

Deploying Wildland Fire Suppression Resources with a Scenario-Based Standard Response Model

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Abstract — Wildland fire managers deploy suppression resources to bases and dispatch them to fires to maximize the percentage of fires that are successfully contained before unacceptable costs and losses occur. Deployment is made with budget constraints and uncertainty about the daily number, location, and intensity of fires, all of which affect initial-attack success. To address the deployment problem, we formulate a scenario-based standard response model with two objective functions: the number of suppression resources deployed and the expected daily number of fires that do not receive a standard response, defined as the desired number of resources that can reach the fire within a specified response time. To determine how deployment levels affect the standard response objective, a weighted sum of the objective functions is minimized, and the weights are ramped from large to small to generate the tradeoffs. We use the model to position up to 22 engines among 15 stations in the Amador-El Dorado unit of the California Department of Forestry and Fire Protection in central California. Each deployment is further evaluated in terms of expected number of escaped fires using CFES2, a stochastic simulation model of initial attack. The solutions of the standard response model form a tradeoff curve where increasing numbers of engines deployed reduces the expected daily number of fires not receiving the standard response. Solutions concentrate engines in a small set of centrally-located stations. We use a simple heuristic with CFES2 to incrementally remove engines based on simulation estimates of expected utilization frequency. The deployments obtained with the heuristic contain about the same number of fires as do solutions of the standard response model, but the heuristic solutions deploy engines to more stations.

Keywords California Fire Economics Simulator, fire suppression, integer programming, linear programming, scenario optimization, wildfire management

1. INTRODUCTION

Deploying initial-attack resources to meet expected demands for fire suppression in coming days or weeks is an important part of wildland fire planning (Martell 1982). When fires occur, those resources are dispatched to achieve the earliest possible containment of fire spread by encircling the fires with a line that is cleared of all readily combustible material or wetted to make combustion unlikely (Fried and Fried 1996). Initial-attack resources include fire engines and aircraft that produce a containment perimeter by wetting vegetation fuels, and bulldozers and crews operating hand tools that cut a containment line. It has long been recognized that a strong and fast

initial attack will contain a fire within a prescribed time window (e.g., six hours) and prevent the fire from escaping and incurring substantial suppression and damage costs (Parks 1964). At the same time, most fire managers have limited resources for initial attack, and as a result, they must deploy and dispatch resources efficiently to minimize escapes.

Both simulation and optimization models have been used to aid initial-attack planning (see Martell 1982 and Martell et al. 1998 for reviews). Deploying and dispatching decisions can be viewed in the context of a spatial queuing system with stochastic fire occurrence and growth, rules for dispatching resources to fires, and stochastic fire line production rates (Martell et al. 1998). Detailed representations of these processes are included in stochastic simulation models (e.g., Islam and Martell 1998, Fried and Gilles 1999), which are used to evaluate changes in the number and location of resources and dispatching rules (e.g., Fried et al. 2006). However, because of their computational requirements, initial-attack simulation

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models have not been directly incorporated into optimization algorithms.

Researchers have formulated optimization models to address deploying and dispatching of suppression resources as separate problems without consideration of stochastic fire occurrence or behavior (Martell 1982). Deployment models assign suppression resources to stations to minimize operating costs while meeting pre-defined resource requirements in surrounding areas (Hodgson and Newstead 1978, Greulich and O'Regan 1982, MacLellan and Martell 1996). Models of dispatching problems are typically built for a single fire and determine the number and type of suppression resources to dispatch to minimize suppression cost plus damage subject to resource availability constraints (Kourtz 1989, Mees et al. 1994, Donovan and Rideout 2003).

We present a mixed-integer programming model that optimizes both daily deployment and dispatching decisions while accounting for uncertainty about the number, location, and intensity of fires. The model includes locations of fire stations and possible locations of fires along with times required for travel between stations and fires. Ignition uncertainty is characterized with a set of fire scenarios, each listing the location and intensity of fires that could occur in a single day. Resource deployment and dispatching decisions are included in a two-stage formulation. Deployment takes place at the beginning of the day before the number, location, and intensity of ignitions are known, and dispatching takes place during the day contingent on the fire scenario. The objective is to minimize the expected number of fires that do not receive a standard response—defined as the required number of resources that can reach the fire within a maximum response time—subject to resource availability constraints. We demonstrate the standard response model with data for a 3,642 km² study area in central California (Fig. 1). We use the model to deploy up to 22 engines among 15 stations in the Amador-El Dorado unit administered by the California Department of Forestry and Fire Protection (CDF). We compute the tradeoffs between the objectives of minimizing the number of engines deployed and the expected number of fires that don't receive a standard response.

A common objective of deploying and dispatching suppression resources is to contain all fires within a specified size or time limit. Although our model optimizes deployment and dispatching decisions based on a standard response objective, the model does not estimate the number of escaped fires. To evaluate the initial-attack effectiveness of solutions obtained from the standard response model, we use the California Fire Economics Simulator Version 2 (CFES2), a stochastic simulation model of initial attack (Fried and Gilles 1999, Fried et al 2006), to estimate the percentage of fires that escape initial attack. Further, we compute alternative engine deployments using a simple heuristic combined with CFES2 simulations and compare their performance with engine deployments obtained with the standard response model.

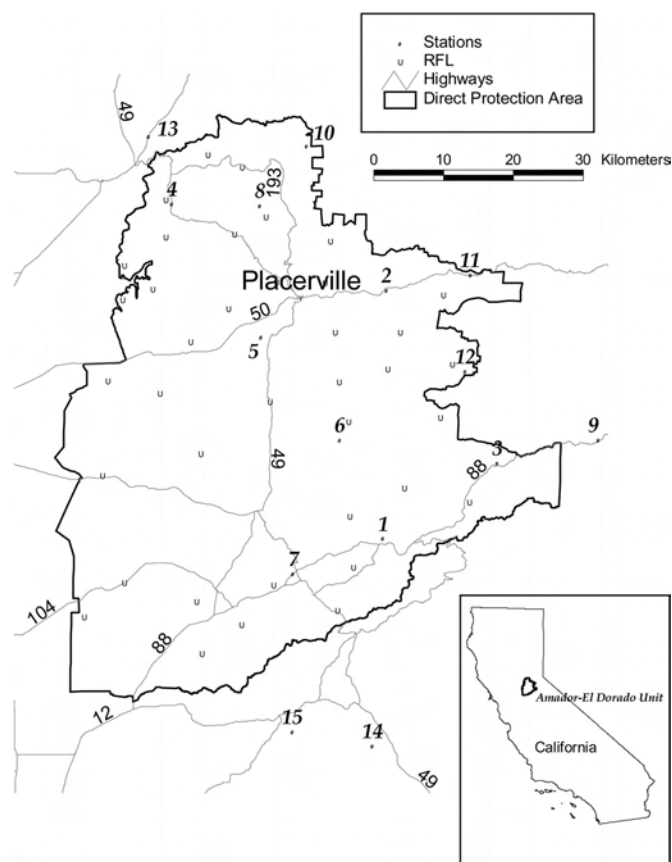


Figure 1. Amador-El Dorado ranger unit located in the western foothills of the Sierra Nevada in central California.

2. COVERING MODELS FOR EMERGENCY SERVICE DEPLOYMENT

Our scenario-based standard response model is an extension of the maximal covering location model for emergency service deployment. In covering models, the goal is to provide coverage to demand areas, where a demand area is covered if a facility or vehicle is available to serve the demand area within a distance or time standard (see ReVelle 1989 for review). Recognizing that the number of resources available for deployment is not sufficient to cover all of the demand areas, the maximal covering location problem deploys a fixed number of resources to maximize the number of demand areas covered (Church and ReVelle 1974). For example, Hodgson and Newstead (1978) determine the location of a fixed number of home bases for airtankers to maximize the number of potential fire locations that are within a maximum distance for effective service. The maximal covering location problem has been extended to handle standard response requirements. Urban planners define a standard response for fire protection service based on expected fire size, and a standard response may include several types of suppression resources and maximum response distances (e.g., three engines within 2.4 km and two trucks within 3.2 km). In this context, the

problem is to deploy suppression resources to stations to maximize the number of demand areas that are covered with the standard response (Marianov and ReVelle 1991).

While covering models for emergency service deployment typically assume that model parameters are known with certainty, we want to build a standard-response model that accounts for uncertainty in number, location, and intensity of wildfires. One approach to handling uncertainty in the number of calls for service is to make server availability a fixed probability and include reliability constraints for the likelihood that each demand area is covered (Daskin 1983, ReVelle and Hogan 1989). A more flexible approach is to create scenarios of possible fire occurrences and include those scenarios in a maximal covering location problem.

Scenario optimization is commonly used to model uncertainty in the parameters of facility location models (Owen and Daskin 1998, Snyder 2006). With scenario optimization, planners specify a set of scenarios that represent the possible realizations of unknown parameters and determine a compromise or robust solution that performs well across all scenarios (Mulvey et al. 1995). Objectives include optimizing expected performance, optimizing the worst-case performance, and optimizing the worst-case regret. Although scenario optimization problems can be difficult to solve when the number of scenarios is large (100s or 1000s), they are often more tractable than problems with continuous random variables. Further, the two-stage structure of scenario formulations—choose locations for deployment first and then react once the uncertainty has been resolved—makes scenario optimization attractive to practitioners.

Our model is the first example of scenario optimization in a maximal covering location problem for emergency service deployment. There are two important relatives in the urban and wildfire suppression modeling literature. Serra and Marianov (1998) formulate a scenario-based location model for fire stations in the city of Barcelona. Scenarios are used to model uncertainty in demand for service and time for equipment travel. The model locates emergency service facilities to minimize the maximum total travel time achieved across all scenarios. MacLellan and Martell (1996) formulate a model to locate airtankers in home bases in the Province of Ontario. From their home bases, planes are deployed to meet daily demand for airtankers at initial attack bases. The daily demand for airtankers is represented by a set of scenarios. The problem is to determine airtanker home bases and daily deployment to minimize costs and meet the demand requirements across all scenarios.

3. METHODS

3.1 Scenario-based standard response model for initial attack

The formulation is a scenario-based standard response model with two objective functions: the number of suppression

resources deployed to stations and the expected daily number of fires that do not receive a standard response. A weighted sum of the objective functions is minimized, and the weights are ramped from large to small to generate the tradeoffs between the objectives. The model is for a single fire planning unit. The data include the locations of fire stations and representative fires. Each station has a capacity to house initial attack resources, and the times required for those resources to reach each representative fire location are known. Uncertainty about the daily number, location, and intensity of fires is represented by a set of independent fire scenarios along with their probabilities of occurrence. Each scenario represents a different set of fire occurrences during a single day. Each fire is characterized by location, intensity, and standard response, which is the number and maximum response time of suppression resources that are required to contain the fire during initial attack. The standard response varies with fire intensity: more intense fires require more resources and faster response times. The model has decision variables in two stages. The first stage includes integer variables for the number of resources assigned to each station at the beginning of the day. The second stage includes integer variables for the number of resources dispatched from each station to each fire during each potential fire day. The two-stage model is formulated with the following notation:

Indices:

j, J = index and set of fire stations,
 k, K = index and set of potential fire locations,
 s, S = index and set of fire days (scenarios),

Objective functions:

Q_1 = number of suppression resources,
 Q_2 = expected number of fires that do not receive the standard response,

Parameters:

w = objective weight; $0 \leq w \leq 1$,
 b_j = upper bound on number of resources at station j ,
 p_s = probability that fire day s occurs,
 r_{ks} = number of resources required at location k during fire day s ;
 t_{jk} = response time from station j to location k ,
 T = maximum response time,
 N_k = set of stations from which resources can reach location k within the maximum response time; i.e., $N_k = \{j \mid t_{jk} < T\}$.

Decision variables:

x_j = integer variable for number of resources deployed at station j ,

y_{jks} = integer variable for number of resources at station j that are dispatched to fire location k during fire day s ,
 z_{ks} = 0-1 variable; 1 if fire location k receives a standard response during fire day s ; 0 otherwise.

The model is formulated as follows:

Minimize: $wQ_1 + (1 - w)Q_2$

subject to:

$$Q_1 = \sum_{j \in J} x_j \quad (2)$$

$$Q_2 = \sum_{s \in S} p_s \sum_{k \in K} (1 - z_{ks}) \quad (3)$$

$$x_j \leq b_j \quad \text{for all } j \in J \quad (4)$$

$$\sum_{k \in K} y_{jks} \leq x_j \quad \text{for all } j \in J \text{ and } s \in S \quad (5)$$

$$z_{ks} r_{ks} \leq \sum_{j \in N_k} y_{jks} \quad \text{for all } k \in K \text{ and } s \in S \quad (6)$$

$$z_{ks} \in \{0, 1\} \quad \text{for all } k \in K \text{ and } s \in S \quad (7)$$

The objective (Eq. 1) is to minimize the weighted sum of the two objective functions: the number of resources deployed at stations in stage one (Eq. 2) and the expected number of fires that do not receive the standard response in stage two (Eq. 3). The weight w represents the decision maker's preference for the two objectives. When w is closer to one, more weight is put on minimizing the number of resources deployed. When w is closer to zero, more weight is put on minimizing the number of fires that do not receive a standard response. In Eq. 3, the expectation is the weighted sum of the daily number of fires not receiving the standard response, where weights p_s represent probabilities of occurrence of the fire days. Eq. 4 defines the capacity of each station. Eq. 5 requires that the number of resources dispatched from each station during each fire day is less than the number of resources deployed at the station. Eq. 6 is the condition for whether a fire receives a standard response in stage two. A fire receives a standard response ($z_{ks} = 1$) only if the number of resources that are within the standard response time and dispatched to the fire $\sum_{j \in N_k} y_{jks}$ is greater than the number of resources required r_{ks} . If $r_{ks} = 0$, there is no fire at location k during fire day s and $z_{ks} = 1$ without any resource commitment.

It is important to recognize that each stage represents a different time period. The first stage includes resource deployment decisions to meet possible resource demands in the coming day. Once the resources are deployed, the second stage represents the dispatching of those resources to fires that may occur during the day. The dispatching rules assume that fires in a single fire day occur close enough in time to compete for the same resources.

The dispatching objective and data requirements differ from previous optimization models of initial attack. For example, Donovan and Rideout's (2003) model has an objective of minimizing area burned and includes binary containment variables for a single fire based on the ratio of fire line to fire perimeter in discrete time intervals (e.g., hours) after ignition. With an objective of minimizing area burned, the model dispatches resources to contain the fire in the earliest possible time interval. Further, the model requires rates of fire line production and fire area and perimeter growth. In contrast, our standard response model assumes that multiple fires may occur in a day and has the objective of minimizing the expected number of fires that don't receive a standard response. As a result, a single binary covering variable is defined for each fire along with resource and response time requirements, which are related to expected fire intensity. Because the standard response is a proxy for fire line production and spread rates, those parameters are not incorporated in the model.

3.2 Application

We apply the standard response model using data for a portion of the Amador-El Dorado unit administered by the California Department of Forestry and Fire Protection (Holmes 2005). The unit is located on the western slope of the north-central Sierra Nevada range in central California (Fig. 1). The study area (3,642 km²) is composed of federal, state, and private lands for which CDF has contractual or statutory protection responsibility. The study area includes rolling hills and steep, rugged river canyons with elevations rising 300–1200 m, west to east. Over 70% of the study area contains hazardous fuels including grass, brush, oak-woodland, and conifer vegetation. The fire history includes numerous small fires with large fires occurring every 30–40 years, the most recent burning 138 km² in 1961. Low fuel moisture and severe fire weather combine to create the greatest potential for large fires during the period June–October. Over half of the study area is wildland-urban interface, which has grown rapidly over the past 20 years and become a significant factor in the complexity of the fire protection environment. The resident population in 2005 was estimated to be greater than 300,000 people. The study area is a good choice for demonstrating our model because of the availability of data, diversity of fire environments, wide range of accessibility for firefighting, and fire load.

The analysis focuses on the deployment of fire engines among 15 stations owned and operated by the CDF or the USDA Forest Service (Fig. 1). The study area includes 46 representative fire locations (RFLs) identified by CDF staff for fire protection planning and analysis (Fig. 1). Given the estimated response time for engines to travel from each station to each RFL, we construct a set of stations within 30 minutes of each RFL. We use a 30-minute response threshold because

fast-spreading fires tend to escape initial attack if firefighting is not well underway within 30 minutes following a fire report.

We formulate the optimization model to deploy engines in days during the “high” fire season when multiple fires occur. We focus on days with multiple fires because draw-down of suppression resources on such days increases the likelihood that fires escape initial attack (Fried and Gilliss 1988). We construct 100 fire days representing days in which four or more fires occur. The fire days are constructed using stochastic simulation of the fire occurrence and behavior models of CFES2. The fire occurrence model includes random variables for whether or not any fires occur, and if so, number of fires, RFL of each fire, and ignition time (Fried and Gilliss 1988). The behavior model includes random variables for the rate of spread and dispatch index of each fire depending on fire weather and time of day (Gilliss and Fried 1999). Distribution functions for the random variables are estimated from fire occurrence and weather data recorded in the ranger unit during 1980–1990.

The parameters of the 100 fire scenarios in the optimization model are derived from information in the fire days obtained from stochastic simulation. Each fire scenario represents a single fire day and includes a list of RFLs where fires occur along with the number of engines required in the standard response to each fire. Mean daily number of fires is 4.82 with range 4–10. The standard responses range from 1 to 3 engines (i.e., $r_{ks} = 1, 2, \text{ or } 3$) reaching the fires within 30 minutes. The standard response to each fire depends on the fire’s dispatch index, which is derived from the maximum burning index for the day and scaled by a diurnal adjustment factor based on the time of occurrence. The higher the dispatch index, the more engines are required in the standard response. For each location k without a fire, the standard response is zero (i.e., $r_{ks} = 0$). We do not estimate the probability of occurrence of each fire day. Instead, we assume that each scenario is equally likely (i.e., $p_s = 0.01$, $s = 1, \dots, 100$).

Our analysis focuses on the trade-offs between the number of engines deployed to stations in stage one and the expected number of fires per day that do not receive a standard response in stage two. We compute optimal engine deployment for problems in which the objective function weight w is decreased from 1.0 (minimize number of engines deployed) to 0.0 (minimize number of fires not receiving standard response) in increments of 0.05 subject to a capacity constraint of four engines per station.

The two-stage standard response model (Eqs. 1–7) is a mixed-integer program. Applications are solved on a Dell Pentium 4 laptop computer (CPU 2.4 GHz) with the integrated solution package GAMS/Cplex 9.0 (GAMS Development Corporation 1990), which is designed for large and complex linear and mixed-integer programming problems. Input files are created in GAMS (General Algebraic Modeling System), a program designed to generate data files in a format that

standard optimization packages can read and process. Cplex solves a mixed-integer programming problem using a branch and cut algorithm, which solves a series of linear programming sub-problems.

Although the standard response model provides a spatial optimization of engine deployment based on a standard response objective, the model does not estimate the number of escaped fires. Therefore, we use CFES2 to evaluate the initial-attack effectiveness of optimal engine deployments obtained with the model. CFES2 simulates fires and initial attack in chronological order during each fire day. When a fire ignites, the model identifies the closest resources of the user-specified types to dispatch while accounting for resources previously committed to earlier fires. Fire perimeter growth and fire line production are simulated to determine whether or not containment is achieved within specified time and size limits. When all of the day’s fires are contained or declared escapes, resources are reset at initial positions and the simulation of the next fire day begins. Statistics for the expected number of escaped fires and expected area of contained fires are calculated over the set of fire days.

We configure CFES2 using data for the Amador-El Dorado planning unit. The model has the same 15 fire stations owned and operated by CDF or USDA Forest Service, each capable of hosting up to four engines staffed by personnel trained in wildland firefighting and considered capable of a relatively high rate of fireline construction. In addition to these primary engines, the model includes other initial-attack resources available to the planning unit, including hand crews, bulldozers, air resources (tankers and helicopters), and secondary engines operated by volunteer or local fire protection districts. The crews of secondary engines primarily protect buildings and produce fire line at much lower rates than do the crews of primary engines.

We use CFES2 to estimate the expected number of escapes associated with each deployment of primary engines obtained with the standard response model. Initial attack is simulated over the same set of 100 fire days from which the scenarios in the standard response model were derived. Hand crews, bulldozers, air resources, and secondary engines are present in their current number and position. We also compare the performance of primary engine deployments obtained with the standard response model with the performance of primary engine deployments obtained with a simple heuristic based on CFES2 estimates of expected engine utilization frequency. Starting with the current deployment of 22 primary engines in 15 stations, we incrementally drop the primary engine least utilized on fires greater than 4 ha during the 100 fire days and compute expected number of escapes for the resulting deployments.

4. RESULTS

The curve showing the tradeoff between number of primary engines deployed and expected number of fires per 4+ fire

TABLE 1
Objective function values and number of engines deployed per station for solutions from spatial optimization

Solution	Objective value		Engines deployed per station number														
	Engines deployed	Fires not covered	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A	0	4.82															
B	1	4.12					1										
C	3	3.05					2			1							
D	5	2.17					2	1		2							
E	7	1.52					3	2		2							
F	9	1.02		1			3	3		2							
G	11	0.66		3			3	3		2							
H	14	0.35		3			4	4		3							
I	16	0.22	3	3			4	3		3							
J	18	0.13	3	4			4	3		4							
K	22	0.05	4	4		4	4	3		3							

day (days on which 4 or more fires occurred) not receiving the standard response has a convex shape in which non-coverage decreases at a decreasing rate as number of engines deployed increases (Fig. 2). The points on the curve represent non-dominated solutions and their relative performance with respect to the two objectives. For each non-dominated solution, improvement in one objective cannot be achieved without simultaneously causing degradation in the value of the other objective. As a result, the points represent a frontier below which there were no better solutions.

The best deployment of primary engines depends on the objective function weight. If minimizing the number of engines deployed is most important (i.e., $w = 1$), the choice is solution A in which the expected number of fires not receiving the standard response is equal to the average daily fire frequency of 4.82 (Fig. 2). As more weight is given to minimizing the number of uncovered fires, more engines are deployed and fewer fires are not covered. For example, with 11 engines

deployed (solution G), the expected number of fires left uncovered is 0.66 (14% of the average number of fires per 4+ fire day). Increasing the number of engines from 11 to 22 (solution K) reduces the number of uncovered fires to 0.05 (1% of the daily average). The slope of the tradeoff curve, which represents the gain in daily number of fires covered per unit increase in number of engines deployed, is relatively steep between solutions A and G (0.40 fires/engine). Between solutions G and K, the slope is relatively flat (0.06 fires/engine).

Optimal solutions concentrate engines in stations that are close to RFLs with the highest fire loads. Over half of the fires (242) in the 100 fire scenarios occur in 12 RFLs near Highway 50, which crosses the northern half of the planning unit (Fig. 1). As a result, optimal solutions deploy engines to stations 2, 5, 6 or 8, which are within 30 minutes of those RFLs (Table 1). Locating 3–4 engines in each of those stations covers more than 90% of the fires (solution H). Engines are deployed elsewhere only when more than 14 engines are available (solutions I, J, K).

Because the engine deployments obtained with the standard response model (Table 1) are computed with a single set of 100 fire scenarios, we investigate the robustness of optimal engine deployments to changing the set of fire scenarios. Alternative solutions with 3, 11, and 22 engines are computed using four different sets of 100 scenarios with four or more fires per day. Relative to the solutions in Table 1, engine deployments obtained with different sets of scenarios differ by at most one station.

Using CFES2 to evaluate the performance of engine deployments obtained with the standard response model (Table 1), we found that the expected number of escapes per 4+ fire day dropped as the number of engines deployed increased (Table 2). With only one engine deployed, the expected number of escapes was 0.97 (20% of the daily average

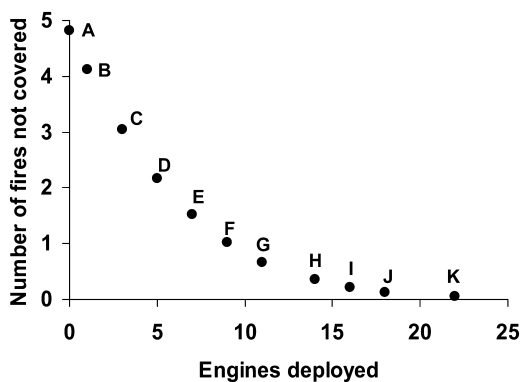


Figure 2. Tradeoff between number of primary engines deployed and expected number of fires per 4+ fire day (days on which 4 or more fires occurred) that do not receive a standard response.

TABLE 2

Expected number of escapes per 4+ fire day (days on which 4 or more fires occurred) computed with CFES2 for engine deployments obtained from the standard response optimization model and from a simple location heuristic combined with CFES2

Engines deployed	Expected escapes for engine deployments obtained from	
	Standard response model	Heuristic with CFES2
1	.97	1.04
3	.82	.80
5	.66	.63
7	.59	.53
9	.42	.43
11	.38	.38
14	.31	.33
16	.31	.33
18	.30	.33
22	.30	.33

number of fires), indicating that hand crews, bulldozers, air resources, and secondary engines contained 80% of the fires without help from primary engines. Increasing the number of primary engines to 14 or more reduced the expected number of escapes to 0.31 (6% of the daily average number of fires).

For comparison with engine deployments obtained with the standard response model, we use a simple heuristic in conjunction with CFES2 to determine engine deployments. Starting with the existing configuration of 22 engines in 15 stations, we incrementally remove engines that are least used on fires greater than 4 ha during the 100 fire days. The resulting

deployments place engines in more stations than do deployments obtained with the standard response model (Table 3). The engine deployments obtained with the heuristic leave more fires uncovered according to the objective function used in the standard response model (Table 3); however, the engine deployments obtained with the heuristic produce almost the same number of escapes as do the deployments obtained with the standard response model (Table 2). When nine or more engines are deployed, solutions obtained with the standard response model contain slightly more fires than do solutions obtained with the heuristic. When fewer than nine engines are deployed, solutions obtained with the heuristic are slightly superior.

For comparison with solutions obtained with the standard response model and the heuristic, we compute the performance of five random engine deployments for each level of engine force. The solutions obtained with the standard response model and the heuristic allow up to 30% fewer escapes compared with random engine deployments, suggesting that engine location does affect the likelihood of fire containment.

The setup and computation times required for the optimization and simulation models provide an interesting comparison of work loads. All of the applications were run on a Dell Pentium 4 laptop computer (CPU 2.4 GHz). Once the optimization model has been programmed in GAMS, manually changing the setup parameters (e.g., upper bound on number of engines deployed) takes seconds. Computation time required to solve problems with 46 representative fire locations, 15 stations, and 100 fire scenarios using GAMS/Cplex 9.0 is less than 10 minutes. With CFES2, setting up the files for a given engine deployment is done manually and requires about three minutes. Simulating the initial attack performance of a given engine deployment over 100 fire days requires a few seconds.

TABLE 3

Objective function values and number of engines deployed per station for solutions from a simple location heuristic combined with CFES2

Objective value		Engines deployed per station number														
Engines positioned	Fires not covered	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	4.82															
1	4.28								1							
3	3.10					1	1		1							
5	2.40				1	1	1		2							
7	1.90				2	1	1	1	2							
9	1.37	1	1		2	1	1	1	2	2						
11	0.95	1	2		2	1	1	2	2							
14	0.80	2	2	1	2	1	1	2	2		1					
16	0.73	2	2	1	2	1	1	2	2		1		1	1		
18	0.71	2	2	1	2	1	1	2	2		1		2	1	1	
22	0.61	2	2	1	2	1	1	2	2	1	1	1	1	2	2	1

5. DISCUSSION

The problem of deploying and dispatching wildland fire suppression resources can be formulated as a standard response model with resource constraints and uncertainty about the daily number, location, and intensity of fires. The model assumes that fire managers have a desired response to each fire, expressed as the number of resources that must reach the fire within a specified time, and an objective of minimizing the number of fires that do not receive the desired response. Ignition uncertainty is characterized by a set of daily fire scenarios, each listing the location and intensity of fires that occur in a single day. The model includes locations of fire stations and potential fires along with times required for travel between stations and fires. The model does not include rates of fire line construction and fire growth and does not attempt to model or predict fire containment as a relationship between fire line and fire perimeter (e.g., Donovan and Rideout 2003). The model is well suited to determining trade-offs between objectives of minimizing the number of resources deployed and minimizing the number of fires that do not receive a standard response, and those tradeoffs can provide valuable information to fire managers. The tradeoff curve has a convex shape with slope representing the gain in daily number of fires covered per unit increase in deployment. Estimates of the cost of increasing deployment can be compared with estimates of the benefits of reduced fire damage that result from additional fire coverage to determine appropriate levels of initial attack investment.

In contrast to the standard response model that we present, stochastic simulation models of initial attack include more detailed rules for growing fires, dispatching resources, producing fire line, and evaluating initial attack effectiveness. As a result, stochastic simulation models are increasingly used by fire managers to evaluate changes in the deployment of initial attack resources (e.g., Fried et al. 2006). Stochastic simulation models of initial attack are not typically used to optimize resource deployment. Although methods for optimizing stochastic simulation models are well established in research (e.g., Fu et al. 2005), their practical application is often hindered by software and computational requirements. For example, CFES2 currently requires about three minutes to manually setup a given engine deployment. Because heuristic algorithms typically evaluate 100s or even 1000s of alternative solutions, constructing alternative solutions must be automated in conjunction with the heuristic. The automation of engine deployment would require additional software for CFES2.

Another approach to simulation optimization is to formulate a tractable model that is a caricature of the simulation system. Our formulation of a standard response model is an example of this approach. Although the standard response model is a simplified version of an initial attack system, the model can easily be applied to practical problems and solved with commercial software on a laptop computer. The results of standard

response optimization can then be evaluated with stochastic simulation and compared with alternative resource configurations suggested by heuristics or expert knowledge.

Our application in the Amador/El Dorado planning unit in California focuses on the deployment of up to 22 primary engines among 15 stations, assuming that other resources such as hand crews, bulldozers, air resources, and secondary engines are retained in their current locations. The application involves 100 scenarios of potential fire days, each with 4–10 fires occurring at different locations. With this setup, we find that 22 primary engines along with the other initial attack resources contain 94% of the fires. Incrementally reducing the number of primary engines from 22 to 1 reduces the containment rate to 80%. The number of contained fires is sensitive to where the primary engines are deployed, and deployment configurations obtained with the standard response model perform as well as those obtained with a simple heuristic for incrementally removing engines based on simulation estimates of expected utilization frequency.

Solutions obtained with the standard response model and the simulation heuristic demonstrate that different strategies for deploying a given number of engines can have about the same level of performance in terms maximizing the expected number of contained fires. The standard response model concentrates engines at busy, central locations whereas the simulation heuristic disperses engines among a larger number of stations. Having a range of high-performing strategies allows managers to consider other objectives. For example, concentrating engines at a few stations may have lower costs of station opening and maintenance. However, spreading engines among several stations may produce more equitable fire containment across districts of the fire planning unit. Further, a fire planning unit typically has mutual aid agreements with neighboring units thereby increasing the demand for engines at fringe stations.

The strength of the scenario-based standard response model is its tractability. The model is easy to program and can be solved in minutes on a laptop computer using commercial software. Although we used 100 scenarios of fire days in our application, fewer scenarios could be used in cases with less variability in the number and location of fires. Models with fewer scenarios would solve in seconds. More research is needed to evaluate the effectiveness of the standard response model on problems with several types of resource and cost constraints.

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