by crews is often accompanied by a helicopter equipped with a bucket or airtankers. Hot-spotting involves controlling fire behavior rather than removing fuel and has been found to be dependent on the fire behavior variables, rate of spread and flame length. As flame length and rate of spread increase the hot-spotting rate decreases.

Large Fires

Although only a small number of fires escape initial attack, they represent a significant amount of the fire costs (Bratten et. al. 1981). Fire planning efforts have concentrated on the initial attack of small fires. Dimitrakopoulos and Martin (1987) discuss why modeling large fires is difficult. Simple fire growth models assume homogeneous fuels, topography and weather conditions, assumptions generally violated by large fires burning for extended periods. Modes of propagation other than a flaming front through surface fuels, such as crowning and spotting, often occur during large fires. Large fires can blow-up and display other unusual occurrences such as firewhirls, horizontal roll vortices and convection columns. In addition, large fire suppression often includes complicated tactics. In the absence of adequate simulation models, historical

data has been used to determine escape fire sizes. Gaming methods have also been used to estimate the outcome for escaped fires.

Bratten (1970) developed a mathematical model to allocate firefighting resources to different large fire suppression tasks. The fireline required to contain a large wildland fire by a specific time is divided into segments that represent uniformity in the consequences of having the line fail, holding probability, and type of fireline to be constructed. Each fireline segment is assigned a utility value that is the relative importance to fire managers of stopping the fire along the segment. Linear mathematical programming is used to allocate resources to the segments of fireline so that the sum of the overall expected utility for the fire is maximized.

An extension of the Bratten's model completed by Mees and Strauss (1992) optimizes the distribution of suppression resources using the holding probabilities for segments of fireline constructed by different sets of resources. Holding probabilities are calculated using stochastic values for the width of fireline produced by different resources and the associated probabilities that fireline of different widths will hold. The optimal allocation of resources to the different segments of fireline is solved using integer linear programming to maximize the sum of the utility of each segment of fireline and the holding probability for the set of resources building line on that segment of fireline. The size of the problem has to be restricted in order to use this method because all combinations of resources for allocation to a segment have to be enumerated or the problem becomes nonlinear.

The probability that a section of fireline will hold increases as fireline width increases and flame length decreases. This relationship was modeled by Mees et al. (1993) under the assumption that fireline width and flame length are both random variables. Fireline width, modeled using the gamma probability distribution, depends on the suppression resources building the fireline. With flame length modeled using a uniform distribution, the probability can be calculated for whether a section of fireline built by a given set of suppression resources will hold.

The probability that a section of fireline will fail and the consequences of the failure are used by Mees et al. (1994) to evaluate the risks associated with alternate suppression options. Segments of the fireline with different completion times are specified and resources are allocated to the segments so that the firelines are completed in time. The overall allocation of resources that minimize the expected cost consisting of the sum of the net value change for the area burned, the cost of the fire-fighting forces deployed and the expected net value change for the area that burns beyond the fireline should the fireline fail can be found using integer programming.

The behavior of a fire burning under a set of environmental conditions is not necessarily certain, as is evident when a fire blows up. Hesseln et al. (1998) describe how catastrophe theory can be used to model these situations. The cusp model for catastrophic events can be used to predict uncontrollable fire behavior and provide information about environmental conditions that may allow for sudden changes in fire behavior.

Optimal Dispatching

The simulation models discussed so far attempt to model fire growth and the effectiveness of suppression resources to evaluate some aspect of the fire management program or find the best fire program among those evaluated. Another problem that faces fire managers is finding the optimal set of resources to deploy to a fire. From the available suppression resources a set must be selected that will provide the best response. Several models that use optimization techniques to find the most cost effective dispatch of suppression resources have been developed.

Because suppression resources are dispatched as an indivisible unit, integer programming is often used to find the optimal set of suppression resources. For a single fire Donovan and Rideout (2003) developed an integer program to determine the dispatch of suppression resources that minimize $C+NVC$. The integer program includes a temporal dimension to account for the fact that different sets of suppression resources will contain the fire at different times. The model evaluates a set number of time intervals and suppression resources to find the minimum of the sum of all fire related costs and damages under the constraint that the fire is contained, i.e. the length of fireline built exceeds the perimeter of the fire in at least one time interval.

Dispatch strategies that use the closest resources to minimize response time and fire size are not necessarily the least expensive. The most efficient deployment of resources minimizes suppression cost, value of the area burned before resources contain the fire, the cost to mop up area burned, and the cost of other activities not directly related to fireline construction. This optimization problem can be solved using nonlinear mixed-integer

programming, but since deployment decisions need to be made quickly, Wiitala (1999) describes how the problem can be solved with dynamic programming. The problem is formulated in two phases. For each time increment, the least expensive set of resources for constructing the required fireline is found. To this cost the value of the area burned, mop up costs and any additional costs are added. The total costs for each time increment are compared and the set of resources with the least overall cost is selected for deployment. By first estimating the minimum cost set of resources for different fire sizes then selecting the least expensive set of resources this method recognizes that the set of resources with the least overall cost may allow the fire to burn longer.

Kourtz (1989) uses dynamic programming to find the least cost deployment of airtankers and fire crews delivered by helicopters. The suppression resources can be deployed from their current position, either a base or an ongoing fire. An airtanker model determines the capabilities and costs for different airtankers based on location and type of aircraft. With dynamic programming stages representing each airtanker type and location, the least cost for achieving the required level of support is found. Determining the least cost method for deploying the required number of crews with helicopters capable of making multiple trips involves tracking helicopter costs. The dynamic programming stages represent the dispatch of a crew and the trip status of each helicopter under consideration. Together these two programs provide information for a minimal cost deployment to fill deployment requests generated by an expert system.

Locating Suppression Resources

A disproportionate amount of costs and damage are attributed to wildland fires that escape initial attack (USDA Forest Service 2000). A quick aggressive initial attack increases the chances that a fire will not escape. In order to do this fire suppression resources must be located near enough to any new ignition that they can arrive at the fire before it becomes so large that containment is difficult. Thus the positioning of suppression resources for an uncertain fire load is an area of research that has received considerable attention.

Anderson and Lee (1991) divide the region being considered into a grid and use fire behavior models to evaluate fuels, terrain, and weather to establish travel time limits that ensure any ignition within a cell can be contained. Linear programming methods find the minimum number and location of resources so that every cell can be serviced within the specified time limit. The problem is reformulated to determine the locations where a fixed number of resources can be located to provide maximum coverage of the region.

Using a road network with nodes representing resource and fire locations, intersections and other obstacles and lines representing the travel time between the nodes, Mees (1986) developed a shortest route algorithm to generate arrival times for ground resources from each resource location to each fire location. An integer linear programming model uses the computed travel times to find the minimal number of resource locations that can provide suppression resources to a set of historical fires within the required arrival times. He also developed a statistical model that uses the minimum and maximum sums of the travel times for all possible combinations of resource and fire locations to minimize the travel time to the fires.

Maloney (1973) developed a linear model to minimize airtanker costs for initial attack on wildland fires in California. A relevant set of fires is used to determine the quasi demand for each airtanker base. The relative efficiency of airtanker types for initial attack from an airtanker base was determined based on the capacity and airspeed of the airtanker. Different conditions in the area surrounding the airtanker bases led to the conclusion that different airtanker types are more efficient in different areas. The model was used to find the most efficient airtanker basing combinations to meet different levels of regional quasi demand.

Hodgson and Newstead (1978) developed two location-allocation models for initial attack of forest fires to determine where airtankers should be located to optimize suppression effectiveness. Heuristic programming methods are employed to optimize two criteria. The first model, which aims to provide maximum coverage to the values at risk, maximizes the number of fires, weighted by values at risk, within the range of airtankers while the second model, which also recognizes the importance of reducing the response time, also considers the distance to the fires. Both models were used to find the optimal allocation of four sets of airtankers to eleven bases in Alberta based on historical fires. The second model allocated the airtankers in a manner that substantially reduced the distances traveled without leaving many fires without airtanker coverage.

Although airtankers are assigned to specific bases for the fire season, they can be repositioned in order to better serve the expected fire load. When airtankers are reassigned, the increased use of the airtankers is offset by per diem and travel costs.

Greulich and O'Regan (1982) developed a model to select particular airtankers and assign

them to home bases so that the output from the airtankers is maximized while the costs remain within budget. In the model, fire conditions are considered to be a first order Markov process where the probability of a given set of fire conditions on a particular day is dependent on the fire conditions for the previous day. Using mixed integer linear programming a cost effective assignment of airtankers to home bases is found by maximizing the airtanker output for any day during the fire season based on probabilities describing the daily assignment of airtankers to bases. Historical fire information was used to calculate fire condition probabilities that the model used to assign five airtankers to three home bases in California.

The OMNR assigns airtankers to bases on a daily basis in response to the expected fire load. Martell and Tithecott (1991) developed a model to assist fire managers in determining the airtanker need at each base. The model views the initial attack airtanker system as a spatially distributed queuing system with airtankers serving fires that arrive according to a Poisson process. It assumes that there is an unlimited supply of airtankers and that the same number of airtankers would respond to each fire on a given day. The model determines how many airtankers would be deployed from each base on a given day based on the expected fire load. Fire managers can use this information to decide how best to meet the expected need.

Maclellan and Martell (1996) developed models for the OMNR for meeting the daily airtanker need at individual bases and determined home basing to minimize the cost of meeting the daily need. A subjective model for daily airtanker need was developed by querying fire managers on the number of airtankers needed in an area for a given level of

fireline intensity and fire occurrence. Ten years of historical fire weather and occurrence data were plugged into the model to estimate the daily airtanker need at each base. An integer linear programming model then determined the home basing for airtankers to meet the estimated need while minimizing the total cost of airtanker transfers.

Islam and Martell (1998) developed an initial attack airtanker system to investigate the effect of initial attack range on airtanker performance. The model simulates fire arrival rates based on fuels, weather, land-use patterns and diurnal cycles using a Poisson process that allows for simultaneous fires. The initial attack range for an airtanker limits the fires to which an airtanker can respond. When a fire is within the initial attack range for multiple airtankers, the nearest available one responds. When there are no airtankers available, the fire is placed in a queue where it will be served on a first-come first-serve basis. Application of the model to a hypothetical day showed that the initial attack range for airtankers should vary with respect to the fire arrival rate. When the rate is low the initial attack range should be larger so fires are not placed in queues while airtankers are idle. As the fire arrival rate increases the initial attack range should become smaller to decrease the travel time to fires.

Errors can occur when airtanker travel distances are approximated using the distance to the center of the area being modeled. Greulich (2003) presents an analytical method for calculating the flight distance from an airtanker base to a fire. The method uses polygons, lines and points to partition the horizontal plane of the fire protection zone into regions that have equal probability of a fire start. Greulich provides equations for calculating the mean and variance for the travel distance from an airtanker base to any

point in the defined region and the entire fire protection zone. The formulas can then be used to determine the optimal location for an airtanker base by applying a cost function to the flight distances.

Considerations for Fire Planning Models

Donovan et al. (1999) discuss some of the shortcomings of NFMAS and FIREPRO. Two of the inputs for NFMAS, presuppression and suppression, are not independent. Because of this the most efficient level of funding cannot be found by conducting a partial sensitivity analysis on these inputs as NFMAS attempts to do. They suggest the use of an optimization method. They also note that FIREPRO identifies performance targets but cannot determine the least cost for achieving them because it does not evaluate the elements of presuppression and suppression and lacks a simulation component.

Schuster and Krebs (1999) analyzed NFMAS to determine which input variables caused the largest changes in the Interagency Initial Attack Assessment (IIAA) model output variable C+NVC. The sensitivity analysis showed that fireline production rates caused the largest change followed by average acre cost. Net value change caused some change while escaped fire limits and unit mission costs caused the least change. The results of this analysis can be used to direct training and research efforts towards the more influential NFMAS variables.

NFMAS defines escaped fires as those that exceed a defined maximum size, are not contained within a time limit or exceed the capabilities of the deployed suppression resources. The final size of escape is determined from a user defined “escaped fire table.”

This table is based on historical fire sizes and annual frequencies. Twenty years of historical data are needed to establish these tables. Dimitrakopoulos (1987) describes an alternative method for determining the final size for escaped fires using more current data.

Airtankers and Helicopters

Efforts to reduce the cost of large wildland fires must address the high cost areas. Mangan (1999, 2001) notes that aircraft are the single highest cost suppression resource used on large wildland fires, accounting for more than one-third of the total suppression costs on some fires. Different aircraft types have unique characteristics providing them with different efficiencies for different fire suppression situations. Savings can be achieved by ordering the right resource for the job so aircraft should be assigned to fires based on the actual and projected need.

A survey of fire managers to identify and prioritize fire suppression problems identified the need to reevaluate airtanker and helicopter costs and effectiveness (Phillips and George 1991). The national shared resources funded and managed directly by the U.S. Forest Service Washington Office are essential for successful wildland fire management across the nation. These resources include airtanker, smokejumpers, lead planes, and large helicopters. Several studies described by Dudley (1999) have been conducted by the Forest Service to improve the efficient use of these resources.

The objective of the *National Study of Type I and Type II Helicopters to Support Large Fire Suppression* (USDA Forest Service 1992) was to examine historical, current

and future use of large helicopters and determine cost effective methods for procurement and deployment. The primary need for large helicopters is large fire support. A demand profile describing daily helicopter use and the duration of use was developed for data from 1989 to 1991. These demand profiles for helicopter use were modeled using triangular probability distributions. Type I and type II helicopters can be obtained for fire suppression using either the national call-when-needed (CWN) contract or exclusive-use contracts that guarantee an extended period of use and thus provide significant savings. The optimal mix of CWN and exclusive use helicopters was determined by computing the total program cost to meet the demand when from one to twenty exclusive use helicopters were contracted. The analysis showed that over \$4 million could be saved annually by putting three Type I and 13 Type II helicopters on exclusive use contracts.

As of 1999 there were still no Type I helicopters and only seven Type II helicopters on exclusive use contracts. Kirsh (1999) revisited the study using data for Type I helicopter use from 1993 to 1997. He determined that the demand and duration of Type I helicopter use had increased substantially since 1992 and that six Type I helicopters on 105-day exclusive use contracts would meet the demand.

The goal of the *National Study of Large Airtankers to Support Initial Attack and Large Fire Suppression Phase II* (USDA Forest Service 1996) was to determine the optimal airtanker fleet for the future without being constrained by the composition of the current fleet. Existing and potential airtanker types and base locations were analyzed using the NFMAS-IIAA model. Using the current local NFMAS information, airtanker types and base locations were varied and compared. Airtanker production rates are

assumed to be dependent on airtanker volume and the fuel model. The effectiveness of an airtanker drop was incorporated into the model by reducing the length of fireline produced linearly with the spread rate of the fire so that the fireline production is zero when the spread rate of the fire is greater than or equal to 40 chains (805 meters) per hour. Costs per gallon of retardant delivered and cost per chain of line produced were used to evaluate different airtanker types. The study recommends that the future airtanker fleet consist of turbine engine airtankers capable of carrying 3000 to 5000 gallons (11,356 to 18,927 liters) of retardant.

The study (USDA Forest Service 1996) also compared initial attack cost and production capabilities for the 2000-gallon S-64F helicopter and the 3000-gallon P3-A airtanker. The cost per gallon for the two aircraft is equivalent when the S-64F can make three to four times more drops than the P3-A. Assuming retardant is twice as effective as water, the S-64F must make seven times more drops than the P3-A. But if the S-64F is twice as accurate in steep terrain and windy conditions the drop ratio returns to three to four times more drops. A similar analysis for large fires shows that where quick turnarounds can occur Type I helicopters are the most efficient.

The *Aerial Delivered Firefighter Study* (USDA Forest Service 1999) analyzed the size, location, and tradeoff of initial attack smokejumper and helitack/rappel programs. A simulation model that uses an extensive set of rules to closely approximate the dispatching and movement of aerially delivered firefighters showed that smokejumpers and helicopters with rappel crews can make a significant contribution to the initial attack effort. The model uses ten years of historical fire data and simulates the regional and

subregional movement of forces in response to the changing need. Airtanker and ground forces are also modeled with less detail. The stochastic, clock driven simulation model uses fourteen probability models to represent the variability in the system including ground force arrival times, carrying capacity of helicopters and the effectiveness of airtanker drops. Twenty replicate runs are made to capture the effect of this variability.

Assessment of the Effectiveness and Environmental Risk of the Use of Retardants to Assist in Wildfire Control in Victoria (CSIRO Forestry and Forest Products of the Department of Natural Resources 2000) discusses the effectiveness of aerially delivered fire retardants. Aircraft delivering retardants provide several advantages, including the speed that the suppression effort can begin, the ability to locate and access small fires including spot fires, and the safety of suppression crews. Although the spread of low-intensity fires may be halted by long-term retardants, fire controllers expect the fire to creep through areas in the retardant line where coverage is low such as on the lee side of logs. The time it takes for a fire to burn through a drop depends on the fire intensity, retardant type, concentration and width of the retardant drop, and the fuel type. The wind can blow fine retardant particles and affect the retardant distribution on the ground.

Alexander (2000) also discusses the effectiveness of suppression aircraft. Minimizing travel time is an important criterion for successful initial attack. The productivity of airtankers and helicopters dropping water or retardant is generally thought of as the length of effective fireline produced. Since the depth of retardant or water is inconsistent along the pattern, penetration of the drop zone can be expected. The forest canopy can intercept a considerable amount of liquid. The primary purpose of aerial attack is to retard the

progress and hold the fire until ground crews can put a line around it. The greatest role of helitankers is hot spotting where water is used to reduce the fire intensity along the perimeter of the fire. This assists crews building the fireline and keeps the fire from breaching the fireline.

McCarthy (2003) provides some statistics on aircraft operations in Victoria, Australia for the 1997-1998 fire seasons. Aircraft effectively checked the head fire before the ground forces arrived on an average of 69 percent of the fires attended. The average arrival time for aircraft was 40 minutes while the average for crews was 100 minutes. The turn around times for helicopters were 3-5 minutes while for fixed-wing aircraft they were 25 minutes. Fire managers indicated that medium-sized helicopters made a significant contribution to asset protection. Many reports contained comments to the effect that fire bombers used in close support of rappel crews were able to cool sections of the fireline enough to allow the crews to directly attack the fire.

The application of water and water plus retardant chemicals suppress wildland fire by knocking down flaming combustion and holding the combustion below an intensity that supports fire spread (Blakely 1985). Using wind tunnel tests to measure energy released by the fire and weight lost by fuels, Blakely (1985, 1990) found that even though retardant chemicals increase the effect, the majority of the knockdown is attributable to water. Larger amounts of water delay combustion recovery, but if water is in short supply retardant chemicals provide the greatest benefits. Fire spread is stopped if the burning fuels surrounding the treated area cannot provide sufficient energy for combustion recovery.

Slijepcevic and Fogarty (1998) discuss rotor side-wash from helicopters, which can negate the effectiveness of the drops they make. Rotor side-wash is correlated to ground speed, height of rotor, rotor span and helicopter mass. Limits on the amount of rotor-wash that will negatively affect a fire depend on fuels. Speed and height limits to ensure that rotor-wash will not have a negative effect can be calculated for individual helicopters and fuels. Slijepcevic and Fogarty developed 'rules-of-thumb'. For helicopters weighing less than 2000 kg drops should be made at speeds greater than 25 km/hr and heights greater than 25 m. For helicopters weighing between 2000 and 6000 kg the limits are 35 km/hr and 35 m.

Airtanker and Helicopter Effectiveness

A major issue in using aircraft for fire suppression is quantifying their efforts. There are many different types and sizes of aircraft that perform a variety of fire suppression tasks. Airplanes can be used to deliver personnel and equipment to bases, deliver smokejumpers to a fire, and drop water or retardant on a fire. Helicopters can deliver personnel and equipment to any place they can land. When they cannot land, crews can rappel or jump from the hovering aircraft and equipment can be long lined into remote areas. Helicopters are equipped with a fixed-tank or a bucket to drop water, retardant or foam on a fire. Both airplanes and helicopters are also used for reconnaissance and fire mapping.

When aircraft are used to move personnel and equipment, the performance of the aircraft will depend on the location of the aircraft, the location of the personnel or

equipment, the delivery location and how it relates to the final destination, the quantity of personnel or equipment that can be delivered, loading and unloading times, taxi and takeoff times, and the flight speed of the aircraft. In modeling fire suppression the delivery of personnel by aircraft affects only the arrival times for the crews. Simulation of helicopter crew delivery (Kourtz 1989, and Bratten et al. 1981), simulation of smokejumpers operations (Wiitala and Dammann 2003), and simulation of the movement of smokejumpers and helicopters with rappel crews (USDA Forest Service 1999) provide good examples of how the movement of personnel by aircraft has been quantified.

The performance of aircraft dropping water or retardant chemicals on or near a fire is more difficult to quantify. The delivery of the drop to the fire, similar to the delivery of personnel, depends on the location of the aircraft, the location where the aircraft can refill, the location of the fire, the amount that can be carried, loading and reloading times, taxi and takeoff times, and the flight speed of the aircraft.

The effectiveness of aerial drops has not been studied. The suppression effectiveness depends on the ground pattern and placement of the drop along with the fuels, fire behavior, and other suppression resources on the fire. Most of the models assume that drops produce fireline that is equivalent to the fireline built by crews. Fried and Fried (1995) model the arrival of drops and add this contribution to the total length of fireline constructed. Simard (1979) simulates airtanker drops by calculating the length of line that will be produced for a retardant depth that will extinguish the fire. The fireline construction rates by ground crews are increased when they are building line through a retardant drop. Martell et al. (1984) require that airtankers working alone on a fire

contain the fire when they have completed enough fireline to surround the fire twice to simulate the necessary reinforcement of fireline.

The performance of airtankers and helicopters dropping water or retardant chemicals is one area of fire suppression that still needs work, particularly for quantifying the effectiveness of drops. Usually drops do not form a permanent barrier to the advancing fire; and instead they temporarily stop the fire or change the fire behavior. FOCUS as described by Bratten et al. (1981) models the temporary effectiveness of retardant drops. FOCUS models the arrival times for airtanker drops and places the drop using complex logic. The retardant drop then holds the fire for 15 minutes unless the fire burns around the ends of the drop.

Drop effectiveness depends on the tactics used. Although there are guidelines for safety, drops can be made anywhere around or in front of the fire, including within the fire perimeter or half in and half out. Water cools the fire and can be used within the fire to cool hot spots, or it can be used just outside the fire to wet fuels so they do not ignite. Water will evaporate, but it can be reapplied until the fire burns all of the untreated fuels that are available. The use of fire engines, which continuously place water on the fuels is an example of how water can be used to build a barrier between the burning fire and the unburned fuels.

For airtankers that often leave the fireline unattended for extended periods of time, retardant chemicals that alter the chemical composition of the fuels provide a more permanent barrier to fire growth. The fire will still burn untreated fuels within, under and over a retardant drop, so retardant drops are seldom considered impenetrable. Subjective

values have been used to compare the effectiveness of retardant and water drops. In the *National Study of Large Airtankers to Support Initial Attack and Large Fire Suppression Phase II* (USDA Forest Service 1996) retardant drops are assumed to be twice as effective as water drops. The *Aerial Delivered Firefighter Study* (USDA Forest Service 1999) and the *Assessment of the Effectiveness and Environmental Risk of the Use of Retardants to Assist in Wildfire Control in Victoria* (CSIRO Forestry and Forest Products of the Department of Natural Resources 2000) both assume retardant is three times more effective than water. The relative effectiveness of retardant and water drops depends on tactics, whether the drop is on or in front of the fire, and probably the fuels and fire behavior.

The ground pattern, including the depth of the retardant, is a function of the fixed-tank or bucket used by the aircraft. The fixed-tank or bucket and gating system determines the flow rate and configuration that the retardant or water has as it exits the system. There are a wide variety of systems currently in use. The ground patterns produced by several of these systems have been quantified using a grid of cups to measure the ground pattern they produce (George and Blakely 1973). Traditional buckets have a nearly round opening in the bottom. Decreasing head pressure causes the flow rate from these buckets to slow as the bucket empties (Solarz and Jordan 2000a, 2000c, 2001; Johnson 2000). Newer constant flow fixed-tanks have been developed for airtankers and helicopters. These systems have long narrow doors that open more widely as the head pressure decreases to maintain the flow rate. They produce a narrow ground pattern with nearly uniform concentration of retardant along its length (Solarz and Jordan 2000b).

The newest system being developed uses a pressurized container that squirts retardant in a rearward direction.

Once the water or retardant leaves the delivery system external forces modify it. Large airtankers typically make drops at airspeeds between 125 and 130 knots (Swanson and Helvig 1974). Helicopters can vary their airspeeds from a hover to over 100 knots, which can greatly change the length and depth of the resulting drop (Solarz and Jordan 2000a, 2000b, 2000c, 2001; Johnson 2000). The airspeed of the aircraft gives the liquid a forward velocity, while the wind speed and direction apply forces that modify the shape of the liquid until it reaches the ground (Swanson and Helvig 1974). Fogarty and Slijepcivic (1998) note that helicopters can operate in strong winds; however, fire managers suggest that the helicopter suppression operations are less effective in strong winds. Suppression operations in steeply divided terrain and dense vegetation are affected more by windy conditions in part because the winds disperse the water being dropped. More powerful aircraft and skilled pilots can offset some of the decrease in efficiency in windy conditions (Fogarty and Slijepcivic 1998).

Drop height also plays a significant role in defining the final distribution of retardant on the ground (Swanson and Helvig 1974; Solarz and Jordan 2000a, 2000b, 2000c, 2001; Johnson 2000). Airtankers are directed to drop at heights of 200 feet to ensure that the retardant has lost its forward momentum before it hits the ground (Swanson and Helvig 1974). Large helicopters make drops from buckets slung from a 100-foot line to minimize rotor-wash, and thus the water spends less time being dispersed by the wind (Solarz and Jordan 2000a; Slijepcivic and Fogarty 1998). Uneven terrain can cause parts

of the drop to remain in the air longer than other parts, and the canopy intercepts some of the liquid before it reaches the ground (Swanson and Helvig 1974).

When the drop is used along the perimeter or ahead of the fire the pattern of liquid on the ground determines how effective the drop will be. The drop is only as strong as its weakest point, because once the drop is breached the fire will quickly consume the area beyond it leaving only the remnants of an unburned island. These weak points may be low concentration points within the ground pattern, areas where the fuels have intercepted the liquid, or gaps between drops. Because the probability of these occurrences is high, ground resources are often used to reinforce retardant drops.

Helicopters are often used to directly support ground resources. Helitack crews are delivered to the fire by helicopter, which then supports the crew by cooling the fire and reinforcing the fireline. Although the helicopter is not building fireline, it is contributing to the suppression effort. Helicopters are also used to stop the fire when it breaches the fireline and put out spot fires caused by embers or burning logs that have rolled downhill. These efforts, although valuable, are not quantified.

The diversity that exists within the fleet of aircraft used for fire suppression, and their tank and gating systems, produce an extremely wide distribution of performance. Beyond the quantification of select delivery systems over flat terrain in preferably calm conditions, little work has been done to quantify the effectiveness of these systems. In order to understand the strengths and weaknesses of these systems so they can be used efficiently, suppression effectiveness needs to be quantified.

Research Effort

In light of the extensive amount of research that is needed to quantify the effectiveness of aviation resources for fire suppression, I am focusing on comparing helicopters on the basis of their performance. This area received just a brief acknowledgement in all the literature reviewed. In the *National Study of Type I and II Helicopters to Support Large Fire Suppression* (USDA Forest Service 1992) it is recommended that:

“The development of cost and performance data to aid dispatchers in selecting helicopters best suited for a mission should occur. Lacking this data, any Type I and II helicopter is dispatched without full consideration of performance capability. While mobilization may be cost effective, performance at the incident is not.”

Helicopter performance capability is the payload capacity, which can be directly related to the benefits a helicopter will provide at a fire. Helicopter performance depends on the lifting capabilities of the engines at the altitude and temperature of operation and the weight of the helicopter, pilots, and fuel. It varies significantly for individual helicopters and fire locations and directly affects the number of people and the amount of water or cargo that can be carried. A cost effective deployment of helicopters must include helicopter performance information, but since this is difficult to determine and must be done for every helicopter under consideration, it has not been a part of the decision-making process.

Since 1994 I have worked on developing a database that contains cost and performance information for all the Type I and Type II helicopters on national CWN and exclusive use contracts. These data have been used to set minimum performance standards for contracting purposes. Since helicopter performance varies greatly among the contracted helicopters, performance information needs to be included when deploying helicopters to ensure that the most efficient helicopter is deployed.

A four-hour comparison index can be used to compare the costs and benefits provided by individual helicopters at the altitude and temperature of a fire. Using this index to deploy helicopters can significantly improve the efficiency of helicopter operations, as shown by a cost benefit analysis that compares making deployment decisions with and without performance information. The U.S. Forest Service has finally decided that this may be true and has asked for my help developing a prototype system to be tested during the 2004 fire season.

The four-hour comparison index does not include the effect of mobilization in the decision-making process. Mobilization adds cost and delays the start of helicopter suppression efforts. The added cost of mobilizing a helicopter can be included in the calculation of costs and benefits, but including the effect that different mobilization times have on the area burned requires modeling. This modeling cannot be done until the effectiveness of water drops can be simulated more accurately.

The best allocation of helicopters to fires will provide optimal benefits while containing the costs and ensuring the mobilization times do not jeopardize the suppression effort. This problem can be formulated as a mixed integer-programming

problem by minimizing the cost per pound and constraining mobilization time. The problem can also be formulated as a multiple object optimization problem with three objectives. Solving the problem with multiple objectives gives a set of solutions that describes the tradeoffs between the costs, benefits, and mobilization time. The decision maker can then deploy helicopters based on the relationship between these criteria.

I developed a genetic algorithm to solve the multiple-objective optimization problem for multiple fires. Because requests for helicopter and the availability of helicopters can change before the problem is solved the genetic algorithm is dynamic. The problem is also formulated as an integer-programming problem and the results of the two optimization methods are compared.

CHAPTER 2

USING COSTS AND BENEFITS TO COMPARE THE EFFICIENCY OF HELICOPTERS

Abstract

Helicopters used for wildland fire suppression are categorized into three types according to their carrying capacity. Within a type, helicopter carrying capacity and in turn the benefits that a helicopter can provide to the fire suppression operation vary significantly. The carrying capacity also depends on the altitude and temperature of operation. Helicopters used for suppression on large wildland fires are ordered by type. Costs and mobilization times, which are easily obtained, are used to compare the helicopters and the cheapest helicopter that meets mobilization time constraints is deployed. Estimating the benefits a helicopter can provide to the suppression effort is not straightforward and requires knowledge of the helicopters and helicopter operations. Because calculating the benefits a helicopter can provide at a fire is expensive and time consuming, a helicopter comparison index is developed which incorporates both cost and benefit information for individual helicopters. The index provides a means for quickly comparing the efficiency of individual helicopters so the most efficient one can be

deployed. Deploying the most efficient helicopter can mean substantial savings for fire suppression efforts on large wildland fires.

Introduction

The United States government spent approximately \$150 million on helicopters for fire suppression during 2000 (Stone 2002). Much of this money was spent contracting large helicopters for use on large wildland fires. Through the Interagency Call-When-Needed (CWN) contract, hundreds of helicopters are available, each with unique capabilities and costs. At deployment time decision makers must determine which CWN helicopter should be deployed. Decisions need to be made quickly. The unpredictable nature of wildland fires ensures that decisions will be made with incomplete information.

For wildland fire suppression, helicopters are grouped according to payload capabilities. Type I helicopters carry 700 to 3000 gallons of water at sea level while Type II helicopters carry 300 to 700 gallons and Type III helicopters carry less than 300 gallons (USDA Forest Service 2002). Helicopters are ordered for wildland fire suppression operations by helicopter type and category. Standard category helicopters can carry personnel while limited category helicopters cannot. The cheapest available helicopter that meets type and category and the mobilization time constraint is deployed (Roth 2004).

The problem with deploying helicopters in this manner is the wide range of capability within a type and category. The benefit a helicopter provides at a fire, which is directly

related to the payload capability, is not included in the decision process. This allows for inefficient helicopters to be deployed.

The payload capability of helicopters depends on the altitude and temperature of operation so it will vary from fire to fire. This makes directly calculating the payload capability, or benefits, for comparing helicopters difficult.

To ensure that fire suppression money is well spent, it is imperative that deployment decisions are based on helicopter efficiency. Helicopter costs are based on the cost of doing business. These costs are not necessarily related to the benefits the helicopter can provide at the fire, so an analysis of helicopter costs and benefits is required to ensure that good deployment decisions are made. It requires some extra effort to compile accurate information about the capabilities of individual helicopters, but I will show that inclusion of this information in the decision process can mean savings of 30 to 40 percent.

Evaluating CWN Helicopter Benefits

Helicopters are versatile and effective in wildland fire suppression. Their uses cover a wide range of activities such as moving people and cargo, building and supporting firelines, and reconnaissance. The helicopter fleet consists of an assortment of makes and models of helicopters with a wide range of capabilities. Many of the available helicopters are military surplus and not certified to haul people. Evolution also contributes to the diversity in the helicopter fleet as older models are upgraded for better performance and specific tasks.

Because of the wide range of tasks helicopters can perform for fire suppression and in the private sector, they carry a variety of equipment. The weight of the equipment that allows a helicopter to perform a specific task, such as seats for hauling people, may make it less efficient at performing other tasks like bucket work. Thus, two similar helicopters that are equipped for different tasks will have different payload capabilities. As fire suppression tools, individual helicopters have unique capabilities.

Beyond the ability to perform specific tasks at a fire, the lifting capability of a helicopter at the fire is a limiting factor for the benefits a helicopter can provide. The lifting capability, often referred to as helicopter performance, depends on the altitude and temperature of operation. Each make and model of helicopter has its own set of performance charts. These charts give the lifting capabilities of the engines at the altitude and temperature of operation (USDA Forest Service 2002). The maximum allowable payload for the helicopter at the altitude and temperature of operation is calculated using these performance values. These calculations are complicated further because fire suppression activities occur over a range of altitudes.

Since it would be difficult to obtain all the necessary information and calculate helicopter performance as requests come in, decisions need to be made using an estimate of helicopter performance. I developed the Interagency Helicopter Approval and Performance (IHAPI) database with J.P. Johnston, U.S. Forest Service Helicopter Operations Manager, to manage the contract, performance, and inspection information for all the helicopters on the National CWN and Exclusive-use contracts. The contracting

and helicopter staff at National Interagency Fire Center (NIFC) maintains the information in the database. In the IHAPI database, helicopter performance is calculated at five representative altitude and temperature conditions, determined by J.P. Johnston. These conditions are:

- 2500 feet and 35 degrees Celsius
- 5000 feet and 30 degrees Celsius
- 8000 feet and 25 degrees Celsius
- 10000 feet and 20 degrees Celsius
- 12000 feet and 15 degrees Celsius.

Maximum gross weight data are obtained from the performance charts for each make and model of helicopter on contract for these conditions. The maximum allowable payload for individual helicopters is approximated by subtracting the weight of the equipped helicopter, the weight of 1.5 hours worth of fuel, 200 pounds for each pilot, and any applicable download from the maximum gross weight. The maximum allowable payload for different helicopters of the same make and model varies significantly because helicopters carry equipment for a variety of missions.

The majority of the fire suppression efforts for Type I helicopters are bucket work where the benefit is the amount of water, foam, or retardant that can be delivered to the fire. Because these load sizes can be adjusted to utilize the helicopter's full capacity, the weight delivered is directly related to the maximum allowable payload for the altitude and temperature conditions. Thus the total amount of suppressant delivered by weight or the

total benefit the helicopter can provide is the maximum allowable payload (P) multiplied by the number of loads delivered per hour (L) and the flight time (t).

$$(2.1) \quad \text{Total benefit} = P * L * t$$

The unique capabilities of individual helicopters, their payload performance at representative altitudes and temperatures, along with their costs need to be available so decision makers can use the information to efficiently allocate helicopters for fire suppression. Helicopters need to be certified and equipped in order to perform certain tasks, such as hauling crews (USDA Forest Service 2002). These special capabilities need to be documented so the appropriate helicopters can be considered for individual fire suppression tasks.

Evaluating CWN Helicopter Costs

The CWN helicopter contract provides a method for federal agencies to obtain large helicopters for extended attack and large fire support. Through the CWN contract, helicopter operators offer helicopter services to the government but are not required to respond when ordered. This allows the federal agencies to maintain information on a large number of suitable helicopters without actually contracting them unless the need arises.

CWN helicopter bids are solicited from operators for daily availability. In addition the government fixes an hourly flight rate based on the cost of operating the helicopter. Hourly flight rates are established for each helicopter make and model based on the costs that can be attributed to an hourly cost such as fuel. The total cost for contracted helicopters is the flight time (t) multiplied by the hourly flight rate (fr) plus the daily availability (dr) multiplied by the number of days the helicopter is on contract (d).

$$(2.2) \quad \text{Total cost} = \text{fr} * \text{t} + \text{dr} * \text{d}$$

where flight time (t) includes the time required to fly the helicopter to and from the incident. (USDA Forest Service 1992)

Helicopters are also placed on exclusive use contracts. In this case helicopters are put on contract for a set period of time and often for a particular purpose. Because operators know in advance the length of the contract, these helicopters are offered at a lower daily availability rate. By the same token they are paid even if they are not needed. Exclusive-use helicopters are usually assigned to a particular forest for the fire season and are used primarily for initial attack.

Allocating Helicopters for Large Fire Suppression

Once fires have grown beyond initial attack, the suppression operation changes. Initial attack resources are released so they are available for initial attack and new

resources are assigned to the incident. The helicopters deployed for assignment to extended suppression efforts are obtained from the National CWN contract through the NIFC. There are hundreds of helicopters on this contract. An effective allocation must provide a helicopter that can perform the required tasks. Efficiency is achieved through the deployment of helicopters that can provide the most benefits at the least cost.

An efficient allocation of helicopters for extended attack can be found by evaluating the tradeoffs between performance, cost, and mobilization time for the available helicopters on the CWN contract. Mobilization time decreases the effectiveness of a suppression effort by delaying the suppression effort and allowing the fire to grow in size, which subsequently increases the cost. For the allocation of helicopters, mobilization time is an important factor for consideration in deployment decisions; not only the mobilization time for the helicopter but also the time required to mobilize all the personnel and equipment required for helicopter operations.

Helicopters are very expensive and can make up a large percentage of the total cost for a suppression effort (Mangan 2001). Since suppression costs are a major concern the cheapest helicopters for a given type is deployed. It is easy to compare helicopter costs but difficult to calculate estimates of helicopter performance. By considering only the costs a significant amount of information regarding helicopter efficiency is ignored. An alternate method for making deployment decisions is to evaluate the costs and performance for the available helicopters and deploy the helicopter with the lowest cost per pound.

Example

To illustrate selecting helicopters based on costs versus making the selection based on costs and benefits, consider a request for a Type I helicopter to drop water on a hypothetical fire an altitude of 5000 feet and a temperature of 30 degrees Celsius. Assume that the fire manager has accurately sized up the fuels and the current and expected conditions at the fire and believes a Type I helicopter is the appropriate suppression resource. Only nearby helicopters are considered for deployment to minimize the effect of mobilization time on the suppression effort. This scenario is simulated by randomly selecting 10 helicopters from the 2002 CWN Type I Limited contract to represent the helicopters near enough to the fire to be considered. Table 2.1 gives the cost and maximum allowable payload for these helicopters (obtained from the IHAPI database) for this fire.

Table 2.1 -- Costs and maximum allowable payload values for example helicopters.

Helicopter	Daily availability (dollars)	Hourly flight rate (dollars)	Maximum allowable payload (lbs)
1	\$14,784	\$2372	5494
2	\$19,096	\$2372	5360
3	\$29,017	\$4606	18952
4	\$11,998	\$2002	5204
5	\$13,986	\$2372	1955
6	\$13,118	\$2494	4515
7	\$29,540	\$4503	12938
8	\$14,000	\$2375	7780
9	\$28,000	\$4503	11734
10	\$29,982	\$4606	13666

In order to estimate the costs and benefits for these helicopters, estimates for the numbers of days on contract, the average number of hours flown per day, and the number of loads that can be delivered in an hour are required. Since this is a hypothetical problem, average values are used (USDA Forest Service 1992). Assume the helicopter will be on contract for seven days and fly an average of five hours per day. The water source is near by so the helicopter can deliver ten loads per hour. Table 2.2 shows cost and performance estimates calculated using equations (2.1) and (2.2) with the average contract values and pounds converted to gallons (1 gallon of water weighs 8.3454 pounds).

Table 2.2 – Total costs, volume delivered and cost per volume delivered for example helicopters.

Helicopter	Total Cost $7*(dr+5*fr)$ (dollars)	Total Amount Delivered $7*5*10*P/8.3454$ (gallons)	Cost per Gallon Delivered (dollars/gallon)
1	\$186,508	230,414	\$0.809
2	\$216,692	224,805	\$0.964
3	\$364,329	794,833	\$0.458
4	\$154,056	218,252	\$0.706
5	\$180,922	81,991	\$2.207
6	\$185,192	189,356	\$0.978
7	\$364,385	542,610	\$0.672
8	\$181,125	326,288	\$0.555
9	\$353,605	492,115	\$0.719
10	\$371,084	573,142	\$0.647

Helicopter 4, the least cost helicopter, can accomplish the fire suppression effort for \$154,056. Approximately 218 thousand gallons are delivered to the fire by Helicopter 4 at a cost per gallon of about 71 cents per gallon. Helicopter 3 is an example of economy of scale where the unit price for the large size is lower. At 46 cents per gallon the unit price for Helicopter 3 is 35 percent less than the unit price for Helicopter 4. The cost for Helicopter three is \$364,329; almost 2.4 times more than Helicopter 4, but Helicopter 3 delivers 795 thousand gallons, over 3.6 times more. Helicopter 3 is more efficient than Helicopter 4 based on an analysis of the expected costs and benefits.

There is some controversy surrounding the effect time has on fire suppression due to the uncertainty of the weather. Given enough time the fire will eventually go out when it rains or snows out without any suppression effort and at no cost. A drenching rain may extinguish the fire regardless of how much money was spent on suppression. Situations also exist where no amount of suppression effort will alter the course of the fire. An argument could be made for saving money and waiting for nature to put the fire out. But since suppression resources are in use it is reasonable to assume that it is important to control the fire as soon as possible and to expect that the fire can be controlled with the suppression resources requested.

Under this assumption it will cost more to put out the fire tomorrow than it will today. By delivering more water per hour to the fire the time required to control the fire is decreased by the helicopter with more capacity. If the fire only requires 218 thousand gallons for control in seven days, then helicopter three can provide the necessary 218 thousand gallons in less than two days. The cost for two days of effort by helicopter three is \$104,094, 32 percent less than seven days of work from helicopter four. Since the extra water delivered by helicopter three can be used to shorten the suppression effort, the most efficient helicopter should be deployed.

Using cost alone for deployment decisions will not provide efficient allocations because helicopter costs and efficiency are not well correlated (Figure 2.1). As mentioned before, the hourly flight rate is related to the cost of flying the helicopter, which can vary greatly for different makes and models. Since CWN helicopters are used

elsewhere until they are contracted the daily availability rates can include the costs of not doing the other job along with the other costs of doing business. “You get what you pay for” does not apply to CWN helicopters.

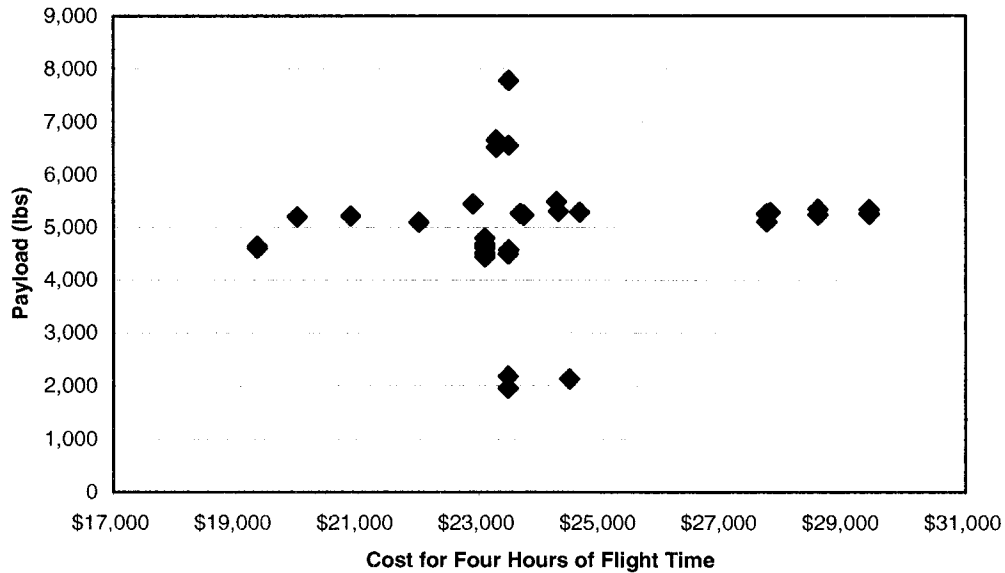


Figure 2.1 -- Relationship between helicopter cost and helicopter payload for all Type I helicopters on 2002 CWN contract (data from IHAPI database)

Development of Four-Hour Comparison Index

Though it would be possible to estimate the efficiency of individual helicopters for a specific wildland fire, it is not practical. The uncertain future of the fire prevents accurate knowledge of the values needed to estimate the cost and performance, such as the number of days the helicopter will be on contract. Estimating the performance at the altitude and temperature of operation for each helicopter is tedious because it requires interpreting

performance charts. A comparison index that is highly correlated with the cost per pound provides decision makers with information for quickly determining the most efficient helicopter.

Helicopter performance varies continuously with altitude and temperature leading to an infinite number of possible combinations. Since helicopters operate at a range of altitudes and temperatures for a single fire this precision is unnecessary. A set of representative altitude and temperature values simplifies the information contained in the performance charts and provides a method for comparing helicopter costs and benefits at different fire locations. These altitude and temperature combinations should reflect reasonable fire situations and the precision desired for decision-making.

Using performance values at 5000 feet and 30 degrees Celsius, the costs and performance can be calculated using equations (2.1) and (2.2). Graphing the cost per pound as it relates to the time on contract shows that the cost per pound is large initially and approaches a constant value, the asymptote, as the length of the contract increases (Figure 2.2). The asymptote is:

$$(2.3) \quad \text{Asymptote} = (dr / h + fr) / (P * L)$$

where h is the average flight time per day

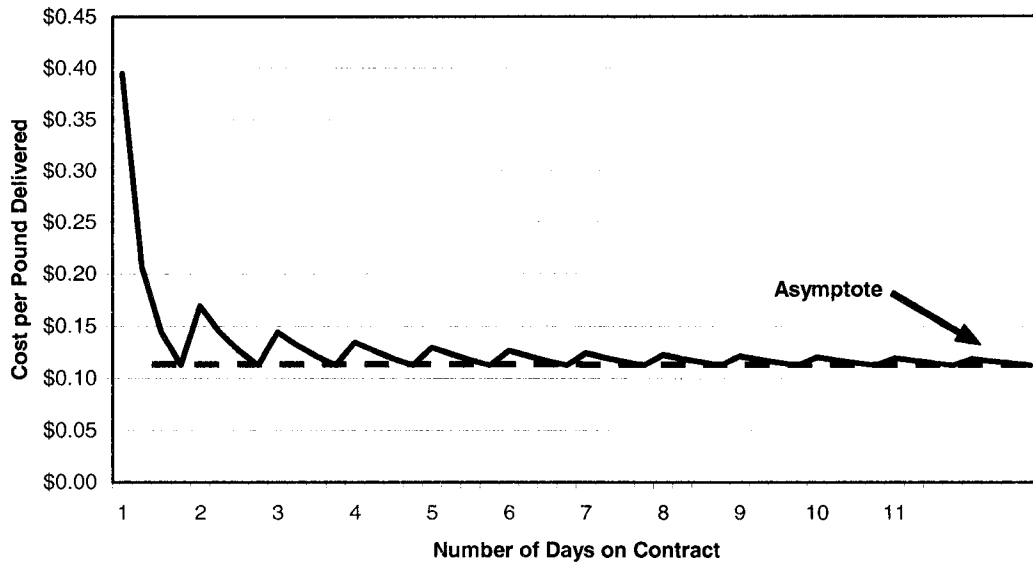


Figure 2.2 -- Cost per pound delivered to a fire at 5000 feet and 30 degrees Celsius over time assuming four hours of flight time per day and ten loads per hour. (Data from IHAPI database)

At the time of deployment the duration of the contract is unknown. Historically the duration of use for Type I CWN helicopters has varied from 1 to 30 days with an average of about 7 days per dispatch (USDA Forest Service 1992). Since fires often occur in the same area due to weather conditions and ignitions, CWN helicopters are often moved from fire to fire increasing the total time on contract. With long contract times the asymptote approximation of the cost per pound delivered provides an appropriate value to use for comparing CWN helicopters.

The asymptote depends on two values that are unknown at deployment time, the number of loads that can be delivered in an hour (L) and the average number of hours that will be flown in a day (h). The number of loads delivered in an hour will vary with the

incident but can be assumed to be the same for helicopters being compared for the same mission. With this assumption a comparison value for helicopters responding to the same incident can be written as:

$$(2.4) \quad (dr / h + fr) / P$$

where dr and fr are the daily availability rate and flight rate for the helicopter, P is payload at the altitude and temperature of the fire and h is the average number of hours flown per day.

Since both the fire and the weather are relatively hard to predict, it is very difficult to estimate the average number of hours per day the helicopter will fly while it is on contract. Fortunately the comparison value with four hours of flight time per day is linearly related to the cost per pound no matter how many hours are flown each day. Figure 2.3 illustrates the relationship between the index calculated using four hours of flight time per day and the actual cost per pound when the average flight time is two, six, and eight hours per day for the Type I Limited helicopters on the CWN contract using data obtained from the IHAPI database. With correlation coefficients for the four-hour comparison value and the actual cost per pound delivered of approximately 0.99, a comparison value calculated using four hours of flight time per day provides a method for comparing the efficiency of helicopter for deployment decisions. The points that deviated

furthest are newer, more efficient helicopters that have a lower relative flight rate and higher relative daily availability than the majority of the helicopters in the fleet.

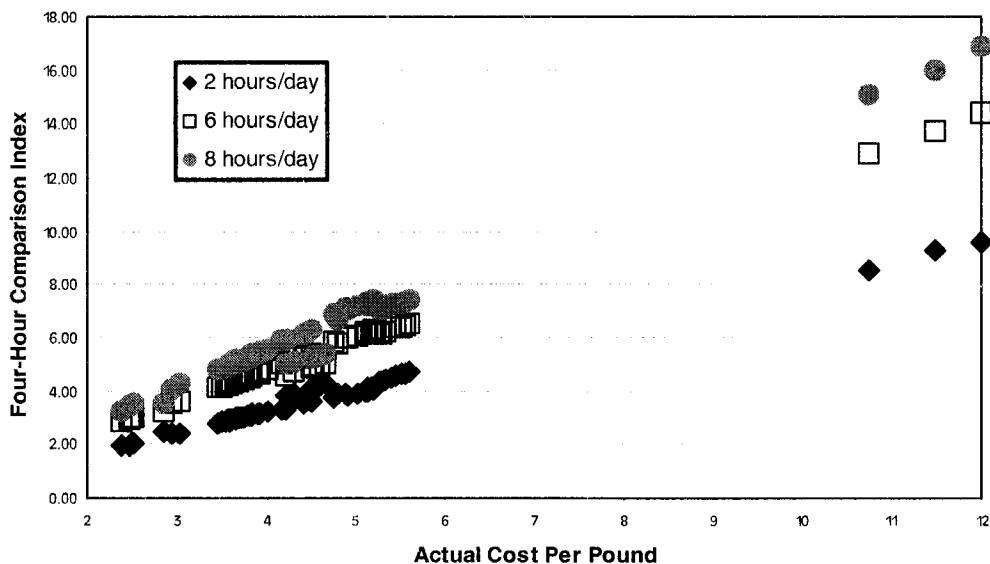


Figure 2.3 -- Comparison between the comparison value and actual cost per pound when an average of two, six, and eight hour are flown per day for helicopters on the CWN Type I Limited contract. Correlation ≥ 0.99 .

Assuming the helicopter will average four hours of flight time per day, (2.4) can be written as:

$$(2.5) \quad (dr / 4 + fr) / P = \frac{1}{4} * (dr + 4 * fr) / P.$$

where dr and fr are the daily availability rate and flight rate for the helicopter and P is payload at the altitude and temperature of the fire.

The four-hour comparison index is defined as $(dr + 4 * fr) / P$, the cost for a day with four hours of flight time divided by the maximum allowable payload at the altitude and temperature conditions. The four-hour comparison index summarizes the cost and performance information for individual helicopters providing a means to easily compare the efficiency of individual helicopters. It is proportional to the approximated cost per pound and can be thought of as the relative efficiency (costs versus benefits) for individual helicopters:

$$(2.5) \quad \text{Cost / Pound} = \frac{1}{4} * \text{4-hr index} / L.$$

where L is the number of loads that can be delivered in an hour.

Savings Estimate

The four-hour comparison index quantifies the efficiency of individual helicopters at any predefined altitudes and temperatures. As such it provides a method for quick comparison of helicopters allowing decisions to be made based on cost and performance rather than costs alone. An estimate of the potential savings achieved by using the four-hour comparison index is made to show that it is worth the extra effort needed for calculation.

The helicopters available for deployment to any fire are restricted by their ability to perform the required tasks at the fire, their availability, and their proximity to the fire.

Thus only a subset of the helicopters on the CWN contract is considered for deployment to any fire. Analysis of the possible subsets of helicopters allows for comparison of the expected cost per pound for selections made using minimum cost versus the expected cost per pound for selections made using minimum four-hour comparison index.

The probability that each helicopter will be selected for a fire can be calculated by evaluating all the possible subsets of helicopters that could exist. The number of subsets of a size k from a group of n helicopters is given by:

$$(2.7) \quad \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

where n is the number of helicopters that could be in the subset and k is the number of helicopters in the subset.

The number of subsets where a particular helicopter will be selected is the number of subsets where all the other helicopters in the subset have a larger value for the selection criteria: cost or four-hour comparison index. Let m denote the number of helicopters with a larger cost or index than the one being considered. The number of possible subsets is given by:

$$(2.8) \quad \binom{m}{k-1} = \frac{m!}{(k-1)!(m-k+1)!}$$

where m is the number of helicopters that would not be selected if the helicopter being considered was in the subset and k is the number of helicopters in the subset. The probability a particular helicopter will be selected from a subset of size k is given by (2.8) divided by (2.7).

For example, there were 82 Type I limited helicopters in the IHAPI database in 2002. Because of unavailability or long mobilization distances only a few of these will be in the subset being considered for deployment. For the case where there are five in the subset being considered, there are 27,285,336 different possible subsets of five helicopters. For a particular helicopter to be selected it must be the best member of the subset. If helicopter A has a lower four-hour comparison index than 68 of the 82 Type I limited helicopters then there are 814,385 subsets that consist of helicopter A and four helicopters that are inferior to helicopter A, i.e., where helicopter A will be selected. The probability that helicopter A will be selected from a subset of five helicopters is 0.299.

The expected efficiency for a subset of a given size is obtained by multiplying the probability a helicopter is selected by the efficiency of the helicopter for all helicopters. Figure 2.4 shows these averages for all the possible subset sizes using helicopters on the 2002 Type I Limited contract. This plot clearly shows that for all subset sizes greater than one there is a big advantage to choosing the helicopter with the lower four-hour comparison index as opposed to minimum cost. In fact the percent savings range from 20 percent to 45 percent as shown in Figure 2.5, with the most probable savings being in the

range of 30 to 40 percent. With millions of dollars being spent annually on helicopters for fire suppression, this means substantial savings.

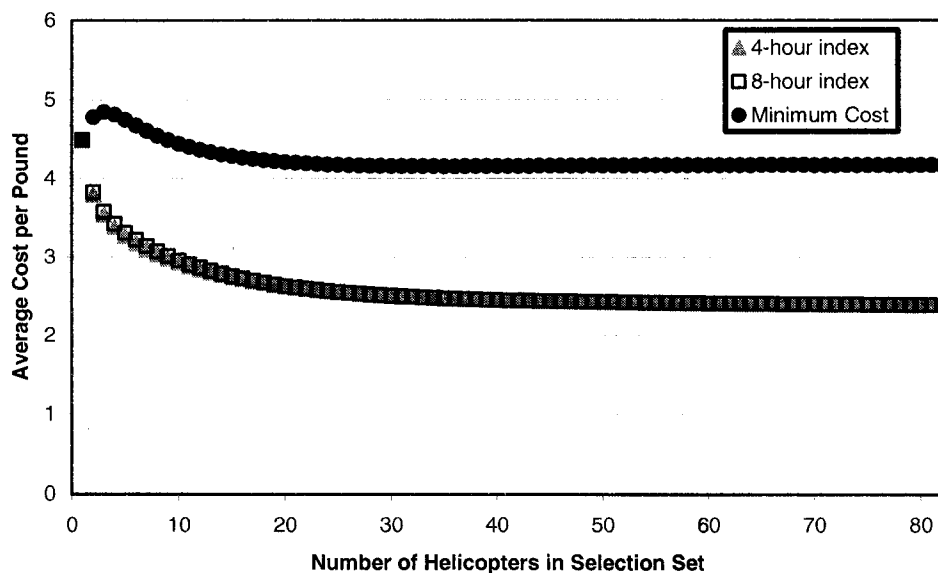


Figure 2.4 -- Average cost per pound for different sized subsets of the CWN Type I Limited contract when least cost, four-hour comparison index and eight-hour comparison index are used as the selection criteria. (data from the IHAPI database)

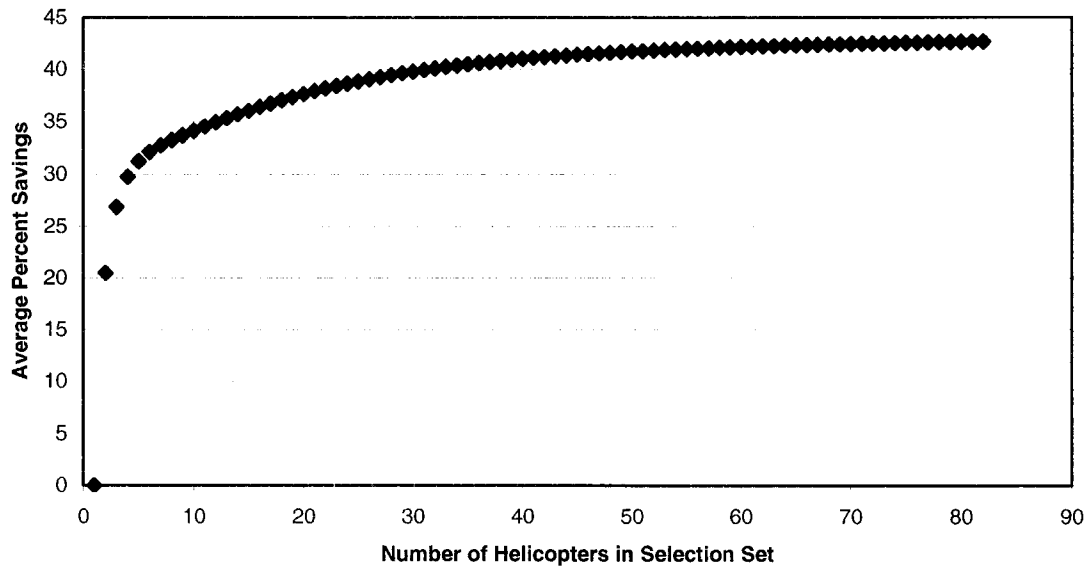


Figure 2.5 -- Percent difference between the average cost per pound values for the choices made using the least expensive helicopter or the four-hour comparison index.

Relaxing the Assumptions

The earlier discussion concludes that the costs and benefits for different daily flight times are correlated; thus the four-hour comparison index can be used for making deployment decisions. An analysis similar to the one used to estimate the savings shows that when eight hours are flown per day little is gained by using an average of eight rather than an average of four hours for the computation of the comparison index (Figure 2.4). Hence the assumption that there will be an average of four hours of flight time per day has a minimal affect on the final decision.

CWN helicopters can be located anywhere prior to contracting, making the time and money needed to mobilize a helicopter an important consideration during deployment. The four-hour comparison index was generated under the assumption that only nearby

helicopters are considered for deployment. This is not always the case. In many situations the additional costs associated with mobilization need to be included in the cost-benefit analysis. This can be done by including in the costs for the ferry time associated with mobilization. This is only one approach to the issue. It may also be desirable to add a penalty to the cost to represent the effect of delaying this facet of the suppression effort.

Mobilization time can be an important component for some allocation decisions, but the magnitude of the effect depends on other parameters in the decision-making process. When the helicopters being compared have significantly different mobilization times, the four-hour comparison index does not provide enough information. The most efficient helicopter will depend on the contract length. Mobilization costs are a fixed addition to the operating costs. As the length of the contract increases the mobilization costs have less of an effect on the comparison of costs and benefits. For longer contracts the four-hour comparison index can be used to determine the most efficient helicopter. This is because as the contract length increases, mobilization costs become less relevant in the estimation of cost per pound. In these situations a nearby helicopter may be more efficient in the short term, but as time goes on it could become much more expensive (Figure 2.6).

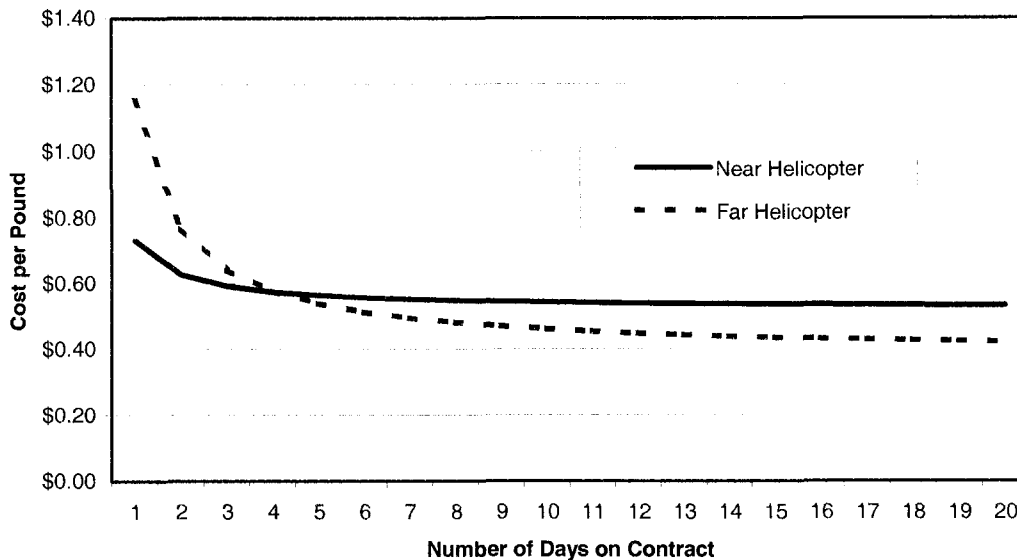


Figure 2.6 – Example of cost per pound for two helicopters with increasing contract length. Near helicopter is within four hours of the fire and has a comparison index of 5.22. Far Helicopter requires two days for mobilization and has a comparison index of 3.84. After 5 days on contract the far helicopter is more efficient than the near helicopter.

Mobilization time is an important factor for consideration when the expected contract length is short. In these cases it is preferable to deploy nearby helicopters since the four-hour comparison index does not consider the costs of delaying the suppression effort.

Conclusion

Helicopters are a valuable yet costly fire suppression resource. To ensure that they are used effectively, knowledge about the costs, capabilities and performance of individual helicopters has to be included in the decision making process. The four-hour comparison index summarizes the costs and benefits of individual helicopters and

provides a concise means for comparing the efficiency of individual helicopters for deployment to large fires. Though calculating helicopter performance for the comparison index is not a trivial task, using the four-hour comparison index rather than just cost alone can provide significant savings.

CHAPTER 3

USING GENETIC ALGORITHMS TO FIND THE OPTIMAL SOLUTIONS TO A DYNAMIC MULTIOBJECTIVE ALLOCATION PROBLEM

Abstract

The allocation of helicopters for the suppression of large wildland fires requires methods to optimize multiple objectives: maximizing the suppression effort, minimizing the cost and minimizing the mobilization time. Since these are competing objectives, no single solution exists that optimizes all the objectives at the same time. A tradeoff does exist between the objectives that can be described by several optimal solutions. The solution method for allocating helicopters must also allow for changes in the problem since new fires may request helicopters, requests may be canceled and helicopters may become available or unavailable at any time.

The allocation of helicopters to large wildland fires is a dynamic problem for which genetic algorithms can provide an efficient solution. Genetic algorithms use a population of binary encoded solutions to search for an optimal set of solutions. Through the genetic operators selection, recombination, and mutation the genetic algorithms use information from the good solutions in the population to create better solutions. Many variations of the genetic operators exist. The genetic algorithm proposed for this allocation problem uses a combination of genetic operators employed in other successful genetic algorithms

along with modifications developed to speed the convergence to a set of Pareto-optimal solutions and allows for modifications to the problem domain without having to restart the algorithm.

Introduction

The allocation of helicopters to large wildland fires is a complex problem. Each helicopter provides unique contributions to the suppression effort that depend on the individual helicopter, location of the fire and the equipment it carries. This variety in the helicopter fleet is valuable because individual fires have unique needs for the helicopters deployed to them. The allocation problem requires determining the contribution that each helicopter will make at each fire and then assigning helicopters to fires to meet the needs of each at minimum cost. The dynamics of fire suppression operations further complicate the problem. Orders may be canceled, new fires may start, fire behavior may change, and helicopters may be released, deployed or break down.

Advances in technology have made it possible to analyze larger quantities of data and solve larger problems. Before these advances, solving complex problems like the dynamic allocation of resources to jobs with multiple objectives would have required simplifying assumptions, and restrictions on the solution space. Algorithms now exist which can stochastically search the solution space for the optimal solutions. Genetic algorithms are noted for their ability to solve combinatorial optimization problems. I propose a genetic algorithm as a tool for solving a complex allocation problem: assigning

helicopters to wildland fires. I will show that the genetic algorithm will converge to a set of solutions that represent the tradeoffs between multiple optimization objectives.

Defining the allocation problem

Many allocation problems have characteristics similar to the fire suppression problem, so the proposed genetic algorithm is described in general terms. The efficient allocation of resources to multiple jobs involves maximizing the utility of the allocations for each job at a minimum cost, subject to constraints that define acceptable allocations.

The general characteristics of the allocation problem are:

- To find the most efficient allocation.
- Multiple independent jobs require resources. Each has a unique set of requirements and constraints.
- Each resource will make unique contributions to each job in terms of capabilities and costs.
- Resources can be allocated to only one job at a time.

An efficient allocation of resources will optimize the objectives and satisfy the constraints for the job at minimum cost. The overall objective of the problem is to allocate the available resources in a manner that is optimal for all the jobs. A small and completely defined allocation problem can be solved using integer programming. This discussion focuses on the more complex situation in which the tradeoffs between

objectives and cost for individual jobs are poorly defined. The future status of jobs and resources is unknown, which requires a dynamic optimization method.

The generalized allocation problem seeks to optimize the assignment of I resources to J jobs. Define a solution to the allocation problem as a J x I matrix of elements x_{ji}

$$(3.1) \quad x_{ji} = \begin{cases} 1 & \text{if resource } i \text{ is assigned to job } j \text{ and} \\ 0 & \text{otherwise} \end{cases} \quad i = 1, \dots, I, j = 1, \dots, J$$

The objectives for each job j are:

$$(3.2) \quad \text{Max } U_{kj} = \text{Max } \sum_i u_{kji} * x_{ji}, \text{ and}$$

$$(3.3) \quad \text{Min } C_j = \text{Min } \sum_i c_{ji} * x_{ji},$$

where U_{kj} is utility for the assignment for job j and objective k,

u_{kji} is the individual contribution from resource i to job j for objective k,

C_j is the total cost to for the assignment to job j,

and c_{ji} is the individual cost of assigning resource i to job j.

The allocation problem is subject to constraints that disallow some assignments, place limits on the objective values, and limit the number of assignments made.

The constraint that a resource can only be assigned to one job is expressed as:

$$(3.4) \quad \sum_j x_{ji} \leq 1 \quad \text{for all } i.$$

Other constraints take the form:

$$(3.5) \quad V_{lmin} \leq \sum_i v_{lji} * x_{ji} \leq V_{lmax}$$

Where V_{lmin} and V_{lmax} are the upper and lower limits for the constrained value,

and v_{lji} is the individual contribution from resource i to fire j for constraint l .

With the allocation matrix defined as above, the contributions to objectives, costs and constraints for the allocation of a resource to a job are matrices in which element i,j gives the contribution of resource i to job j . The total value for each objective, cost or constraint for a job is the sum of the contributions made by the individual resources.

Mixed integer programming (MIP) is the traditional method used for solving allocation problems. Since MIP can optimize only one objective, the other objectives can be included in the problem as constraints. The solution to the MIP is an optimum solution for fixed values of the other objectives. When there are multiple competing objectives, with no clear preference between them, the MIP must be run with different constraint values for one objective to find a variety of solutions (Coello Coello 2000). Or, where prior knowledge of the tradeoffs between the competing objectives exists, a

weighted combination of the multiple objectives can be solved (Deb 1999; Coello Coello 2000).

Pareto-Optimal Solutions

The solution space for the allocation problem is the set of all possible assignments of resources to jobs. For each assignment within the solution space, values can be calculated for each of the objectives. These calculated values represent how well an assignment meets the objectives. The competing objectives of utility and cost make it impossible to find a single solution that optimizes all the objectives. Rather, there is a tradeoff - more money generally buys more utility. The Pareto-optimal solution set consists of those solutions from the solution space for which the value for one objective cannot be improved without decreasing the value of another objective (Zitzler and Thiel 1998). The Pareto-optimal solution set describes the trade-offs between objectives because the value of one objective can only be improved by making concessions in meeting another objective (Fonseca and Fleming 1993).

In order to find an approximation of the Pareto-optimal solution set, elements in the solution set are compared to each other to determine which are more desirable. Multiple objectives eliminate any single ordering for the members of the solution set; rather multiple search paths lead to multiple solutions. The Pareto optimal set can be found using the dominance order function (Coello Coello 1999; Zitzler and Thiel 1998).

Definition: One assignment, X , is said to *dominate* another assignment, X' , written

$$X \succ X'$$

if and only if for each job j and all objectives k , $U_{kj} \geq U'_{kj}$ and $C_j \leq C'_j$, and for some j and k either $U_{kj} > U'_{kj}$ or $C_j < C'_j$. The finite set of all possible allocations along with the dominant order function defines a partially ordered set.

Tradeoffs between objectives are usually not well understood in complex allocation problems. But once the problem is solved the Pareto-optimal solution set describes the tradeoff surface for the multiple objectives (Zitzler and Thiel 1998). Using the set of feasible non-dominated solutions, decision makers can make informed decisions by evaluating the tradeoffs between the objectives and apply other knowledge about the domain of the problem.

To illustrate the Pareto-optimal set, assume only one job and one utility to be optimized for that job. The utility and cost for the assignments can be plotted in two dimensions. Expanding the concepts to more jobs and utility functions is straightforward.

Any solution is dominated by solutions with greater utility and less cost, represented by the upper shaded area in Figure 3.1. Any solution dominates solutions with less utility and more cost, represented by the lower shaded area. Both relationships include the solutions lying along the line with the exception of the solutions with the same utility and cost. Note that many points neither dominate nor are dominated by the solution. The Pareto-optimal front is the set of points that are not dominated by any other point in the solution space (Figure 3.2).

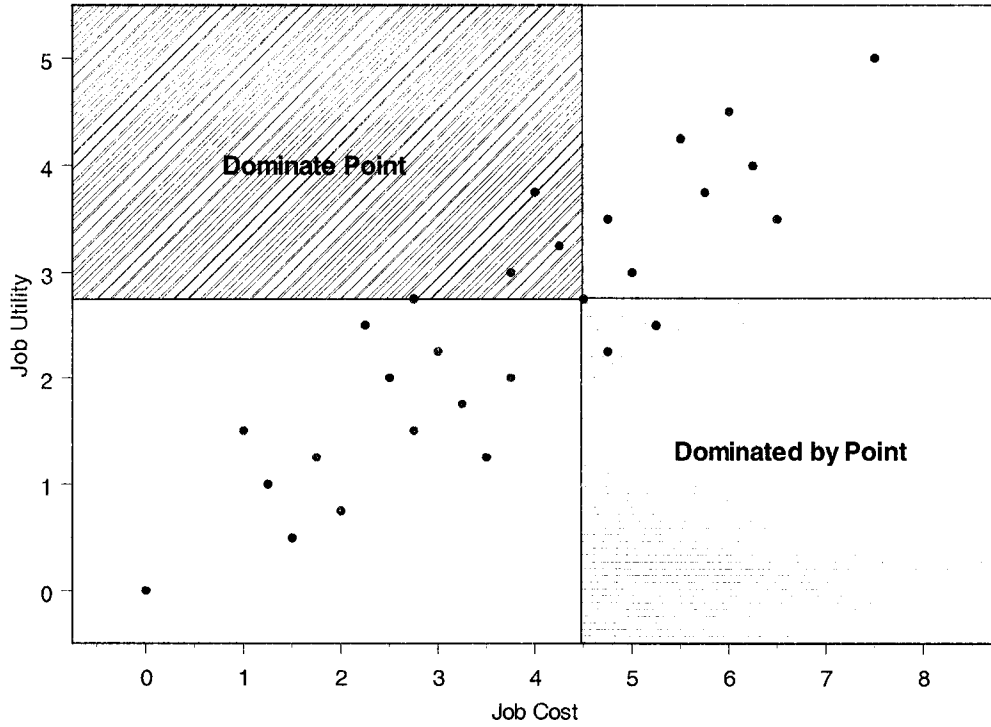


Figure 3.1 -- In the objective space it is easy to see which points a particular point dominates and which points dominate that point.

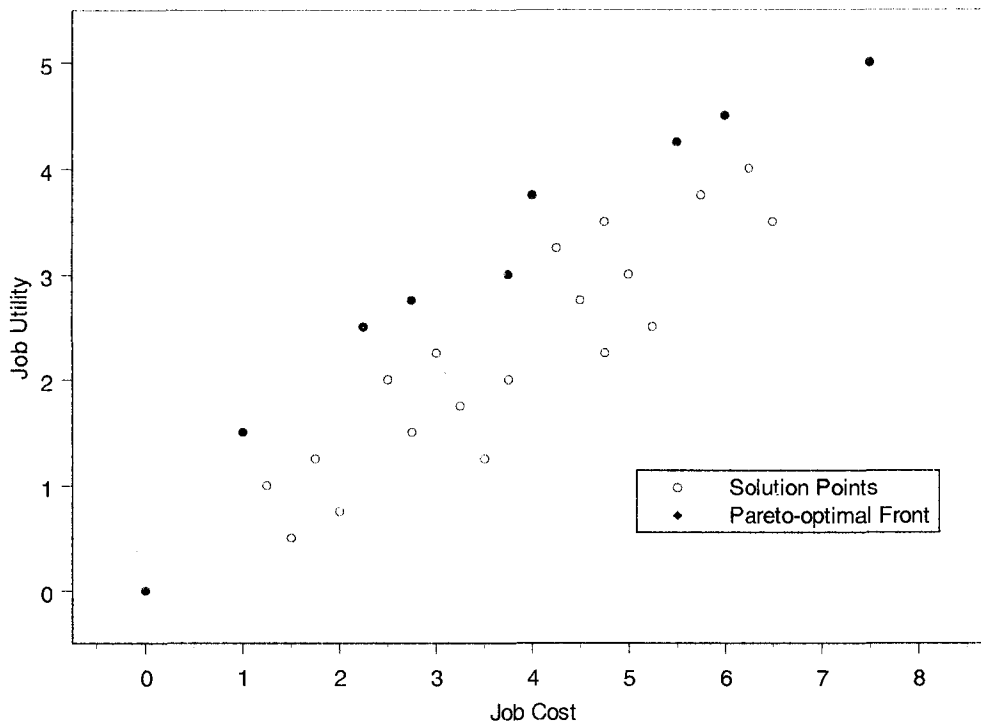


Figure 3.2 -- The Pareto-optimal set.

Genetic Algorithms

The goal of multiobjective optimization is a fast and reliable convergence to the Pareto-optimal region while maintaining diversity among the solutions (Deb 1999). Genetic algorithms are particularly well suited for estimating the Pareto-optimal set. By mimicking processes from nature genetic algorithms perform a parallel search of the solution space using a population of individuals. With each generation the population of solutions created by the genetic algorithm evolves towards the Pareto-optimal solution set. Genetic algorithms are well suited for finding discontinuous and concave Pareto-optimal solution surfaces that are difficult for other optimization methods to find (Zitzler and Thiel 1998; Coello Coello 1999; Fonseca and Fleming 1993).

Genetic algorithms use a binary encoding to represent a solution. This string of 0's and 1's resembles a natural chromosome and can be thought of as a gene having particular allele values that completely specify a solution to the problem. The encoded solution may be better or worse than other solutions in the population. Survival of the fittest suggests that the better solutions in the population contribute more genetic information for the next generation. The genetic operators selection, recombination and mutation operate on the binary strings to create these new individuals.

Genetic algorithms provide a method for searching the solution space by using information about the suitability of individuals in the population to create new individuals. The driving force behind the genetic algorithm is the determination of which individuals have superior genetic material. The fitness function describes how well a particular solution meets the objectives and constraints of the problem. To maintain diversity and prevent premature convergence individuals in crowded areas of the solution space are sometimes penalized. Guided by the fitness function, individuals with desirable characteristics are selected from the population to contribute genetic information for the next generation.

Assuming that individuals are fitter because they have better genetic information, new individuals are created from the genetic information in the selected individuals. Pieces of genetic information are used to create new individuals by breaking apart the genes and recombining them. The simplest recombination operator, single point crossover, swaps the alleles for two individuals at a randomly chosen point. Recombination operators that

swap genetic information at two or more points also exist, along with those that use more than two individuals. The idea is to mix the genetic information to search for better combinations of alleles (Mitchell et. al. 1991; Zitzler and Thiele 1998).

Genetic algorithms introduce new genetic information into the population through the mutation operator. With a low probability randomly chosen bits in randomly chosen individuals are changed. The mutation operator helps to maintain diversity in the population. It also allows the genetic algorithm to explore different areas of the solution space (Zitzler and Thiele 1998).

Elitism ensures that the population converges to the Pareto-optimal front. At any generation the fittest individuals represent the best approximation of the Pareto-optimal front for that generation. Since the gene is destroyed when it is broken apart for recombination or when it is mutated, the best individuals can be lost from one generation to the next. By keeping an unmodified copy of the fittest individuals in an archive and reintroducing them into the next generation, the fitness of future populations will not deteriorate (Zitzler and Thiele 1998).

Genetic algorithms cycle through the selection, recombination, and mutation operators to create improved approximations of the Pareto-optimal front. Stopping criteria based on the quality of solutions found or on the number of generations end the cycle. Unlike many traditional optimization methods genetic algorithms are stochastic and can find a different solution set with replicate runs. There is no guarantee they will find the Pareto-optimal front.

Using Schema to Describe How Genetic Algorithms Work

One popular method used to describe and evaluate genetic algorithms is in terms of schema. A schema is a genetic string composed of defined bits, along with undefined bits which are represented as an '*'. An individual is said to be an instance of a schema if each defined bit in the schema matches the bits of the individual. Thus '01001010' is an instance of the schema '**00**1*'. An individual of length s is an instance of 3^s different schema. The order of a schema is the number of defined bits it contains.

The building block hypothesis states that a genetic algorithm works well when short, low-order, highly fit schema (building blocks) recombine to form even more highly fit higher-order schema. The ability to produce fitter and fitter partial solutions by combining building blocks is believed to be the primary source of a genetic algorithm's search power (Holland 1975, Goldberg 1989).

In a genetic algorithm, the fitness of an individual is an estimate of the average fitness of the different schema that the individual exemplifies. A genetic algorithm evaluates the fitness of a population of individuals through the selection operator and exploits the fittest individuals to create new individuals. Hence the future generations contain a higher proportion of highly fit schema (Mitchell et al. 1992).

The allocation problem considered in this paper is a good application for genetic algorithms. By finding good low order assignments of resources to jobs the genetic algorithm can recombine the low order assignments to find good combinations of

assignments that will optimize the objectives for all the jobs. The proposed genetic algorithm solves the allocation problem by using the building block hypothesis.

Proposed Genetic Algorithm

No common guidelines exist for developing genetic algorithms for multiple objectives. Instead, unique combinations of specific techniques are used to achieve a fast and reliable convergence to the Pareto-optimal front with diversity along it (Zitzler et al. 2001). Using the building block hypothesis for guidance, a genetic algorithm is developed to approximate the Pareto-optimal front for the dynamic allocation of I resources to J jobs. The proposed algorithm incorporates specialized techniques along with the traditional ones to increase the convergence speed and allow for changes to the problem domain.

Encoding

Genetic algorithms code individuals into binary strings that uniquely define the possible solutions. Solutions to the allocation problem can be encoded into a binary string of length $I \cdot J$ with each bit representing the assignment of a resource to a job. A '1' indicates that the resource is assigned to the job while a '0' indicates that the assignment is not made. Coding in this manner allows for infeasible individuals to be created, ones where a resource is assigned to multiple jobs. An alternate encoding that prevents the creation of unfeasible individuals uses one bit to represent each resource, an integer to

indicate which job the resource is assigned to, and a '0' to indicate that the resource is unassigned.

Initial Population

Individuals in the initial population are often generated randomly starting the search of the solution space at random locations. Knowledge about the domain of the specific allocation problem can be used to generate individuals in more promising regions of the solution space. For example, the utility with helicopters is the pounds per load that can be delivered to the fire. Helicopters with lower cost per pound delivered to a fire are more fit than those with a higher cost per pound. For each fire the cost per pound can be estimated for each helicopter. The cost per pound can then be used to calculate weights for each helicopter that are relative to the cost per pound delivered for each fire. The initial population is filled using these weights to bias the selection of a helicopter for each fire. This increases the proportion of fit low order schema (building blocks) in the initial population.

Fitness and the Selection Operator

Selection requires several steps to determine how individuals in the population relate to each other and which individuals to prefer for mating. The first step is to determine how well each of the solutions meets the objectives. Using the objective values, a fitness value is assigned to individuals that indicates how individuals in the population compare

to each other. Since genetic algorithms are often used to find a continuous Pareto-optimal front, many of them incorporate techniques to ensure that the solutions found are spread along the entire front. These techniques penalize individuals by reducing the fitness of individuals in crowded areas of the solution space (Zitzler and Thiele 1998). Individuals can also be penalized for not meeting the constraints of the problem by reducing their fitness so they are less likely to be selected. The amount of the penalty depends on the objective of the constraint. Individuals that do not meet constraints may still contain genetic information that is useful for recombination so completely eliminating them is usually not desirable. Once the fitness function has been appropriately adjusted, it is used to guide the selection of individuals for the mating pool.

Construction of an appropriate fitness function for the allocation problem is important for guiding the population to the desired solutions and identifying individuals that will provide valuable genetic information for recombination. Because it is important that each job is assigned optimal resources, individuals are initially evaluated on their fitness to perform each job independently. The overall fitness of an individual is the sum of the fitness values for each job. These fitness values should be constructed so that individuals that perform near optimally for all jobs are the most fit.

For the allocation problem, the best assignment of resources to a job lies along the Pareto-optimal front. Individuals that are closer to the front are better than those that are farther away. Calculating the distance an individual is from the estimated Pareto-optimal front is not practical. Fortunately, distance to the front can be estimated using the

dominance relationship. Non-dominated individuals provide an estimate of the Pareto-optimal front and are assigned a fitness value of zero. By assigning an individual a fitness value for each job equal to the number of individuals it is dominated by, individuals that are further from the front are assigned higher fitness values. Thus the fitness value of an individual indicates how much superior genetic information is present in the population.

Figure 3.3 illustrates the assignment of fitness values for the total costs and number of pounds that can be delivered by a population of 31 randomly selected Type II helicopters from the 2002 CWN contract. Costs and amount delivered are estimated for a fire at 5000 feet and 30 degrees Celsius for a five-day contract with an average of four hours of flight time per day and 10 loads delivered per hour.

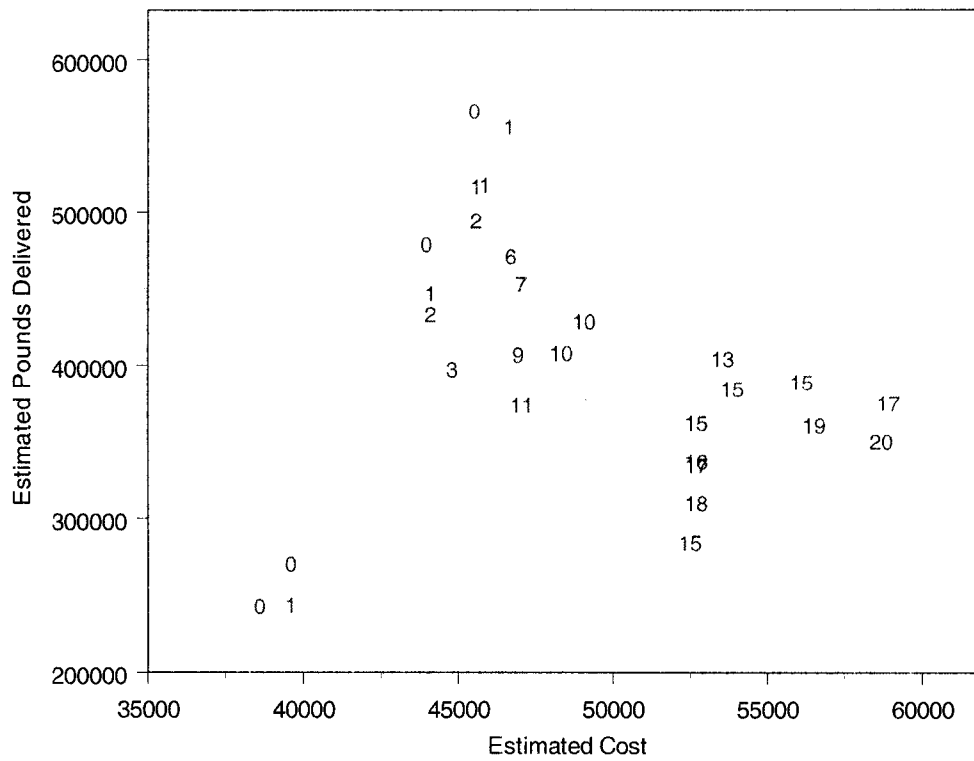


Figure 3.3 -- Fitness values of solutions for a fire using number of individuals a solution is dominated by to determine the individual's fitness. (data from IHAPI database)

Modifications to the fitness values are made independently for each job. Because the solutions are discrete values rather than a continuous function there is a finite number of them that can occur in any area of the solution space so crowding is not an issue. Different allocations that provide the same objective values are desirable because they give decision makers more alternatives, which may be superior in other areas not addressed in the optimization problem. Some of the constraints for the allocation problem are limits on the objective values. A fit solution that just violates this kind of

constraint can still provide useful genetic information for recombination and may even be acceptable as a solution to the problem. By adding penalties to the fitness values that are proportional to the amount the constraint is violated these solutions can still be selected for mating.

To determine the overall fitness of an individual, the fitness values for all jobs are summed. All individuals that have Pareto-optimal solutions for all the jobs are stored in an archive. If the archive is not full, it is filled with the fittest individuals remaining in the population. This archive consists of the individuals with the best overall fitness.

The fittest individuals for each job provide good building blocks for the next generation and ensure that good building blocks for each job remain in the population. For each job a set number of unique individuals are selected for a second archive that contains the fittest allocations for each job. The criteria used to select individuals for this archive are (1) fitness for the job (2) diversity of the assignment from other individuals already selected, (3) number of resources assigned to the job with a preference for fewer assignments, and (4) overall fitness of the individual among individuals with identical assignments for the job. This second archive captures genetic information that is highly fit for a particular job without regards to the individual's fitness for the other jobs.

Recombination and mutation

Individuals from both archives are combined to form the mating pool from which individuals are selected for recombination. Two individuals are randomly selected from

the mating pool without replacement for single point crossover. The genetic information for the two individuals is exchanged up to a random site along the genetic string. With a low probability some of the newly created individuals are subjected to the mutation operator. The mutation operator randomly selects a site along the genetic string and randomly changes the assignment that is made there. If that particular resource cannot be assigned to a specific job the random mutation will be adjusted so that assignment is not made, preventing the creation of infeasible individuals.

Allowing for a dynamic domain

Many allocation problems are dynamic. In dynamic systems the pool of resources and the jobs that require the resources change. Many optimization methods require that the algorithm be restarted when modifications such as these are made to the domain.

Because genetic algorithms operate on a population of individuals, they possess many building blocks that remain good in the new domain. By saving the building blocks for the resources and jobs that remain unchanged the genetic algorithm can exploit the information that it has already learned and eliminate the need to start over.

In order for the genetic algorithm to successfully adapt to a changing domain the population has to contain a diverse set of building blocks. This is one of the reasons for the second archive in the proposed genetic algorithm. When changes are made to the domain of the allocation problem the individuals in the population are recoded to remove the resources and jobs that have been removed from the domain. Bits are added for the

resources that are introduced into the domain. These bits are randomly assigned a job or a '0'. This introduces new building blocks into the population for the new resources. For new jobs, building blocks are introduced by assigning a resource to the job in each individual. This can be done randomly or domain knowledge can be used to bias the assignments as was done in the creation of the initial population. The genetic algorithm is then restarted with a higher mutation rate for a number of generations to explore the solution space of the new domain.

Example Problem

The proposed genetic algorithm was applied to the problem of allocating helicopters to large wildland fires. Forty-three helicopters from the 2002 CWN contract represent the available resources. Helicopter costs consist of a daily availability rate and an hourly flight rate. The utility of a helicopter for wildland fire suppression is the amount it can deliver to a fire, which can be estimated from the number of pounds a helicopter can carry. Helicopter cost and performance information was obtained from the IHAPI database. Because delaying the initiation of the suppression effort allows the fire to grow, minimizing the mobilization time is also important. The assignment of helicopters to a wildland fire should minimize the cost, maximize the amount delivered to the fire and minimize the mobilization time subject to constraints placing upper and lower limits on the amount delivered to the fire.

Three hypothetical fires were considered. All three fires were estimated to last for seven days with five hours of flight time expected each day. The water source was assumed to be nearby so 10 loads per hour could be delivered. It is assumed that fire managers at each fire determined the need for between 1,100,000 to 1,750,000 pounds delivered by the deployed helicopters. This is approximately the amount a Type II helicopter will deliver under these circumstances. To illustrate the difference in helicopter performance that occurs at different altitudes and temperatures, Fire 2 is assumed to be at 8000 feet and 25 degrees Celsius while the others are at 5000 feet and 30 degrees Celsius. Mobilization times to each fire were randomly generated and rounded to the nearest hour.

The proposed genetic algorithm was used to find the Pareto-optimal front for each of the fires run individually. The set of solutions shows the tradeoffs between the three objectives for Fire 2 (Figure 3.4). As expected higher costs will buy more pounds delivered, but to reduce the mobilization times a dispatcher has to accept higher costs and fewer pounds delivered. Compare this to the solutions for Fire 1 where the lower mobilization times belong to the more efficient helicopters (Figure 3.5). Since mobilization times depend on the location of the helicopters and the fires, they are unique for each domain. The solution space of the genetic algorithm describes what concessions must be made to improve mobilization times. Decision makers can then decide if the loss of efficiency is worth getting the helicopter on the fire more quickly.

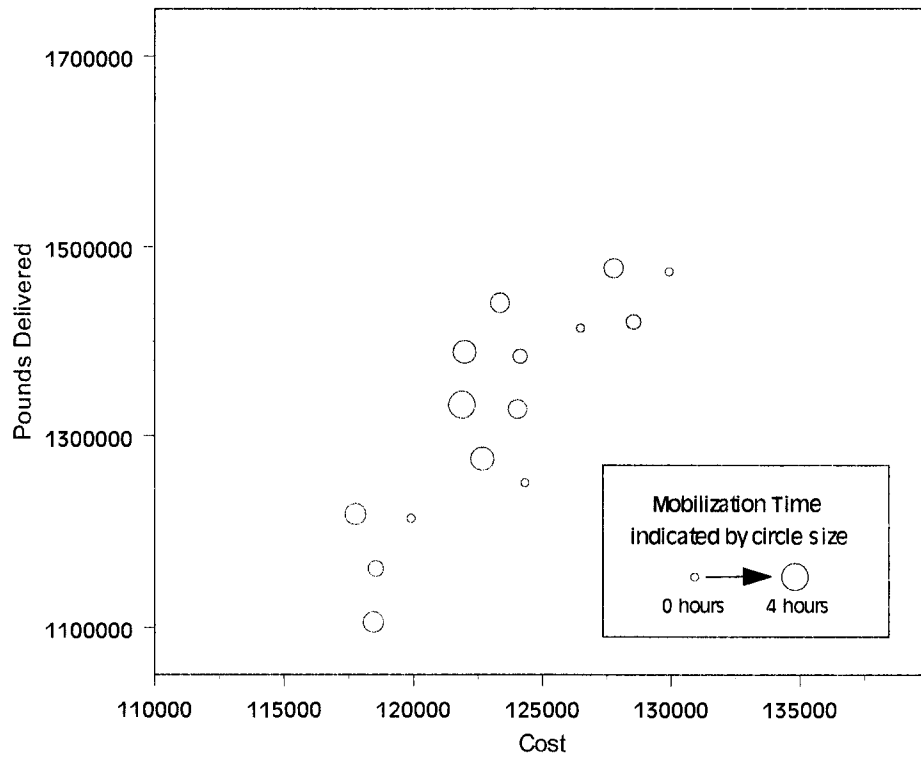


Figure 3.4 -- Pareto-optimal front for the allocation of helicopters to a single fire, Fire 2, using three optimization objectives; minimize cost, maximize pounds delivered, and minimize mobilization times.

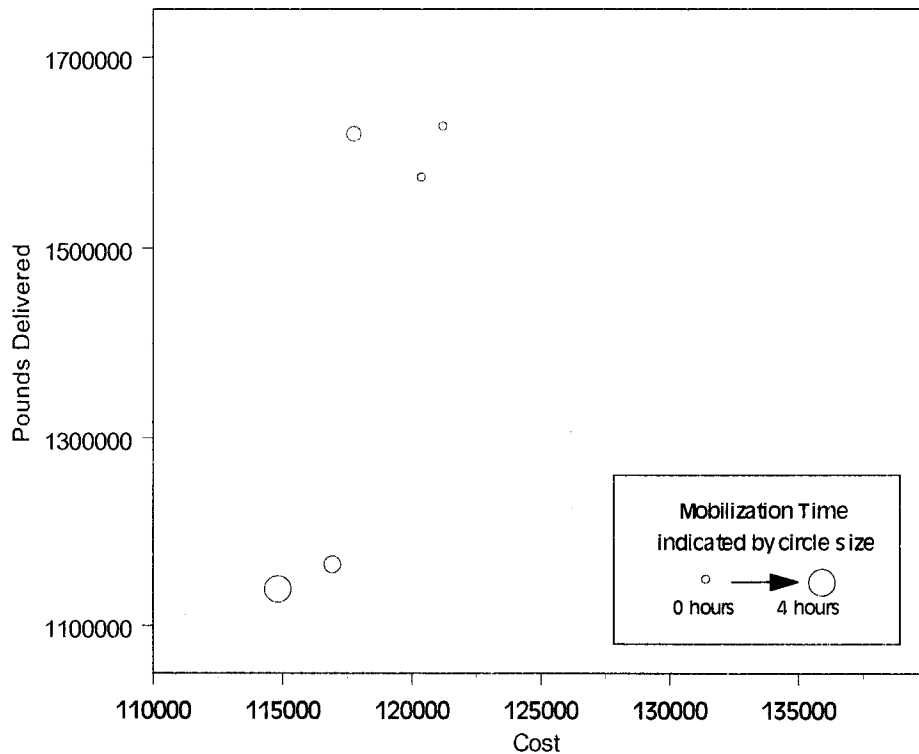


Figure 3.5 -- Pareto-optimal front for the allocation of helicopters to a single fire, Fire 1, using three optimization objectives; minimize cost, maximize pounds delivered, and minimize mobilization times.

With multiple fires the helicopters need to be deployed so that each fire receives an optimal allocation. The genetic algorithm finds optimal allocations for each fire then through recombination searches for solutions that are optimal for all fires. The proposed genetic algorithm was used to find the optimal solution for the three fires using the objectives of minimizing cost, maximizing pounds delivered, and minimizing mobilization times for each fire. The genetic algorithm successfully found several allocations that were Pareto-optimal for all three fires (Figures 3.6 - 3.8). If Pareto-

optimal solutions do not exist the genetic algorithm will find solutions that are Pareto-optimal for as many fires as possible and close to Pareto-optimal for the remaining fires.

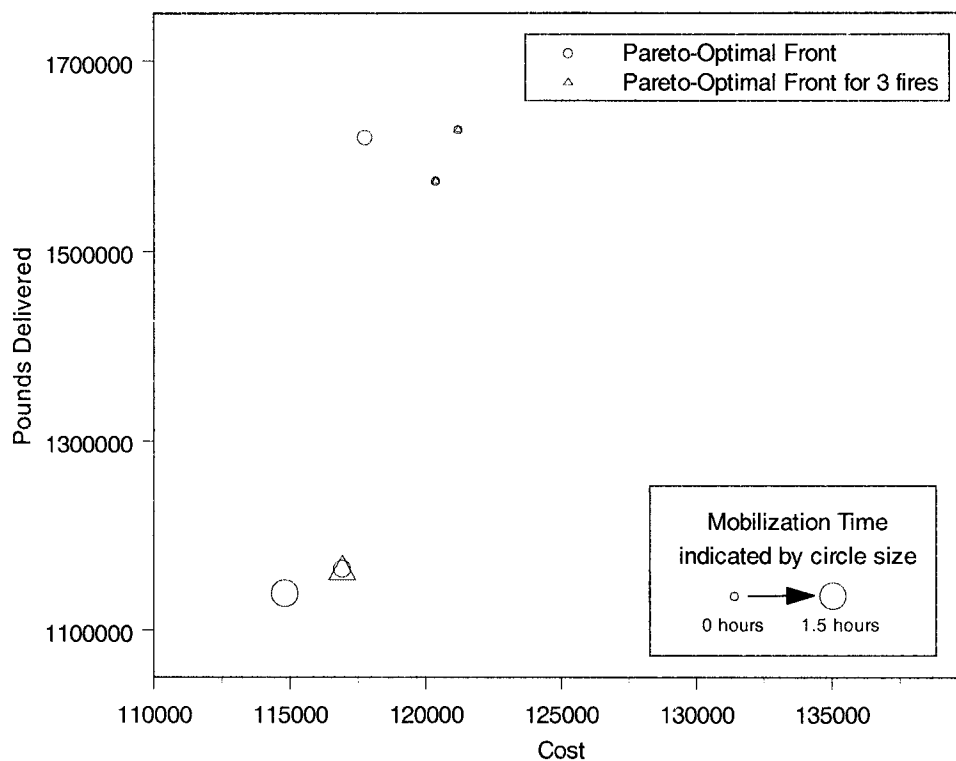


Figure 3.6 -- Pareto-optimal front for Fire 1. Genetic algorithm used to allocate helicopters to three fires using three optimization objectives; minimize cost, maximize pounds delivered, and minimize mobilization times.

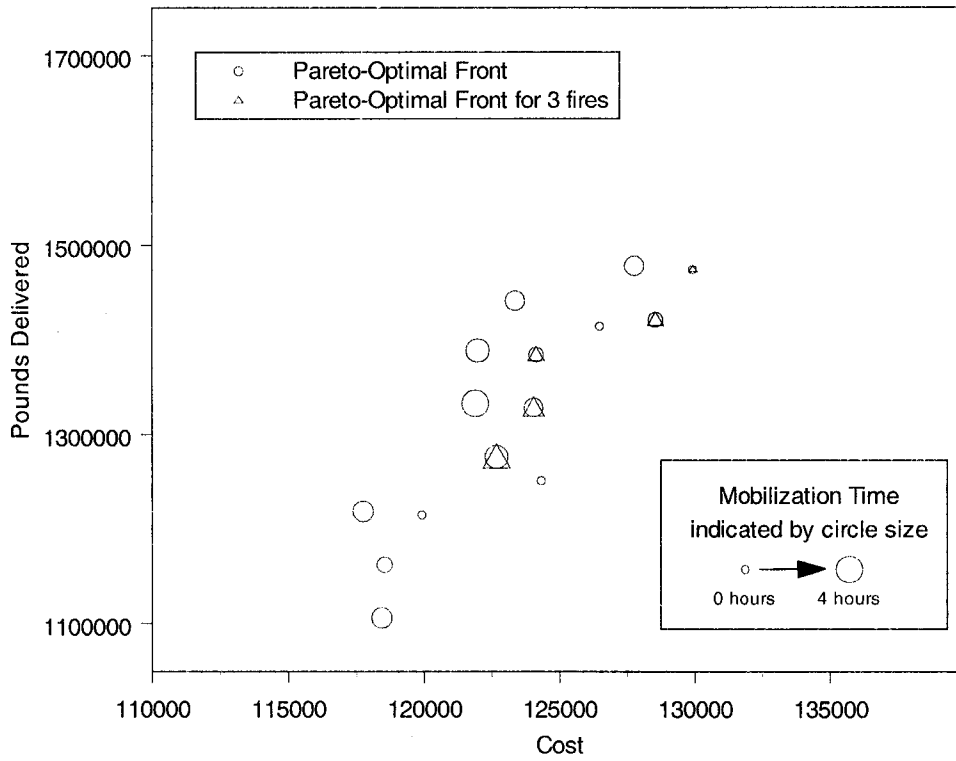


Figure 3.7 -- Pareto-optimal front for Fire 2. Genetic algorithm used to allocate helicopters to three fires using three optimization objectives; minimize cost, maximize pounds delivered, and minimize mobilization times.

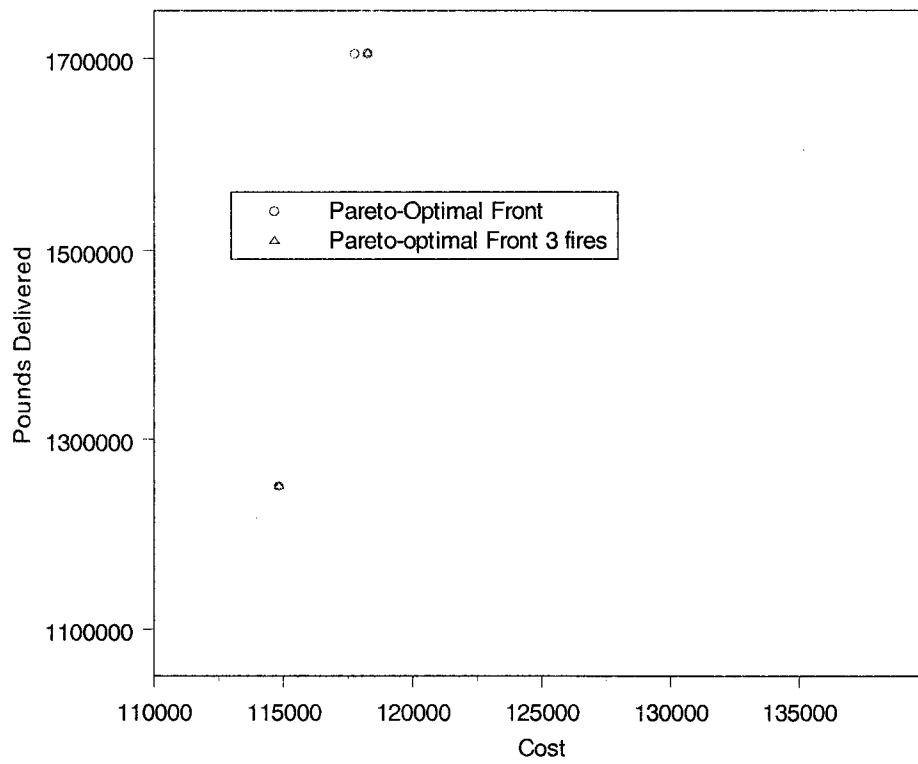


Figure 3.8 -- Pareto-optimal front for Fire 3. Genetic algorithm used to allocate helicopters to three fires using three optimization objectives; minimize cost, maximize pounds delivered, and minimize mobilization times. A mobilization time for all helicopters in the Pareto-optimal front is zero, i.e., less than 30 minutes.

The optimal solutions for each fire are independent of the other fires except that the fires compete for the available helicopters. If an efficient helicopter is part of the Pareto-optimal solutions for several fires the genetic algorithm has a difficult time finding all the Pareto-optimal solutions, because the assignments that include the helicopter compete with each other. In the example situation, the Pareto-optimal solutions that were not located by the genetic algorithm contained helicopters that were assigned to other fires.

Because of the competition for these helicopters, the genetic algorithm allocated these efficient helicopters to the fires that had fewer other options for Pareto-optimal solutions.

Since the genetic algorithm is dynamic this aspect of the genetic algorithm can be investigated further. In the example problem there are two helicopters that are allocated to some of the solutions in the Pareto-optimal fronts for all three fires. Two of the fires have just a few solutions in their Pareto-optimal fronts while Fire 3 has many Pareto-optimal solutions (Figures 3.6 – 3.8). The solutions found by the genetic algorithm allocated these two helicopters to the two fires with few Pareto-optimal solutions. None of the solutions found allocated these helicopters to the fire with many Pareto-optimal solutions.

In an attempt to force the genetic algorithm to find Pareto-optimal solutions with the efficient helicopters assigned Fire 3, the genetic algorithm was started with only Fire 1 and Fire 2. After 19 generations the genetic algorithm found most of the Pareto-optimal solutions for Fire 1 and Fire 2 including solutions that allocated the efficient helicopters to both of the fires. Fire 3 was then added to the problem. After 100 generations the genetic algorithm had found the same set of Pareto-optimal solutions for each fire that was found when all three fires were run simultaneously. This shows that the genetic algorithm prefers these solutions to other combinations and that the genetic algorithm can handle changes in the domain.

The dynamic genetic algorithm was also started without the two efficient helicopters and all three fires. After 19 generations the Pareto-optimal front found by the genetic

algorithm new optimal solutions because the two efficient helicopters were not available. After these efficient helicopters were reintroduced into the domain the genetic algorithm was able to locate some of the Pareto-optimal solutions that were found in the previous runs by generation 100. (Figures 3.9-3.11)

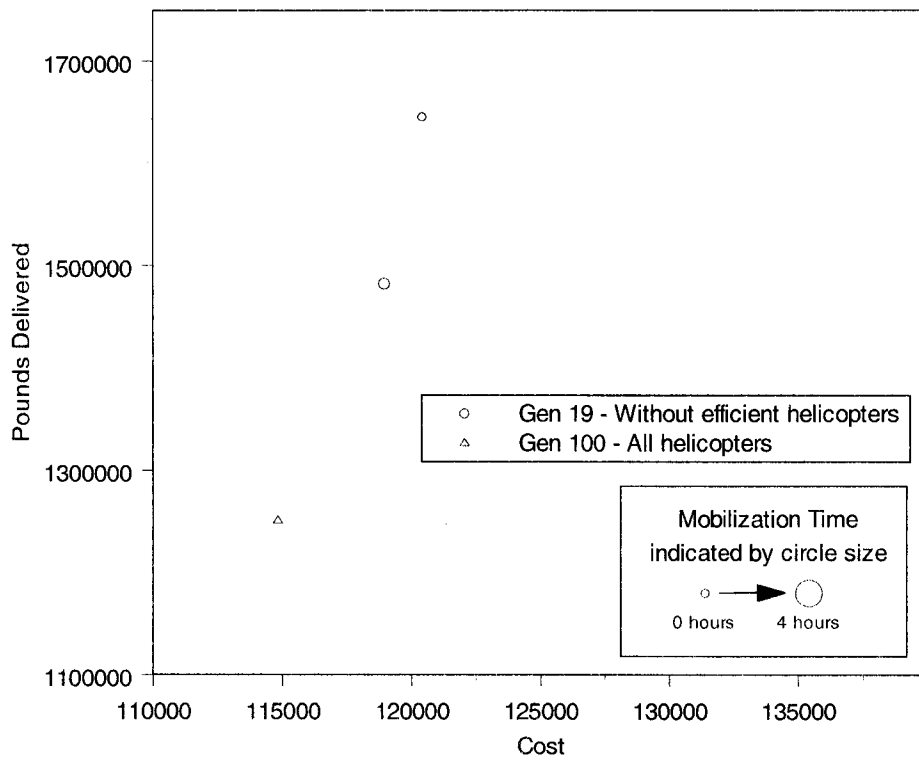


Figure 3.9 – Pareto-optimal front for Fire 1 after 100 generations. Two most efficient helicopters were added to genetic algorithm at 20th generation.

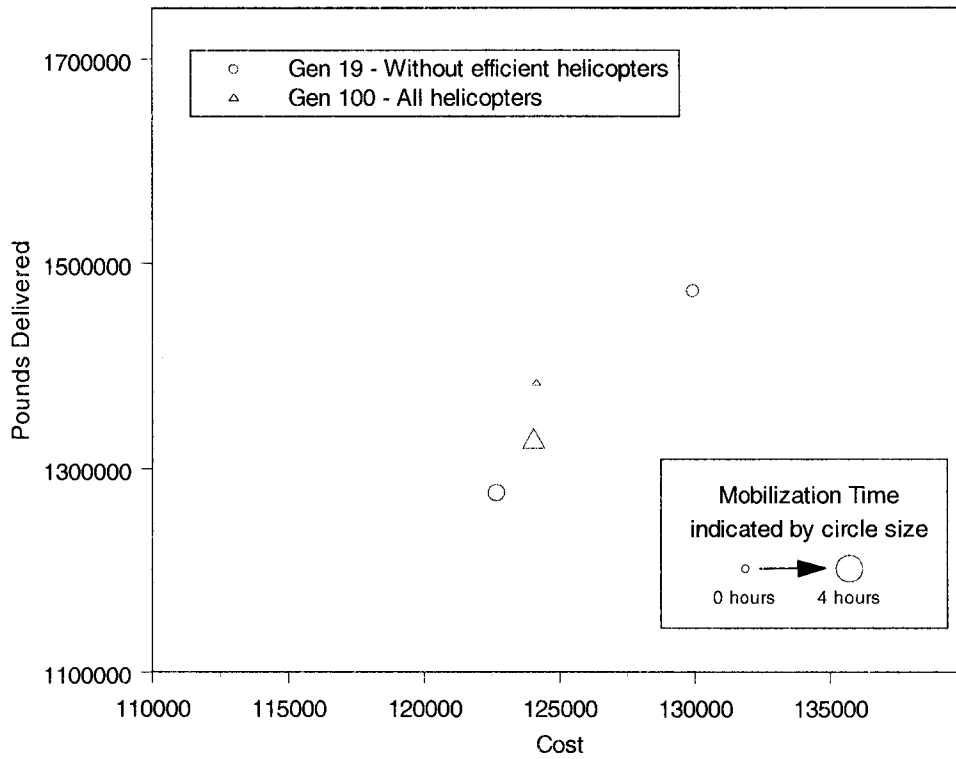


Figure 3.10 – Pareto-optimal front for Fire 2 after 100 generations. Two most efficient helicopters were added to genetic algorithm at 20th generation.

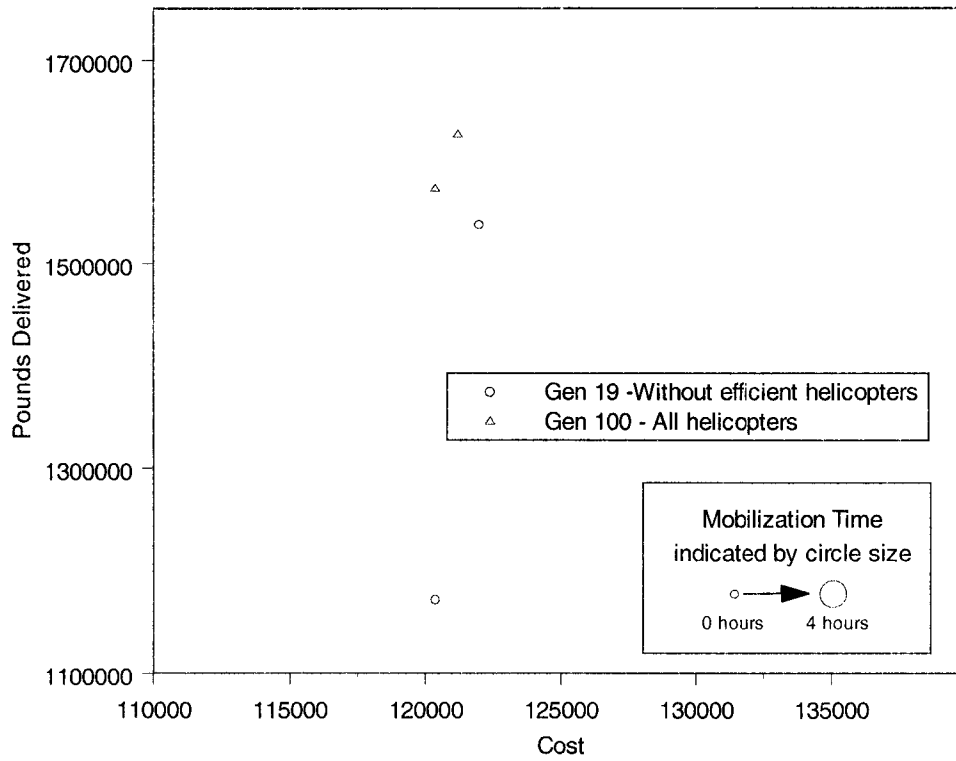


Figure 3.11 – Pareto-optimal front for Fire 3 after 100 generations. Two most efficient helicopters were added to genetic algorithm at 20th generation.

Conclusion

Traditional optimization methods find a single solution that optimizes a single objective function. Many of these methods also require that the optimization problem meet certain criteria, for example: that derivatives exist, the solution surface is convex, certain constraints hold, or the number of variables is limited. Complex optimization problems can be solved using traditional methods but this usually requires simplification

of the problem. Multiple objectives can be combined, or only one objective is used while the others are made into constraints. Then the single solution found by the traditional optimization method reflects the simplifications made to the problem.

The example problem shows that the proposed genetic algorithm can find a set of Pareto-optimal solutions to the dynamic multiobjective allocation problem. Not only do genetic algorithms solve this problem, they also provide information about the solution space. Evaluating the tradeoffs between the objectives is an integral part of the decision making process. The tradeoff surface informs decision makers about the concessions that have to be made to improve the value of an objective. By producing the Pareto-optimal front the genetic algorithm provides decision makers with information so they can make defensible decisions.

Genetic algorithms provide multiple Pareto-optimal solutions to an allocation problem. As with the allocation of helicopters for the suppression of large wildland fires, the problem is often so complicated that some of the information is not included in the optimization. With helicopters this information includes details about the type of equipment carried by the helicopter. Once the set of Pareto-optimal and near Pareto-optimal solutions is found, this additional information can be used to determine which of the solutions is best.

Many ways exist to solve the dynamic multiobjective allocation problem. The method used should depend on the type of solution or solutions that are wanted. Genetic algorithms provide a solution method that can handle changes in the domain without

having to start over. They also provide decision makers with information about the tradeoffs between the multiple objectives and provide multiple solutions so other information can be used to determine which solution is really most desirable.

CHAPTER 4

COMPARISON OF MIXED INTEGER PROGRAMMING AND GENETIC ALGORITHM

Abstract

Traditionally, mixed integer programming algorithms have been used to find solutions to optimization problems such as finding the most efficient allocation of helicopters for wildland fire suppression. The uncertainty associated with wildland fire suppression activities makes multiple runs of the mixed integer programming problem with different constraints necessary. Genetic algorithms, an optimization technique that uses the power of the computer to find a set of solutions, provide an alternate method for exploring the uncertainties in the helicopter allocation problem. The population of solutions found by a genetic algorithm defines the tradeoffs that exist in the problem and allows decision makers to make more informed decisions.

Mixed integer programming and genetic algorithms are very different methods that can be used to solve the helicopter allocation problem. Mixed integer programming produces an optimal solution while genetic algorithms produce a set of efficient solutions that describe the tradeoffs between competing objectives. A comparison of the two methods shows that there are advantages and disadvantages to both methods and that the

context of the problem needs to be considered in order to determine which method is more appropriate.

Introduction

The allocation of helicopters for fire suppression is an optimization problem that assigns helicopters to fires so that the suppression efforts are efficient. Mixed integer programming (MIP) is the traditional method for finding the optimal solution for this type of problem (Nemhauser and Wolsey 1988). The MIP problem assigns helicopters to fires so that the efficiency of the helicopter operations at all fires is optimal. The assignments made to individual fires are controlled by constraints. MIPs are deterministic and will find an optimal solution if one exists.

Recent advances in machine learning have produced new methods for solving optimization problems. Genetic algorithms (GAs), in particular, have been noted for their ability to find solutions to combinatorial problems such as that of helicopter allocation. Genetic algorithms use a population of solutions to search the solution space for solutions that optimize multiple criteria. The search is stochastic so replication can locate different sets of solutions. The method may not even find all the optimal solutions.

MIPs and GAs are very different solution methods that can be used to solve the helicopter allocation problem. Their solutions answer the optimization question differently. The MIP produces an optimal solution to the problem while the GA produces

a set of solutions that describe the tradeoffs between competing objectives. In this Chapter I compare the two methods and illustrate the differences with an example.

Mixed Integer Programming

Linear programming is a mathematical technique for finding the optimal solution for an objective function by changing the values of the decision variables. The potential values of the decision variables are subject to constraints. The problem becomes a mixed integer programming problem when some of the decision variables must have an integer value. Several commercial products are available for solving MIP problems; many of these use variations of the Branch and Bound or Branch and Cut algorithms. The examples in this paper are solved using Frontlines Premium Solver Platform with Microsoft EXCEL.

The helicopter allocation problem can be stated using three attributes of the individual helicopters under consideration at each fire; the cost, the performance and the mobilization time. A MIP problem is formulated using a single objective function and constraints to evaluate the attributes and find the optimal solution. If this is insufficient, the solution space can be explored by running the MIP with different sets of constraints.

There are a couple of ways that the optimization equation can be formulated to determine the efficiency of helicopter operations at multiple fires. Using cost per pound to represent helicopter efficiency, the cost and number of pounds delivered at each fire can be calculated using estimates of the average number of hours flown per day, the

number of loads that can be delivered per hour, and the number of days the helicopter will be on contract. For multiple fires the optimization function can be written as either the sum of the cost per pound at the individual fires or the sum of the costs divided by the sum of the pounds.

The sum of the cost per pound at the individual fires is the preferred optimization function due to the uncertainty in the number of days a helicopter will be on contract. Frequently fires extend beyond the initial estimates. It is also common for contracts to become longer as helicopters are moved to nearby fires. Inaccurate estimates of the number of days a helicopter will be on contract will effectively weight the helicopter efficiency at individual fires in the sum of the costs divided by the sum of the pounds delivered optimization function. This will allow the efficiency at a weighted fire, where more is delivered, to dominate the optimization equation. Because estimates of the number of days a helicopter will be on contract can easily be incorrect weighting in the manner can lead to a solution that is inefficient when it is actually deployed. It is better to find a solution that optimizes the efficiency at all fires so that the effect of the uncertainty of contract length is minimal.

Mobilization time affects the efficiency of a helicopter because delays in the fire suppression activities will require construction of additional fireline. The helicopter may not be needed at the fire immediately because suppression operations cannot begin until support personnel arrive. A constraint on mobilization time will ensure that only helicopters that can arrive within a specified mobilization time are considered. Limiting

the helicopters in this manner may mean an efficient helicopter is not considered even if it is just slightly farther away. A penalty term for excessive travel times can likewise be added to the cost per pound delivered. This term represents the cost per pound that the suppression effort will suffer because of the time delay. Since this value is currently unknown, it will not be included in the proposed MIP. Rather, constraints will be used to limit mobilization times. Constraints are also needed to define upper and lower limits on payload size. Constraints limiting the total costs may be added if budget limitations exist for the suppression effort.

The decision variables represent the assignment of individual helicopters to fires. A value of one indicates that the helicopter is assigned to the fire while a value of zero indicates that the helicopter is not assigned to the fire. Additional constraints are required to ensure that the decision variables are binary and that an individual helicopter is only assigned to one fire.

The mathematical description of the helicopter assignment problem is given below.

$$(4.1) \quad \text{Min } \sum_j \sum_i [c_{ij} / p_{ij}] * x_{ij}$$

subject to:

$$(4.2) \quad C_j \geq \sum_i c_{ij} * x_{ij} \quad \text{for all } j$$

$$(4.3) \quad P_{\min_j} \leq \sum_i p_{ij} * x_{ij} \leq P_{\max_j} \quad \text{for all } j$$

$$(4.4) \quad M_j \geq m_{ij} * x_{ij} \quad \text{for all } i, j$$

$$(4.5) \quad x_{ij} \in \{0,1\}$$

$$(4.6) \quad \sum_j x_{ij} \leq 1 \quad \text{for all } i,$$

where c_{ij} is the estimated cost for helicopter i at fire j , p_{ij} is the estimated payload (in pounds) helicopter i carries at fire j (calculated using either the maximum allowable payload or the weight of the fixed-weight load), m_{ij} is the time required to mobilize helicopter i to fire j , and x_{ij} is the binary decision variable for assigning helicopter i to fire j . Equation (4.1) is the objective function minimizing the sum of the costs per pound delivered for each fire. Equations (4.2), (4.3), and (4.4) are constraints for the maximum cost, C_j for each fire j , minimum pounds delivered P_{minj} and maximum pounds delivered P_{maxj} for each fire j , and maximum mobilization time M_j for each fire j , respectively. Expression (4.5) requires that the decision variables be binary and equation (4.6) requires that each helicopter be assigned to only one fire.

If a feasible solution (one that satisfies all the constraints) exists, the MIP will find a single assignment of the decision variables that meets the constraints and minimizes the objective function. This is the goal for many optimization problems. The nature of wildland fire makes it difficult to know exactly what is needed for a fire suppression effort before it starts. Limits on payload size and mobilization time are often subjective. Multiple runs of the optimization problem with varied constraints can be used to explore the effects of the constraints. Many helicopter attributes are not included in the model so allocations that appear to be equivalent to the MIP may differ greatly in other respects such as equipment and capabilities.

Allocation Problem

Both MIPs and GAs can allocate helicopters to multiple fires simultaneously. A single fire is considered first because it's easier to illustrate and compare optimization methods. The example problem consists of finding the optimal allocation of 245 helicopters to a single fire. Helicopter costs are from the 2002 CWN helicopter contract using the IHAPI database. The fire is assumed to be at 5000 feet and 30 degrees Celsius with estimations that the suppression effort will last for seven days with an average of five hours of flight time each day. Ten loads can be delivered each hour. Because mobilization times don't exist the helicopters have been randomly assigned a mobilization time between zero and ten hours, rounded to the nearest hour, for the purpose of this example. The solution is constrained so that the allocated helicopters will have a combined payload between 3150 and 5000 pounds.

For the first run of the MIP only helicopters that could be mobilized within four hours are considered. Two helicopters are allocated to the fire at an estimated cost of \$121,198 and a cost per pound of 7.45 cents. The MIP is run a second time with a constraint on mobilization time of eight hours. Two helicopters were allocated at an estimated cost of \$117,754 and the reduced cost per pound of 7.27 cents. The two helicopters found in the second run had mobilization times of four and five hours. This savings could be realized by allowing one of the two helicopters to exceed the mobilization constraint by one hour.

The GA was run only once with three objectives for the fire; minimize cost and mobilization time in excess of four hours while maximizing pounds delivered. The

Pareto-optimal front for the solution is three-dimensional but can be represented graphically in two dimensions (Figure 4.1). The two-dimensional graph of costs versus pounds delivered uses variation in the circle sizes to indicate mobilization times. The 50 best GA solutions are plotted. Squares are used to indicate the Pareto-optimal front estimated by the GA. The two solutions found in the two runs of the MIP are shown as triangles for comparison purposes.

The graph illustrates the tradeoffs between the three objectives being optimized. Although randomly assigned, the shorter mobilization times are associated with helicopters that have a higher cost per pound. This means that the decision makers will have to choose between shorter mobilization times and better efficiency at the fire. Another interesting attribute of the tradeoff surface is that many solutions have nearly equal costs despite a large difference in the amount that can be delivered. This shows that because cost is not a good indicator of capability, it is important that a measure of performance is included in the decision.

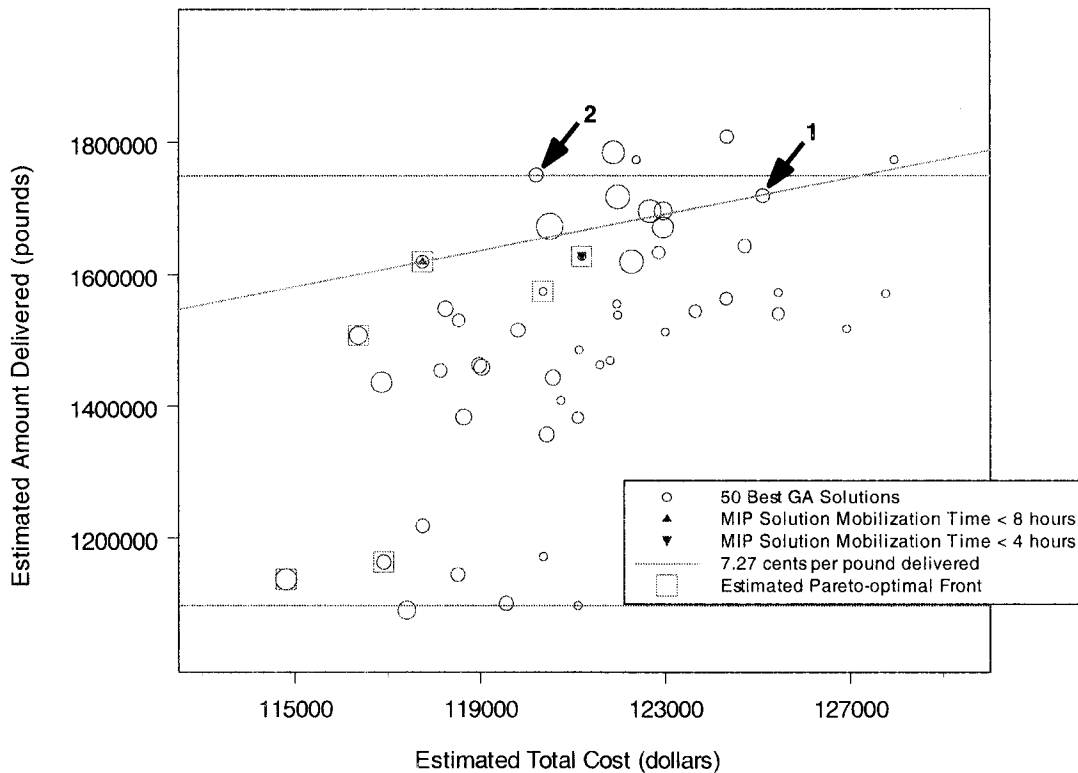


Figure 4.1 -- Genetic Algorithm solutions represented by circles that vary with size based on the number of hours above four required for mobilization. Solutions in square are the estimated Pareto-optimal front. MIP solutions are represented by triangles. Line represents 7.27 cents per pound delivered. Arrows indicate alternate solutions.

The GA found both the solutions the MIP found. Both are part of the estimated Pareto-optimal front. The GA includes a few additional solutions that should be considered in the decision. Point #1 as indicated by the arrow and the number on the graph in Figure 4.1, lies along the line for 7.27 cents per pound delivered. The cost per pound for this solution is actually 7.276 cents. The solution consists of two helicopters with mobilization times of three and five hours. The MIP solutions consisted of two

different helicopters with mobilization times of four and five hours. Regardless of other helicopter attributes, solution #1 may be the better allocation if mobilization time is critical.

Point #2 in Figure 4.1 represents a solution in which the weight carried by the two helicopters is 5002 pounds, which exceeds the upper payload limit of 5000 pounds. The MIP does not consider any solutions outside of the constraints but the GA has been written so solutions close to the constraints are considered but penalized slightly. The cost per pound represented by solution #2 is 6.87 cents, a significant savings that warrants consideration.

Multiple Fires

The GA was written to consider multiple fires independently using the dominance relationship to compare the assignments for each fire. The fitness values for the individual fires are then added to obtain the fitness value for the solution. Solutions that are well suited for all the fires will have a better fitness value. The MIP can evaluate only one objective function so the multiple fires are handled by summing the cost per pound delivered for each of the fires. Both optimization methods consider the fires independently and total the results of the individual fires. The multiple fire results are similar to the single fire case except that the search is more complex and the results are hard to visualize.

An example with three fires was used. All three will need helicopter support for seven days with five hours of flight time per day and ten loads delivered per hour. Fires 1 and 3 are at 5000 feet and 30 degrees Celsius while Fire 2 is at 8000 feet and 25 degrees Celsius. Forty-four CWN Type II standard category helicopters from the 2002 CWN helicopter contract with random mobilization times are considered for deployment. Constraints on combined payload sizes for all three fires are set at 3150 to 5000 pounds. Mobilization times less than four hours were preferred on all three fires.

The MIP solution with mobilization times constrained to four hours allocated two helicopters to each of the fires. With mobilization times relaxed to 6 hours the same two helicopters were allocated to both Fire 1 and Fire 2 while an improvement was found for Fire 3. A more efficient helicopter with a mobilization time of five hours replaced one of the allocated helicopters while the other helicopter allocated to the fire remained the same (Figures 4.2 – 4.4). The combined cost per pound delivered for the two MIP runs were 23.1 and 23.0 cents.

A single run of the GA analyzed the tradeoffs between the three objectives of cost, pounds delivered and mobilization time over four hours for all three fires. With the population size for the GA increased to accommodate the three fires a reasonable approximation of the Pareto-optimal front for the three fires was found. Figures 4.2 - 4.4 show the results for each of the fires separately. A single graph showing the helicopter assignments for all three fires simultaneously cannot be depicted easily.

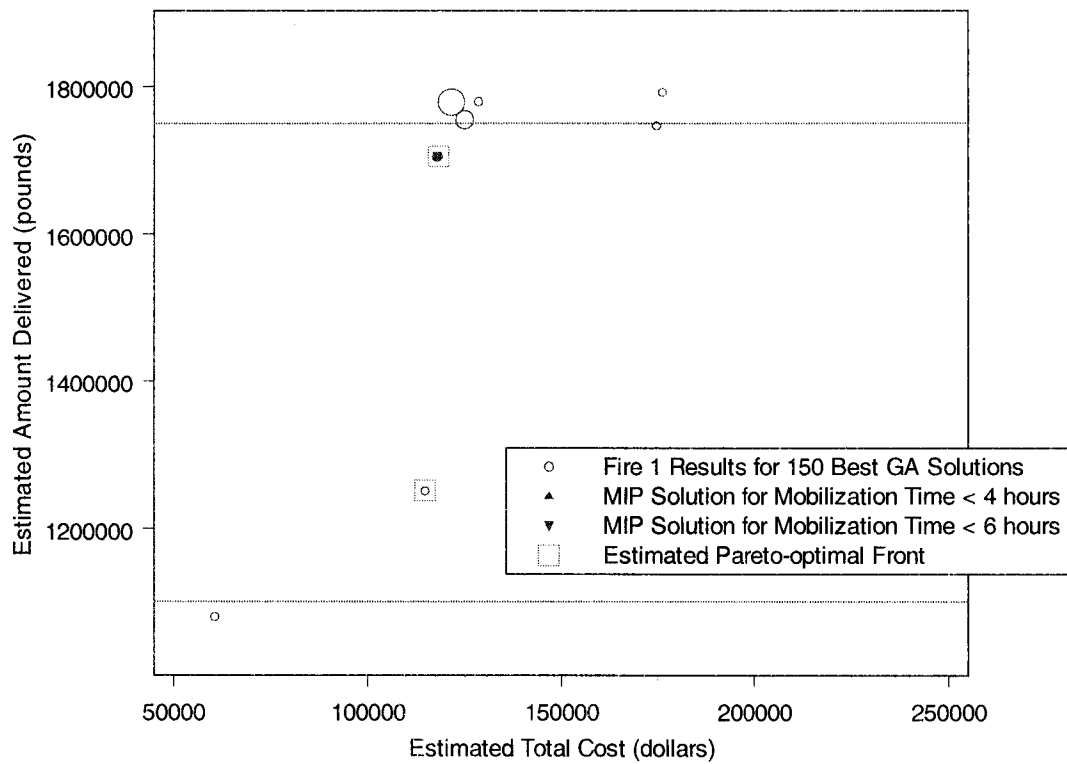


Figure 4.2 -- GA and MIP solutions for Fire 1. Mobilization times are represented for the GA solutions with variation in the circle size. The GA solutions that estimate the Pareto-optimal front are indicated with squares. MIP solutions for Fire 1 are the same for mobilization time constraints of 4 and 6 hours.

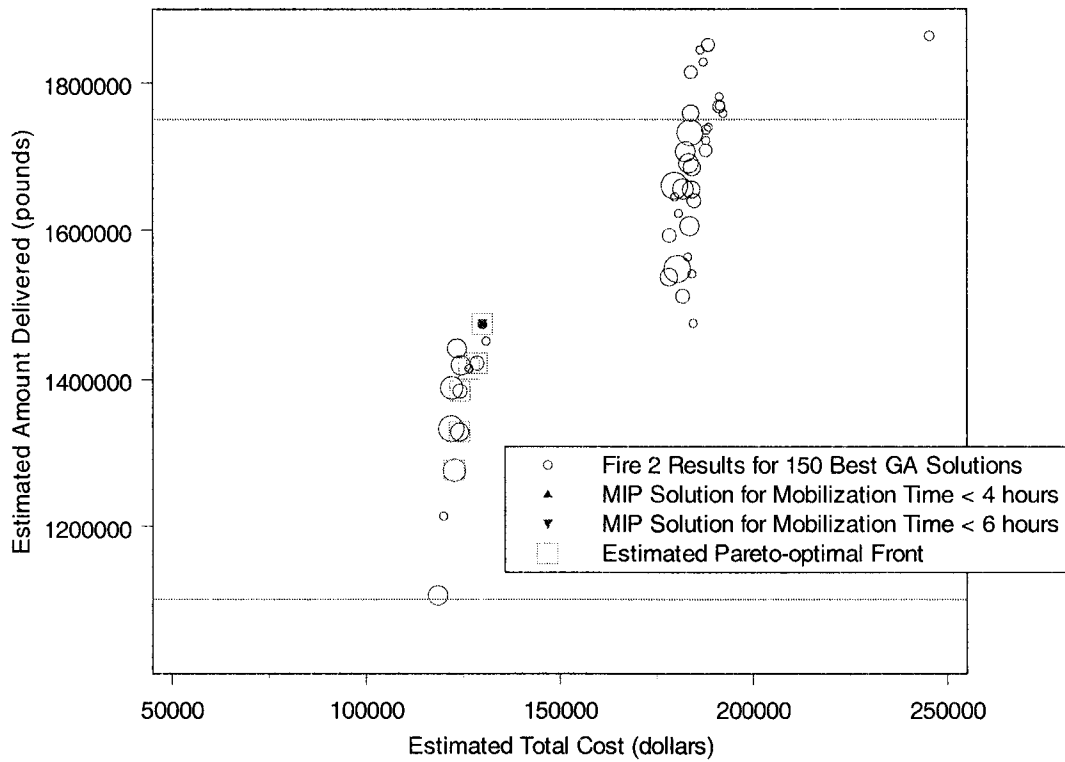


Figure 4.3 -- GA and MIP solutions for Fire 2. Mobilization times are represented for the GA solutions with variation in the circle size. The GA solutions that estimate the Pareto-optimal front are indicated with squares. MIP solutions for Fire 2 are the same for mobilization time constraints of 4 and 6 hours.

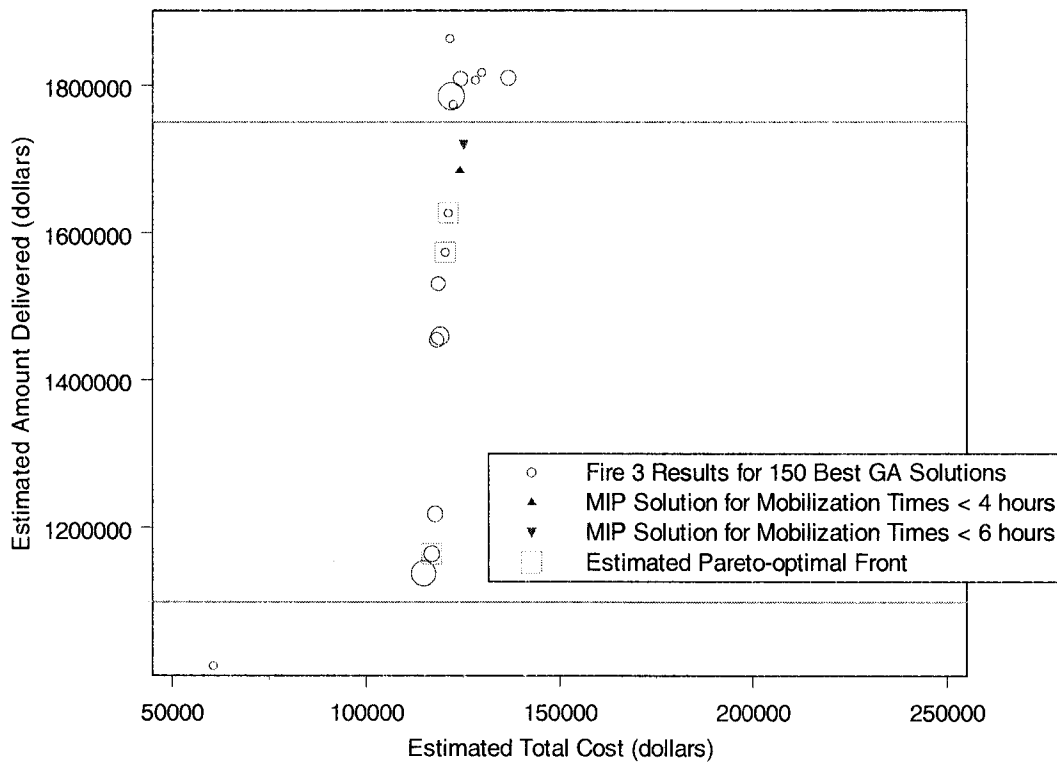


Figure 4.4: GA and MIP solutions for Fire 3. Mobilization times are represented for the GA solutions with variation in the circle size. The GA solutions that estimate the Pareto-optimal front are indicated with squares. Triangles indicate the MIP solutions with mobilization times constrained to 4 and 6 hours.

As in the single fire example, with multiple fires the GA found alternate solutions for consideration. Some of these solutions provide nearly equivalent solutions to the problem. There are also solutions outside the constraints that are more efficient. Note that the GA did not locate the MIP allocations for Fire 3. This is because a solution exists that exceeds the upper limit on pounds delivered but costs less than the solution found by the MIP.

Comparison of MIPs and GAs

MIPs and GAs are two different methods that can be used to find the optimal allocation of helicopters to fires. Both methods have advantages and disadvantages. The best method to use depends on the size of the problem being solved, the accuracy of the information used in the decision process and the skills and knowledge of the decision makers. Understanding the differences in the two methods will enable the decision maker to apply the appropriate method.

MIPs use an algorithm that systematically searches the solution space for an optimal solution that meets all the constraints. The MIP is deterministic and will find the same solution every time the same starting conditions are used. For larger problems, the search time becomes long and the optimal solution becomes unobtainable. In such cases, the MIP stops when it locates a solution that is within a predefined distance from the optimal solution.

The GA does not systematically search the solution space. It uses information about the solution space that it learns from the fitter individuals in the population to direct the search toward promising areas of the solution space. An advantage to stochastic processes is their ability to handle large problems because they avoid regions of the solution space that do not appear to contain optimal solutions. Each generation of the GA contains an approximation of the Pareto-optimal front. As long as these solutions are

retained in the next generation, as the GA continues it will find better approximations. So large problems, stopped at any time, will still provide a solution.

A major difference between MIPs and GAs is how they deal with preferences. With MIPs the preferences are defined in the setup of the problem. Multiple objectives are combined into a single objective function, which requires that the decision maker knows the tradeoffs between the objectives and can express them in a single equation. Some objectives may be applied more effectively if they are reformulated as constraints. With all the preferences defined, the MIP will find an optimal solution, if one exists.

MIPs provide an elegant solution method for optimization problems, but drawbacks exist. A solution that meets the decision maker's preferences may not exist, which causes the MIP to fail. Several optimal solutions may exist, but the MIP will only find one of them. Uncertainty and incomplete information, which are often present in real world situations, make it hard to define the problem explicitly, as the MIP requires. The tradeoffs between objectives must be known to combine them into one objective function. Constraints impose absolute limits, but constraints are often just preferences that decision makers may be willing to violate if the tradeoffs are right. MIPs are rigid and multiple runs with varying constraints are needed to explore the uncertainties in the problem.

With GAs, multiple objectives can be optimized simultaneously. The Pareto-optimal front as approximated by the GA provides an opportunity for decisions makers to evaluate the tradeoffs between objectives. The GA also gives decision makers the opportunity to evaluate the effect of constraints by allowing solutions that almost meet

them. The GA helps the decision makers understand the problem by providing information about the solution space. With this new information preferences can be applied and a decision made.

Solving the helicopter allocation to wildland fires problem with a GA provides insights into some of the issues present when a MIP is used to find the solution. The tradeoff between cost and pounds delivered by the helicopters, as described by the GA, shows that cost per pound delivered is related to payload size. In general, small helicopters are less efficient than larger helicopters. Consequently, by using cost per pound delivered as the objective function, the MIP solution is biased toward the upper constraint for payload size. This is inconsequential if the payload constraints are accurate, but if they are not, larger helicopters will be deployed than are needed.

Conclusions

MIPs can be used to solve the helicopter allocation to wildland fire problem, but multiple runs may be required to explore the solution space and understand the tradeoffs between alternate solutions. Because wildland fires are unpredictable it is impossible to define a single MIP that adequately explores the variability that exists. Multiple MIPs with different payload limits can be used to explore the variability associated with varying levels of suppression effort. MIP runs that vary the mobilization times are needed to ensure that efficient helicopters are not eliminated by constraints on mobilization times.

Multiple runs of the MIP are needed to provide the missing information needed to determine the optimal solution.

Multiple MIP runs provide multiple solutions. These solutions define the solution space and provide information that along with preferences can be used to determine the appropriate solution. As more uncertainty exists in the optimization problem, MIPs must become more like GAs for finding the optimal solution. Faced with enough uncertainty, GAs will provide a better solution method.

Details of the equipment individual helicopters carry and their special capabilities are not included in either optimization process, yet this information is important. Because GAs allow for this information to be incorporated in the decision process, they have an advantage over multiple runs of the MIP. GAs provide the best opportunity for exploring alternatives and determining which helicopters should be allocated for wildland fire suppression.

CHAPTER 5

CONCLUSION

This dissertation discusses three methods that can be used to improve the efficient use of helicopters for the suppression of large wildland fires. Currently helicopters are categorized into three types according to payload capacity, performance, at sea level. Helicopters are ordered for fire suppression by type. Dispatchers determine which helicopter to deploy based on availability, mobilization time, and cost. By using helicopter type to measure performance, inefficient helicopters are deployed. This is because there is a wide range of performance within a helicopter type. Helicopter performance also depends on the altitude and temperature of operation so the performance of an individual helicopter depends on the location of the fire.

A four-hour comparison index is developed that summarizes the efficiency of individual helicopters at representative altitude and temperature conditions. The four-hour comparison index represents efficiency relative to the cost per pound with four hours of flight time per day. The four-hour comparison index can be used to deploy helicopters to a single fire by comparing the efficiency of individual helicopters. It does not include mobilization information but it is robust for contracts with long duration. Use of the

four-hour comparison index for deploying helicopters ensures that efficient helicopters are deployed and means substantial savings.

The four-hour comparison index is not an optimization technique. It is a method for comparing the efficiency of individual helicopters at a particular fire. To find the optimal deployment of helicopters for fire suppression a more rigorous method is required.

Mixed integer programming is often used to solve combinatorial optimization problems of this type. With MIP the optimal allocation of helicopters to multiple fires can be found. This can include allocating two smaller helicopters rather than a larger one to a fire if it is more efficient. The MIP minimizes the sum of the cost per pound delivered at each fire subject to constraints on the total amount delivered at each fire and limits on mobilization times.

Besides being unpredictable there is much that is not known about wildland fire and fire suppression operations, especially helicopter operations. Because suppression on large fires is unlikely to go according to plans, there is motivation to perform some “what-if” analyses for different conditions. Because helicopters vary dramatically in their capabilities and the equipment they carry, there is also motivation to explore the solution space to find other options. This “what-if” analysis and exploration can be accomplished using MIP by rerunning the optimization with different constraints.

Genetic algorithms provide an alternate method for solving combinatorial optimization problems. By optimizing multiple objectives GAs find a set of solutions that describe the tradeoffs between the objectives. The set of solutions the GA finds for

deploying helicopters to multiple fires allows dispatchers to weigh the tradeoffs between the objectives, and to match helicopter capabilities and equipment to the individual fires. One advantage GAs have over multiple runs of a MIP is that all the optimal solutions within the constraints can be found. MIPs will not find solutions with identical objective values that involve different helicopters with different capabilities and equipment. On the flip side GAs are stochastic and may not find one optimal solution.

In a recent conversation with Bob Roth (2004) I was asked to assist in the development of a web based database to be used to deploy helicopters for fire suppression. The database will contain information on helicopter performance by make and model at 1000 foot increments. The cost per pound for helicopters being considered for deployment to a fire will be estimated using equations (1) and (2) in Chapter 2 of this paper. The number of days on contract will be indicated with the helicopter request and average values for average number of hours flown per day and loads per hour will be used.

Bob Roth (2004) also discussed how he envisioned using his flight following system, which will contain the helicopter performance and cost information, to optimize the deployment of helicopters. For flight following, GPS are installed in individual helicopters to provide current position information. This can be used to calculate mobilization distances, flight times and costs. The system also includes a digital elevation map that can provide altitude information for fires. By adding components to

provide information about helicopter availability, the flight following system can provide the information that is needed for either of the optimization methods.

I am excited that the helicopter performance information will be included when helicopters are deployed. This is a big step in improving the efficiency of helicopter suppression operations. As the current state of development is still comparing individual helicopters, determining whether MIPs or GAs are better for this application is premature. I'm excited that I had the opportunity to explore the different optimization methods and when the time comes to develop an optimization system this dissertation will provide insights into some possible solutions.

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