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Optimizing Prepositioning of Equipment and Personnel for Los Angeles County Fire Department to Fight Wildland Fires

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Abstract. Every day, the Los Angeles County Fire Department uses weather forecasts and automated real-time weather observations, together with field-tested moisture content of soil and vegetation, to decide whether and where to position firefighting equipment and personnel, as well as what equipment to use, for the following day. Anticipating a particularly hazardous "red flag" day, they activate off-duty personnel and reserve equipment and add these to the total augmented, prepositioned force. Analysis of years of detailed daily data can advise these costly decisions. Three models, respectively, predict for each region of the county the probability of a fire start, the area burned by a fire given any particular package of equipment and personnel preassigned to fight it, and which packages to form and send to each position. The conflicting objectives are to minimize the expected number of citizens evacuated and the constrained augmentation cost for personnel and equipment.

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O for a Muse of fire, that would ascend the brightest heaven of invention. —William Shakespeare, *Henry V*

The Problem

Many areas of California are subject to the threat of wildfires, particularly in the summer and autumn, when warm temperatures combined with low precipitation, seasonal high winds, and difficult mountainous terrain increase the threat. They pose an acute menace to the densely populated Los Angeles area, which historically has seen many serious wildfires. A recent example is the Woolsey Fire in November 2018, which burned an area of nearly 100,000 acres (40,000 ha) and inflicted losses estimated at more than $6 billion (Cosgrove 2019). The Woolsey Fire destroyed 1,643 structures, caused the evacuation of more than a quarter-million people, and claimed three lives.

Not surprisingly, cities and counties in the Los Angeles area devote substantial resources to combatting the threat of wildfires. The Los Angeles County Fire Department (LACoFD) is responsible for protecting the lives and property of 4 million residents living in 1.2 million housing units in 58 cities and all unincorporated areas of Los Angeles County. This is a land area of about 4,700 mi^2 (12,200 km^2). The LACoFD has almost 3,000 employees, maintains 173 fire stations, and answers almost 400,000 annual emergency calls, with an annual budget of $1.2 billion.

The mission of the LACoFD is "to protect lives, the environment, and property by providing prompt, skillful and cost-effective fire protection and life safety services" (LACoFD 2020, p. 4). Specifically, the LACoFD has three objectives that relate to our research:

1. Protection of life: minimize both population and firefighter loss;

2. Incident stabilization: contain 95% of all wildland fires to 10 acres (4 Ha) or less; and

3. Property and environment protection and conservation: minimize the total wildland acreage burned.

The LACoFD repositions its wildland firefighting resources when "red flag" hazard conditions are forecast for any of its diverse areas of responsibility, a process known as "augmentation." This is a complex problem, given the variety of on- and off-duty resources, their cost, and the inherent uncertainty about potential fires and their severity.

In the following, we refer to relevant literature; review the real-time data used; explain how we predict the probability of a fire and the area burned of one that has started; and introduce the Augmentation Optimization Model (AOM) and explain how it is used.

Literature Review

There is a huge amount of literature on wildfires—their sources, history, prediction, spread, physics, control, economic and environmental impact, etc. Here, we are interested solely in improving the efficacy of daily decisions to augment forces for tomorrow (i.e., move existing forces and/or mobilize off-duty reserves in anticipation of a potential fire).

Even in this restricted domain, there is a lot of legacy research. Sparhawk (1925) presents a least cost plus loss function to evaluate the effectiveness of forest-fire fighting. Pyne et al. (1996) present an analysis of factors (e.g., ease of start, rate of spread, difficulty of control, and fire impact) contributing to the computation of a "burn index" (BI) score, a scalar (numeric) risk assessment. Viitala (1999) presents a comprehensive analysis of initial attack, the interactions of the variety of combined resources, and a dynamic program that quickly solves a nonlinear integer optimization. Donovan and Rideout (2003) present an integer linear program (essentially a knapsack problem with side constraints) to minimize a cost plus new value change function that expresses costs of fire suppression with net fire-related damages, subject to constraints on indivisible resource packages assigned. Schoenberg et al. (2007) present an analysis of the efficacy of standard wildland fire risk metrics for Los Angeles County using data on 592 wildfires burning at least 10 acres from 1976 to 2000. Rahn (2010) assesses personnel effectiveness at, for instance, hose lay rate, establishing that productivity is not a linear function of number of personnel and that steepness of terrain and vegetation type are key influences. Hemme and Cox (2018) work with LACoFD data and develop a "resource capability score," a weighted sum of hose lay rate and production rate (i.e., rate of fireline clearance) for packages of equipment types and crew sizes. Using these scores to rate the capability of each region and the forecast fire threat there, they advise when to augment with additional resources. The National Wildfire Coordinating Group (NWCG 2019) explains the National Fire Danger Rating System (NFDRS) and its components. Scholz (2019) gives considerable additional detail to the subsequent work reported here.

Los Angeles County Fire Department Data

The LACoFD has provided data to model the augmentation problem, including available resources (engines, water tenders, and on- and off-duty personnel) by fire station, *subarea*, or *climatic zone*, as applicable; resource characteristics (e.g., water capacity, staffing requirements, relocation cost, and overtime cost); historical weather data (e.g., wind speed and temperature); and historical fire events (e.g., location, burned acreage, and prepositioned resources at the time of event).

Regarding resources, the LACoFD employs specialized equipment staffed by several classifications of personnel. Most of their fleet consists of four types of truck (types I, III, and VI and water tender). The personnel who staff these vehicles fall into three categories—firefighter (FF), firefighter specialist (FFS), and captain (CA)—but the staffing is not uniquely determined for type I and type VI (see Figure 1). The number of personnel assigned influences truck effectiveness. For example, per-minute rates of hose laying or clearing firebreaks are key determinants of suppression effectiveness, and these depend on the number of personnel on scene.

The LACoFD also uses other resources that can be incorporated in our model (but are not part of the operational testing reported in this paper), including hand crews (consisting of inmates assigned to manually cut fire lines), fire-suppression aides, bulldozers, helicopters, and air tankers.

Los Angeles County has great diversity of climate, terrain, and vegetation types, as well as population density. It is divided by the LACoFD into five climatic zones, each relatively homogeneous by weather, topography, and vegetation. Throughout these zones, 21 remote automated weather stations (RAWSs) are linked to Weather Information Management Systems (WIMS). See Figure 2. We use RAWSs as subareas for the purpose of prepositioning, where each RAWS may contain multiple fire stations.

We use the LACoFD's weather data dating back to 1976 from WIMS (e.g., NWCG 2019) and daily fire events with soil and vegetation conditions.

Table 1 displays a variety of LACoFD data components, some being real-time observations by RAWSs, some from remote sensing, and others simple calendar information that can help assess influences of climactic season and levels of various human activities. We have used these to assess the probability of fire

Figure 1. LACoFD Rolling Equipment

Notes. From left to right are type I, III, and VI engine variants and a water tender. Each type I structural engine is staffed with a CA, an FFS, and one or two FFs. Each type III off-road vehicle carries a CA, an FFS, and two FFs. Each type VI off-road patrol engine carries an FF and perhaps a CA. Each water tender is driven by an FFS.

Figure 2. Five Los Angeles County Climatic Zones

Notes. Each zone has relatively homogeneous climate, terrain, vegetation, and population density. Black dots locate most of the 21 RAWSs, named here. Santa Clarita, Santa Catalina Island, and San Clemente Island are not pictured.

start and the behavior of a started fire (given our preparations of equipment and personnel).

These data are summarized and evaluated in a daily weather and fire-danger analysis report for each climactic zone (Appendix Table A.1 shows an example).

Table A.2 shows the climatic type, burn index thresholds (BITs), and number of daily observations of fire conditions for the five climactic zones of Los Angeles County. The LACoFD sets the BITs at 97% (except 90% in Santa Monica) of the recorded historic

Table 1. Data Components Used to Predict Wildland Fires

Component	Definition
BI	Burn index. Estimate of the potential difficulty of fire containment as a function of flame length at the most rapidly spreading portion of a fire's perimeter (e.g., National Park Service 2019).
TEMP	Temperature. Degrees Fahrenheit.
RH	Relative humidity. Percentage air saturation.
WIND	Wind. Wind speed 20 ft. (6 m) above surrounding vegetation.
LFM	Live fuel moisture. Measured bimonthly in regions by the LACoFD.
DFM	Dead fuel moisture. Percentage of water in vegetation relative to its dry weight and how long it would take for two-thirds of the dead fuel to equalize with the local moisture (NOAA 2019).
SC	Spread component. NFDRS ideal rate of wildland fire spread in feet per minute based on a mathematical model (Rothermel 1972).
ERC	Energy release component. NFDRS available energy per unit area within the flaming front at the head of a fire (Schlobohm and Brain 2002). This uses LFM and DFM indices.
KBDI	Keetch–Byram Drought Index. The relative amount of precipitation that would return the top 8 in. of soil to its full moisture capacity, ranging from 0 (saturated) to 800 (dry) (Keetch and Byram 1968).
Month	Calendar month. Annual numeric ordinal.
Day	Calendar day. Annual numeric ordinal.
Weekend	Weekend indicator. Binary indicator of weekend or holiday day to reflect increased human outdoor activity with respect to regular weekdays.

Note. RAWSs report some components; remote sensing and/or physical inspections of vegetation and soil condition assess others; and some are results of mathematical models using the other components and weather forecasts as inputs.

BIs. This index triggers red-flag-day augmentation of forces: Usual policy is to augment resources only in RAWSs that exceed this BIT.

We have a daily synopsis outlining every brush and wildland fire recorded since 2000 and its consequences. Unfortunately, many of these data were in stored papers, not computer files. Lots of scanning and manual verification produced the unified LACoFD historic database we use. In addition, we have prepositioned resource information, but only since 2015.

Finally, we need the costs of augmentation actions such as point-to-point equipment movement and daily labor of activated off-duty personnel. We need the existing locations of on-duty and off-duty reserve personnel and equipment and the capacities of stations to accommodate our augmenting forces. The LACoFD knows these costs and capacities, and this is a modest volume of data.

Predicting the Probability of a Wildland Fire Start and its Burned Area

Given forecast fire-risk conditions for a RAWS subarea, we focus on estimating the consequences of prepositioning any alternate package of equipment and personnel to a location within that area. This suggests two estimation models to predict

1. The probability of a fire start; and
2. Given any planned prepositioning, the area burned by a fire start.

Each of our models uses a random 80% subset of observations for building the model and reserves the remaining 20% for validation.

Model for Probability of a Fire Start

We use logistic regression for estimating the fire-start probability. Machine-learning techniques such as classification trees and random forests are plausible alternatives for estimating the probability of a fire start from a set of predictor variables. See Faraway (2016) for descriptions of these techniques. However, they pose challenges when used as a front end to an optimization procedure because of the discrete nature of their output (e.g., classification trees) or the lack of a closed form for the estimator itself (e.g., random forests). Most importantly, we did not find that classification trees or random forests perform better than logistic regression in our application.

Using the Los Angeles Basin zone as an example, there are six RAWS subareas: Santa Fe Dam, Henninger Flats, Claremont, Whittier, San Rafael, and Tonner Canyon. We used the sample for each subarea and some cross-products of scalar predictors, seeking significant interactions between these.

Table 2 shows, for the Los Angeles Basin climactic zone, a logistic regression model for predictors $x_q,\ q \in Q$ (here, $|Q| = 14$), where the estimated $\widehat{\eta} = \widehat{\beta}_0 + \sum_{q \in Q} \widehat{\beta}_q x_q$ is used to yield the probability of a fire $\frac{e^{\widehat{\eta}}}{1+e^{\widehat{\eta}}}$. We have produced similar logistic regression analysis for the four other climatic zones.

A common metric used to evaluate the accuracy of a model is the area under the receiver operator characteristic curve, referred to as the "area under the curve" (AUC). See Figure 3. For the given zone, the AUC is good (0.802). We obtain similar results for all other climatic zones.

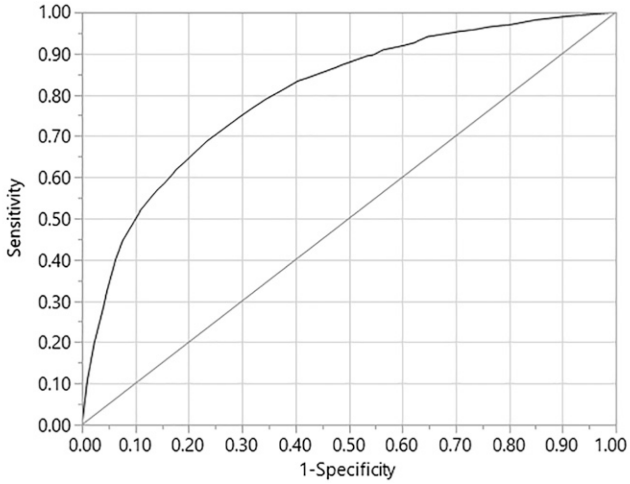
Table 2. Logistic Regression to Predict Daily Fire Start in Los Angeles Basin Climatic Zone

Predictor term	$\widehat{\beta}$	$\widehat{\beta}$ SE	Wald $\chi 2$	p-value	Odds ratio	95% CI odds ratio
Intercept $\widehat{\beta}_0$	−6.66	3.68E-01	327.54	<0.0001		
BI	1.70E-02	6.90E-03	6.07	0.014	1.017	(1.003, 1.031)
Temperature	5.44E-02	3.24E-03	281.75	<0.0001	1.056[a]	(1.049, 1.063)
RH	−1.05E-02	4.08E-03	6.65	0.010	0.990[a]	(0.982, 0.997)
Wind	1.92E-02	9.79E-03	3.84	0.050	1.019	(1, 1.039)
ERC	−2.21E-02	7.92E-03	7.78	0.005	0.978[a]	(0.963, 0.993)
LFM	7.93E-03	9.20E-04	74.45	<0.0001	1.008	(1.006, 1.01)
SC	−2.21E-02	9.44E-03	5.48	0.019	0.978	(0.96, 0.996)
Temperature x RH	7.60E-04	1.63E-04	21.75	<0.0001		
RH × ERC	−3.43E-04	1.10E-04	9.71	0.002		
RAWS Claremont	8.46E-02	5.59E-02	2.29	0.130		
RAWS Henninger Flats	−1.12E+00	9.44E-02	140.58	<0.0001		
RAWS San Rafael	−6.76E-01	6.58E-02	105.74	<0.0001		
RAWS Santa Fe Dam	2.18E-01	5.35E-02	16.62	<0.0001		
RAWS Tonner Canyon	−3.79E-01	7.04E-02	28.97	<0.0001		

Notes. Each row shows a predictor coefficient with its standard error (SE), Wald chi-square (χ^2) test statistic, probability value (p-value) for the Wald test, odds ratio, and the 95% confidence interval (CI) on the odds ratio. The last five predictors are binary for the RAWSs being analyzed. One RAWS in this zone, Whittier, has been omitted to avoid linear dependence among these predictors.

[a]Odds ratios not meaningful owing to involvement with compound effects.

Figure 3. Receiver Operator Characteristic Curve for Los Angeles Basin



Notes. This tests our regression with the randomly chosen 6,417 observations reserved as the validation data set. The horizontal axis shows the false-positive rate (the complement of specificity), and the vertical axis displays the true-positive rate (also called sensitivity, recall, or probability of detection). The AUC is proportionate to the probability that our regression will rank a randomly chosen fire-start day higher than a randomly chosen day without fire. With AUC 0.802, this is a good model.

Model for Burned Area After a Fire Start

Heuristic Capability Score of Resource Package. Prepositioned resources (personnel and equipment) can be used to create a potential explanatory variable for the estimation of burned area of a wildland fire. Given that we only have prepositioning data since 2015, in comparison with the large number of possible combinations of resources, we have a limited number of fire events for each combination (in most cases, none). Thus, we use a heuristic *capability score* as a proxy for the total combined firefighting capability of a package of personnel and equipment.

A typical fire progresses (and is eventually contained) in the shape of a pie slice: two sides, "flanks," of an isosceles triangle with "anchor" apex angle x degrees (where x depends mainly on wind) and a circular arc segment base, "head," centered on the apex. The fire starts at the anchor and continues downwind to the advancing head. For example, for a 10-acre area and $x = 45°$, the perimeter is 3,092 ft. (942 m), 1,110 ft. on each side, and 872 ft. across the head arc. The fire suppression starts at the anchor and continues down each flank in a pinching action, eventually moving in on the head to achieve containment.

Fighting a fire may involve many tactics, but two basic operations are always crucial: laying fire hoses to get water to the fire and cutting fire lines to create a barrier to the fire. Rahn (2010) derives initial estimations for both of these: hose lay rate (feet/minute per crew) as a function of the engine's crew size and steepness of terrain; and production rate of firebreak cleared (feet/minute) as a function of total personnel, steepness, and vegetation type. Specific examples of these rates are shown in Tables A.3 and A.4, respectively.

Hemme and Cox (2018) use Rahn's estimates and work with LACoFD data to develop a heuristic capability score of prepositioned resources based on the ratio of firefighting personnel (excepting the FFS driving each water tender), F, to engines carrying hoses, H. In addition, the capability score of Hemme and Cox uses water capacity of engines (shown in Table A.5, along with other attributes). The estimated capability is expressed in number of feet per minute of firebreak cleared according to the following model.

Index Sets

$r \in R$: resource type (engines and personnel).

Given Data

n_r: number of resource type r prepositioned (engines or persons)

f_r: firefighters in a unit of resource type r (persons)

H: number of engines carrying hoses (see Table A.5) (engines)

ω_r: water capacity of resource type r (see Table A.5) (gallons)

ρ_r: production rate of fire line clearing by personnel type r [feet/(minute × person)] (see Table A.4).

Derived Data

F: total firefighting personnel, excluding water tenders: $F = \sum_{r\in R\setminus\{WT\}} n_r f_r$

$AvgCrew$: average hose-laying crew size: $AvgCrew = \begin{cases} F/H & \text{if } F/H \geq 3 \\ \dfrac{F - n_{T\_VI} - n_{CA}}{H - n_{T\_VI}} & \text{if } F/H < 3 \end{cases}$

$\bar{\lambda} = \lambda(AvgCrew)$: hose lay rate of average crew size [feet/(minute × crew)] (see Table A.4).

Output

C: combined capability score of prepositioned resources (feet/minute):

$$C = \begin{cases} \bar{\lambda} \times H \times AvgCrew \times \left(1 + \dfrac{\omega_{WT} n_{WT}}{\sum_{r\in R\setminus\{WT\}} \omega_r n_r}\right) & \text{if } \dfrac{F}{H} \geq 3: \\ \bar{\lambda} \times H \times AvgCrew \times \left(1 + \dfrac{\omega_{WT} n_{WT}}{\sum_{r\in R\setminus\{WT\}} \omega_r n_r}\right) + \rho_{T\_VI} n_{T\_VI} + \rho_{T\_VI\_CA} n_{T\_VI\_CA} & \text{if } \dfrac{F}{H} < 3. \end{cases}$$

If F/H is three or more, we use it as the average number of personnel laying hose: Typically, at least two firefighters are needed laying a hose, while one stays back operating the pump. If under three, we apply the same ratio after excluding type VI engines: For each engine, we subtract one FF (the driver) and one CA (if any) from the numerator and one engine from the denominator. In such a case, these FF and CA personnel will be devoted to clearing fire lines, at their given production rates. The baseline hose laid $\bar{\lambda} \times H \times AvgCrew$ is measured in feet/minute. The additional (unitless) factor is the ratio of water-tender capacity to all other engines. The idea behind this additional coefficient is to factor in the positive effect water tenders have when there are limited resources on site (because it allows those resources to remain longer, without the need to travel to resupply). It is understood that the capability score C is not uniquely defined. Precise estimates require a deeper study beyond the original scope of this paper. We use C as one of many factors to predict fire spread (i.e., once a fired has started) in the following paragraph.

Burned-Area Regression Model. The LACoFD provided 2,919 fire-start incident reports, ranging in area from 41,000 acres (16,592 ha) to merely 100 ft^2 (0.00093 ha). Areas are replaced by their logarithms to make this more amenable for multiple regression. We also decided not to separate these data by the five climate zones, concluding that a single multiple regression would be better, given the limited amount of data for some zones. In addition, some cross-products of scalar predictors are used, seeking significant interactions between these.

We use a heuristic k-means clustering (Lloyd 1982) of observations in order to group similar weather conditions and fire danger indices and determine whether certain weather clusters are associated with similar burned acreage results. The cluster predictors used are temperature, wind, relative humidity (RH), and dead fuel moisture (DFM); and the four fire danger indices are BI, energy-release component (ERC), spread component (SC), and Keetch–Byram Drought Index (KBDI). This analysis yields 29 clusters, used as candidate predictors. More precisely, we perform a multiple linear regression for each cluster; then, we classify the above four danger indices for the day into one of the clusters by finding the cluster at minimum total squared distance between the day data and the cluster's mean (normalized by the cluster's standard deviation). The chosen weather cluster ($\widehat{wc}$) has a coefficient $\widehat{\beta}_{\widehat{wc}}$ used as a predictor (see Table 3; for brevity, we omit details of individual cluster coefficients for each danger index). The table also shows, for each cluster predictor, the standard error (SE), t-statistic (the coefficient divided by its SE), and its exceedance probability.

In addition to the 29 weather clusters (contributing a specific $\widehat{\beta}_{\widehat{wc}}$), we also use stepwise regression applying a 1-OPT local myopic heuristic to minimize the Akaike information criterion (Akaike 1973, Faraway 2016) to produce the model in Table 4. This shows the resulting model for predictors x_q, $q \in Q'$ (here, $|Q'| = 26$) and their statistics.

Table 3. Regression Coefficients for Expected Burned Acreage by Weather Cluster

Weather cluster (wc)	$\widehat{\beta}_{wc}$	$\widehat{\beta}_{wc}$ SE	t-statistic	p-value $\Pr(>\lvert t \rvert)$
Weather cluster 1	0.238	0.205	1.16	0.246
Weather cluster 2	−0.024	0.277	−0.09	0.931
Weather cluster 3	−0.211	0.213	−0.99	0.321
Weather cluster 4	0.531	0.351	1.51	0.131
Weather cluster 5	−0.038	0.487	−0.08	0.939
Weather cluster 6	−0.137	0.213	−0.64	0.521
Weather cluster 7	−0.203	0.186	−1.10	0.274
Weather cluster 8	0.032	0.265	0.12	0.905
Weather cluster 9	−0.222	0.333	−0.67	0.505
Weather cluster 10	−0.088	0.213	−0.41	0.680
Weather cluster 11	0.062	0.435	0.14	0.887
Weather cluster 12	0.180	0.256	0.70	0.483
Weather cluster 13	−0.031	0.359	−0.09	0.932
Weather cluster 14	−0.203	0.196	−1.03	0.302
Weather cluster 15	−0.546	0.254	−2.15	0.032
Weather cluster 16	0.339	0.252	1.35	0.178
Weather cluster 17	0.249	0.368	0.68	0.498
Weather cluster 18	−0.158	0.237	−0.67	0.506
Weather cluster 19	−0.079	0.197	−0.40	0.689
Weather cluster 20	−0.146	0.200	−0.73	0.465
Weather cluster 21	0.074	0.232	0.32	0.750
Weather cluster 22	0.027	0.241	0.11	0.910
Weather cluster 23	1.490	0.395	3.78	0.000
Weather cluster 24	−0.485	0.214	−2.26	0.024
Weather cluster 25	0.314	0.419	0.75	0.454
Weather cluster 26	−0.227	0.195	−1.16	0.245
Weather cluster 27	0.195	0.352	0.56	0.579
Weather cluster 28	−0.325	0.219	−1.48	0.138
Weather cluster 29	−0.894	1.709	−0.52	0.601

Finally, burned acreage is estimated as follows: $\ln(area) = \widehat{\beta}_{\widehat{wc}} + \widehat{\beta}_0 + \sum_{q \in Q'} \widehat{\beta}_q x_q$.

Unfortunately, these data do not include terrain slope, elevation, or type of brush cover, and each fire is estimated to have started at the nearest RAWS location. Future data collection will capture these important details.

We have also been careful to collect data on personnel and equipment prepositioned *before* a start, and not the forces sent in later when a fire escapes initial containment. Otherwise, our model would predict that more forces lead to bigger fires. The purpose of this research is to determine how *prepositioning* can be optimized.

Augmentation Optimization Model

Our linear, integer optimization model advises what personnel and equipment to position where, in order to minimize the following day's expected numbers of evacuations without exceeding a given budget (and also with a small incentive to avoid needless costs). The courses of action include repositioning on-duty

Table 4. Multiple Linear Regression Model Estimating Expected Burned Acreage of a Wildland Fire

Predictor term (q)	$\widehat{\beta}_q$	$\widehat{\beta}_q$ SE	t-statistic	p-value Pr(>|t|)
Intercept $\widehat{\beta}_0$	−0.805	0.616	−1.31	0.191
Wind	0.028	0.013	2.19	0.029
BI	0.010	5.24E-03	1.86	0.064
Temperature	0.013	4.38E-03	2.86	0.004
RH	5.91E-03	0.007	0.81	0.419
ERC	−0.020	0.010	−2.13	0.033
SC	−0.012	3.65E-03	−3.40	0.001
KBDI	−1.12E-03	3.43E-04	−3.26	0.001
DFM	−0.143	0.056	−2.57	0.010
Combined capability score, C	−3.14E-04	5.10E-05	−6.15	<0.0001
BI × RH	−3.29E-04	1.14E-04	−2.88	0.004
BI × KBDI	−2.80E-05	1.45E-05	−1.94	0.053
Wind × temperature	−1.42E-03	4.89E-04	−2.91	0.004
RH × SC	3.06E-04	1.01E-04	3.03	0.002
RH × C	−1.73E-05	8.69E-06	−1.99	0.047
Wind × ERC	−9.31E-04	4.87E-04	−1.91	0.056
Wind × DFM	−0.018	4.41E-03	−4.06	<0.0001
ERC × KBDI	6.15E-05	1.98E-05	3.11	0.002
ERC × C	6.77E-06	2.19E-06	3.10	0.002
SC × KBDI	2.43E-05	9.52E-06	2.56	0.011
KBDI × DFM	2.87E-04	1.30E-04	2.21	0.027
DFM × C	1.70E-04	5.74E-05	2.97	0.003
Week number	8.01E-03	2.83E-03	2.83	0.005
Los Angeles Basin	−0.108	0.103	−1.05	0.295
Santa Monica Mountains	−0.153	0.104	−1.47	0.142
Santa Clarita Valley	0.197	0.100	1.97	0.049
High Country	0.394	0.146	2.70	0.007

Notes. The combined capability score turns out to be a significant predictor (including interactions with other predictors), and there are no counterintuitive predictors of significance. There are four indicator variables for region, with one region (Antelope Valley) omitted to avoid linear dependence among predictors.

equipment and personnel, fortifying preparations for red-flag locations, while at once preserving minimal required presence in other locations. We can also advise calling up (augmenting with) off-duty equipment and personnel to join on-duty forces.

Engine costs (see Table A.5) are relatively small, given that distances for the LACoFD are within 100 mi. (161 km.). On-duty personnel do not incur additional expenses, except \$0.55 per mile to drive from their home fire station to a destination RAWS location, so the main cost is for calling up off-duty personnel, who constitute approximately one-third (152 CAs, 141 FFSs, and 166 FFs) of all personnel. Their daily rates at the beginning of 2020 are \$1,968, \$1,656, and \$1,392, respectively.

Because the LACoFD deals with wildland fires, we are less concerned with the economic value of particular assets at risk; rather, we view the number of evacuees required as a good surrogate for loss. Accordingly, we estimate loss for each subarea as the product of the probability of start, expected burned area *given firefighting resources assigned*, and population density per area. (There is no implicit independence assumption here: These regression estimates share a largely common set of predictors.)

We estimate the burned area for every admissible combination of firefighting resources using our regression model with all relevant factors to include the capability score C for the given resources. Although there are many of these combinations, for this problem, total enumeration is feasible, and we term each of those combinations a candidate resource *package*.

The AOM formulation is as follows.

Index Use [~Cardinality]

$w \in W$:	RAWS subarea, alias w' [~20]
$w^+ \in W^+ \subseteq W$:	RAWS subarea that can gain resources
$w^- \in W^- \equiv W \backslash W^+$:	RAWS subarea that can lose resources
$s \in S$:	fire stations [~200]
$S_w \subset S$:	subset of stations in RAWS w
$r \in R$:	resource unit, alias r' [~20]
$e \in E \subset R$:	subset of off-duty engine types, $E = \{$o_T_I, o_T_III, o_T_VI, o_WT$\}$
$p \in P \subset R$:	subset of off-duty, personnel types, $P = \{$o_CA, o_FFS, o_FF$\}$
$d \in D \subset R$:	subset of on-duty resources (engines, staffed engines, and personnel; see Table A.5)
$b \in B$:	resource assembly type recipe [~20]

$k \in K$: prepositioned resource package [~700,000]

$k \in K_w \subset K$: prepositioned resource package for RAWS subarea w [~24,000].

Given Data [Units]

BI_w, BIT_w: Burn Index and Burn Index Threshold ($BI_{w^+} \geq BIT_{w^+}$, $BI_{w^-} < BIT_{w^-}$)

$expected\_loss_{w,k}$: expected loss from RAWS subarea w with package k stationed there (estimated via the probability of fire from Table 2, the combined capability score C of the package, the regression equation in Table 3, and the population density of the RAWS subarea) [expected number of evacuees]

$number_{k,d}$: number of units of on-duty resource $d \in D$ in package k [d-units]

$off\_duty\_pool_p$: number of units of off-duty resource $p \in P$ and available for call-up [p-units]

$off\_duty\_station_{s,e}$: number of off-duty resource $e \in E$ at station s and available for call-up [e-units]

$component_{b,r',d}$: for assembly recipe b, the number of resource units r' required per unit of on-duty resource $d \in D$ (see Table 5) [r'-units/d-unit]

$on\_duty\_avail_{w,d}$: in RAWS subarea w, baseline on-duty resource $d \in D$ available [d-units]

$move\_cost_{w^-,w^+,r}$: cost to move a unit of resource type $r \in R$ from RAWS subarea w^- to subarea w^+ [cost units/r-unit]

$call\_up\_equipment\_cost_e$: 24-hour cost of employing off-duty resource $e \in E$ [cost units/e-unit]

Table 5. Assembly Recipes

Assembled resource							
Recipe	Input	T_I_3	T_I_4	T_III	T_VI	T_VI_CA	WT
Use_T_I_3	T_I_3	1					
Use_T_I_4	T_I_4		1				
Use_T_III	T_III			1			
Use_T_IV	T_IV				1		
Use_T_IV_CA	T_IV_CA					1	
Use_WT	WT						1
Make_T_I_4	T_I_3		1				
	FF		1				
Make_T_VI_CA	T_VI				1		
	CA				1		
Call_T_I_3	o_T_I	1					
	o_CA	1					
	o_FFS	1					
	o_FF	1					
Call_T_I_4	o_T_I		1				
	o_CA		1				
	o_FFS		1				
	o_FF		2				
Call_T_III	o_T_III			1			
	o_CA			1			
	o_FFS			1			
	o_FF			2			
Call_T_VI	o_T_VI				1		
	o_FF				1		
Call_T_VI_CA	o_T_VI					1	
	o_CA					1	
	o_FF					1	
Call_WT	o_WT						1
	o_FFS						1

Notes. For each assembled resource unit (in a column), each row is labeled with a recipe and an input component followed by the numbers of this component needed. For example, the process Make_T_I_4 uses an on-duty (staffed) T_I_3 and an additional FF to produce an on-duty T_I_4. Call_T_III activates an off-duty (reserve) o_T_III and staffs it with an off-duty o_CA, an off-duty o_FFS, and two off-duty o_FF (all of whom will be paid overtime). These data appear in the model as $component_{b,r',d}$. WT, water tender.

$call\_up\_personnel\_cost_p$: 24-hour cost of employing off-duty resource $p \in P$ [cost units/p-unit]

$budget$: limit on total daily cost (including moving cost) [cost units]

$cost\_tie$: small penalty conversion to encourage selection of smallest total daily cost among all solutions satisfying daily budget limit [expected loss units/cost unit].

Decision Variables [Units]

$CALL\_UP\_POOL_{w^+,p}$: Number of off-duty units of resource $p \in P$ called up for duty in RAWS subarea w^+. (The source location of these units is not known.) [r-units]

$CALL\_UP\_STATION_{s,e,w^+}$: Number of off-duty units of resource $e \in E$ called in from station s and sent to subarea w^+ [r-units]. (Station s is not necessarily in subarea w^+.)

$MOVE_{w^-,w^+,r}$: Number of units of resource r to remove from RAWS subarea w^- and deliver to RAWS subarea w^+. (This is limited to zero if $BI \geq BIT$ in RAWS area w^-.) [r-units]

$ACTIVE_{w,b,d}$: In RAWS subarea w, assembly formula b produces these units of on-duty resource $d \in D$ [d-units]

$STATION_{w,d}$: Number of units of on-duty resource $d \in D$ at RAWS subarea w for selected package [d-units]

$PACKAGE_{w,k}$: For RAWS subarea w, select package k to position there [binary]

$COST$: Cost to pay overtime and move equipment and personnel [cost units].

Formulation

$$\min_{\substack{CALL\_UP\_POOL,\\ CALL\_UP\_STATION,\\ MOVE,\ ACTIVE,\\ STATION,\\ PACKAGE,\ COST}} \sum_{w \in W, k \in K_w} expected\_loss_{w,k} PACKAGE_{w,k} + cost\_tie\ COST, \qquad (0)$$

subject to

$$\sum_{k \in K_w} PACKAGE_{w,k} = 1 \qquad \forall w \in W, \qquad (1)$$

$$\sum_{k \in K_w} number_{k,d} PACKAGE_{w,k} = STATION_{w,d} \qquad \forall w \in W, d \in D, \qquad (2)$$

$$\sum_{w^+ \in W^+} CALL\_UP\_POOL_{w^+,p} \leq off\_duty\_pool_p \qquad \forall p \in P, \qquad (3)$$

$$\sum_{w^+ \in W^+} CALL\_UP\_STATION_{s,e,w^+} \leq off\_duty\_station_{s,e} \qquad \forall s \in S, e \in E, \qquad (4)$$

$$\begin{aligned} \sum_{b \in B, d \in D} component_{b,r',d} ACTIVE_{w,b,d} &= on\_duty\_avail_{w,r'}|_{r' \in D} \\ &+ CALL\_UP\_POOL_{w,r'}|_{w \in W^+ \wedge r' \in P} \\ &+ \sum_{s \in S_w} CALL\_UP\_STATION_{s,r',w}|_{w \in W^+ \wedge r' \in E} \\ &+ \sum_{w^- \in W^-} MOVE_{w^-,w,r'}|_{w \in W^+} \\ &- \sum_{w^+ \in W^+} MOVE_{w,w^+,r'}|_{w \in W^-} \quad \forall w \in W, r' \in R, \end{aligned} \qquad (5)$$

$$\sum_{b \in B} ACTIVE_{w,b,d} = STATION_{w,d} \qquad \forall w \in W, d \in D, \qquad (6)$$

$$\begin{aligned} COST = &\sum_{\substack{w^- \in W^-, w^+ \in W^+,\\ r \in R}} move\_cost_{w^-,w^+,r} MOVE_{w^-,w^+,r} \\ &+ \sum_{\substack{w^+ \in W^+,\ s \in S_{w^+},\\ e \in E}} call\_up\_equipment\_cost_e\ CALL\_UP\_STATION_{s,e,w^+} \\ &+ \sum_{w^+ \in W^+, p \in P} call\_up\_personnel\_cost_p\ CALL\_UP\_POOL_{w^+,p}, \end{aligned} \qquad (7)$$

$$\begin{array}{ll} CALL\_UP\_POOL_{w^+,p} \geq 0 & \forall w^+ \in W^+, p \in P \\ CALL\_UP\_STATION_{s,e,w^+} \geq 0 & \forall e \in E,\ w^+ \in W^+,\ s \in S_{w^+} \\ MOVE_{w^-,w^+,r} \in Z^+ & \forall w^- \in W^-,\ w^+ \in W^+,\ r \in R \\ ACTIVE_{w,b,d} \geq 0 & \forall b \in B,\ w \in W,\ d \in D \\ STATION_{w,d} \geq 0 & \forall w \in W,\ d \in D \\ PACKAGE_{w,k} \in \{0,1\} & \forall w \in W,\ k \in K_w \\ COST \in [0, budget]. & \end{array} \qquad (8)$$

Discussion

The Objective Function (0) assesses the expected loss (i.e., number of evacuees) resulting from prepositioning augmentations across all RAWS subareas, plus a small penalty for the cost expended (to encourage selection of the least expensive of multiple optimal solutions). Each Partition Constraint (1) selects one prepositioning package (a set of resources) for a RAWS subarea (there are only 21 of these). Each Constraint (2) accounts for the number of a resource type selected for a RAWS subarea. Each Constraint (3) limits the number of off-duty resources that can be called on duty; this resource is not specifically located. Each Constraint (4) limits the number of an off-duty resource that can be called on duty from a specific fire station. Each Constraint (5) accounts for a type of component that is required to complete fielded on-duty units in a RAWS subarea (see Table 5). Each Constraint (6) accounts for the number of completed resource units remaining in a RAWS subarea after activation there. Each Constraint (7) assesses the total cost of stationing, moves and off-duty call-ups. Constraint (7) can be substituted into (0), but would introduce some notational clutter. Constraint (8) shows decision variable domain limits. AOM restricts moving resources (i.e., the *MOVE* variables), such that a RAWS subarea must have a BI less than its BIT to send resources, and a receiving RAWS subarea must exceed its BIT. The LACoFD may violate this restriction if they choose.

Actual LACoFD prepositioning can violate these constraints; to evaluate an LACoFD prepositioning plan with such violations, more elastic model features are added (but not shown here to minimize clutter). LACoFD records of prepositioning plans do not show the sources of units in position, so an ancillary optimization must be used to induce the best way these units could have been sourced.

We have investigated generating packages with fewer than the minimum numbers of each truck type assigned to each RAWS by changing the minimum constant bounds to goals and encouraging achieving these minimum numbers via an elastic lower penalty (with units of expected evacuations per truck shortfall; not shown in the formulation). By reducing this penalty, AOM would allow the LACoFD to explore other solutions that reflect situations where they are willing, perhaps even well advised, to violate these limits.

AOM is implemented in the Python computer language (Rossum and Drake 2009) and Pyomo optimization software (Hart et al. 2011, 2017); the entire decision-support tool comprises about 500 lines of Python code. Of this, AOM consists of 150 lines and is currently solved using the CPLEX Optimizer for Pyomo (IBM 2019). Each model instance contains about 700,000 variables and 1,000 constraints and solves in about three minutes with a relative optimality tolerance (the difference between the best solution found and the best solution possible) of 1%.

Initial Testing and Operational Experience

During December 2017, the LACoFD responded to 29 wildland fires—an unprecedented number—with fire starts located throughout the county. Most of the fires were successfully contained, but six led to widespread evacuations and property loss. These fires burned more than 300,000 acres (120,000 ha), forced evacuation of more than 230,000 people, and inflicted losses of $3.5 billion (2018 USD), including $2.2 billion in insured losses and $300 million in fire-suppression costs.

A year later, we chose this month to test our methods.

Using LACoFD data available each day, we proceeded day by day through this month, suggesting augmentation when necessary, estimating resulting losses, and comparing the costs of our advice with what was actually done at the time. We showed that significant improvements to augmented staffing could be made at lower cost, at least in terms of expected outcome.

Table A.6 shows the LACoFD augmentation plan for December 6 in contrast to that suggested by AOM. We note that AOM seems reluctant to augment with CAs when other personnel are available. This is possibly the result of combined capability scores for augmentation packages with more expensive CAs who are not more capable than an FF in laying hose or producing fire line. This is a flaw in our primitive combined capability-score function inviting more analysis, which is ongoing. AOM chose not to augment as many reserve forces as the LACoFD because, by LACoFD direction, it should only augment when the BIT is exceeded. AOM spent $29,110 out of a $30,000 budget, in contrast with $267,000 by the LACoFD, which actually carried out augmentations in RAWSs without the BIT restriction.

We installed AOM on LACoFD computers in May 2019 and left their expert planners to their own devices for the entire fire season (extending from about May to December). AOM advised prepositioning and augmentation, but the final decisions were still in the hands of domain experts. The LACoFD performed a deep-dive analysis of all fires that burned more than five acres in the fourth quarter of 2019. This filtered out 13 fires on eight days of the brush-fire season, ranging from five acres (two ha) to 3,950 acres (1,600 ha). They concluded that AOM advises sending similar resources in comparison with legacy methods, but at a fraction of the cost.

The LACoFD decided that AOM worked well for them, so we have continued to refine the models and make the user interface less hostile (the LACoFD initial users of AOM put up with a very primitive one).

Daily planning proceeds as follows. The LACoFD compiles environmental (e.g., weather forecast) and resource (firefighters and engine availability and location) data. Using environmental data, the logistic regression estimates the probability of a fire start for each RAWS. Using resource data, all feasible resource packages are enumerated for each RAWS. Using environmental data, the linear regression calculates expected burned area for each candidate resource package in each RAWS. Using candidate resource packages and estimates of probability of fire start and expected burned area for each RAWS, the AOM optimization suggests resource augmentation of engines and personnel from each donating RAWS to each receiving one.

The number of candidate resource packages in each RAWS can vary from just a few to tens of thousands. A typical instance of AOM has approximately 725,000 decision variables (700,000 binary and 25,000 continuous) and 25,000 constraints, with 7 million nonzero coefficients (0.035% density). Typical running time is about five minutes (Intel Core i7-8650U at 1.90 GHz and 2.11 GHz, and 32 Gb of RAM; PassMark 2020, 6,575). Two minutes are spent building the candidate packages and calculating their estimated burned acreage, and three minutes are spent solving AOM to an integrality gap (the difference between the solution discovered and the best possible one) of 1%.

The LACoFD already maintains the data required for the fire probability and expected burned-area models so that adjustments can be made whenever new significant information becomes available. This includes a wholesale review and revision of data at the end of each fire season. New explanatory variables may arise and be deemed relevant and should be included in the models. For example, since 2012, electric utilities in California can de-energize power lines under certain high-fire conditions in order to reduce the risk of a downed-line-induced fire (CPUC 2021). This intrinsically affects the probability of fire, and the LACoFD has started incorporating real-time de-energization forecasts from the California Independent System Operator for the logistic regression model.

Conclusions

In 2019, there were $14.8 billion in direct U.S. property losses to fires, and during the prior year there were $12.4 billion in losses in California wildfires alone (e.g., NFPA 2019). This is an important problem, worthy of analysis to advise better courses of action.

The models presented here include two regression models to assess probability of a fire start and, should it happen, its burned acreage and an optimization model to minimize expected population displaced at a given budget level. These models can be used by the LACoFD to guide optimal prepositioning of personnel and assess the burdened costs of shifting personnel and equipment between full-time employment, on-call overtime mobilization, and perhaps contracting.

The LACoFD has installed, tested, tuned, and even tweaked our models on client computer systems with new users who are already domain experts (and might initially be understandably skeptical that any automated system could be of much practical use). AOM handles cases especially well where the budget-constraint limitation is taut. With continued experience, the domain experts have frequently anticipated model advice, or at least closely mimic suggested courses of action.

We have advised that the discrete decision rule to augment forces whenever the BI exceeds the BIT may deserve additional analysis. For example, what should happen when the BI is 99% of the threshold? The opposite situation occurs, too: For example, the LACoFD admits that on some days in Antelope Valley, a BI over the threshold may not require augmentation because of the sparseness of the vegetation fuel bed, flat terrain, road system acting as fuel breaks, and low population density.

We are refining the capability score to include more elements that influence the rate at which we can line a fire perimeter, such as the time to withdraw from a fire to refill from a water source and return, the time for a water tender to refill an engine, and camp crews on foot clearing fire breaks.

An obvious area of improvement for our models deals with current deterministic regression estimations of Mother Nature's stochastic complexity. We conjecture that our prediction of fire starts is about as good as we can make it, whereas our estimation of burned area is not. We are looking for more explanatory data and/or alternate means to refine our estimates. Given the data here, we could draw random samples from, or induce distributions for, daily conditions and simulate thousands of entire fire seasons to gain insight into this random behavior—especially the rare conditions leading to catastrophic events. AOM could also be improved to consider a seasonal budget rather than assuming a day-by-day input.

Epilogue

After installing AOM, and in parallel to the later submission of this manuscript, Los Angeles County has suffered the longest and worst fire season in its history. We have used feedback from daily application of AOM to improve the user interface and, more importantly, to refine our ability to estimate the area of fires once they start. Our capability score has been refined and augmented with a simulation of arriving engines and ground crew to estimate initial-attack containment (Seeberger 2021).

Acknowledgments

Derek Alkonis, Assistant Fire Chief, Air & Wildland Division, County of Los Angeles County Fire Department, and his staff spent a lot of time patiently teaching us, digging up data, and putting up with a very crude prototypic AOM decision support system during a hectic fire season. They provided their training videos and even arranged a demonstration fire, filming their actions from a drone. The LACoFD vividly illustrated strategy, tactics, and outcomes by flying us over recent major wildfire scenes in one of their fire-attack helicopters. When the alarm rings, they have no idea what they will face, but they go. We admire them.

Appendix

Table A.1. Extract from a Daily Weather and Fire Danger Analysis Report

Area (zone)	RAWS name	Jurist. fire station	Sta. no. model	Temp. (°F)	RH (%)	20' wind (mph)	10-hour DFM (%)	BI
Los Angeles Basin	Santa Fe Dam	44	045437B	77	8	3	2	88
	Henninger Flats	66	045439B	75	10	4	3	115
	Claremont	62	045443B	71	11	4	3	98
	Whittier	28	045446B	74	9	5	3	88
	San Rafael	19	045451B	75	8	6	2	126
	Tonner Canyon	119	045453B	72	9	11	3	140
Averages				74	9	6	3	109
						LFM		62

Notes. For the Los Angeles Basin climatic zone, there are six RAWSs. Santa Fe Dam reports a temperature of 77°F (22°C), RH 8%, and wind speed 20 ft. (6 m) above vegetation of 3 mph (5 kph); DFM content of 2%; and a BI of 88. For the entire Los Angeles Basin, the aggregate live fuel moisture (LFM) score is 62. The LACoFD views an LFM score of 60 or less as a critical indicator of fire hazard. Jurist., jurisdiction; Sta. No., station number; Temp., temperature.

Table A.2. Los Angeles County Climactic Zones

Climatic zone	Type	BIT	Observations
Los Angeles Basin	Coastal lowland, low desert	105	32,084
Santa Monica Mountains	Coastal mountains	94	29,512
Santa Clarita Valley	Dry chaparral	140	22,286
High Country	Steep forest	222	12,070
Antelope Valley	Dry grass, high desert	116	16,534

Notes. Per historic records, the LACoFD sets the BIT for each climatic zone at the 97th percentile of recorded BIs within that area, with exception of Santa Monica at the 90th percentile. This is an amalgam of daily weather and fire-danger analysis from 2015 to 2018, daily weather data retrieved back to 2000 from WIMS, and augmented staffing records dating back to 2015. This day, three of six RAWS subareas exceed the Los Angeles Basin BIT of 105 and the average of the entire climatic zone. This is a hazardous day for fires.

Table A.3. Average Hose Lay Rate

Personnel (crew size) (including FFs on engine)	Average hose lay rate (λ) (feet/minute) per crew
3	35.97
4	45.25
5	88.50
6	94.34

Notes. A crew of four firefighters are estimated to be able to lay hose at a rate of 45.25 ft. (almost 14 m) per minute on a 0% slope grade with 100 ft. (30 m) hose segments. For a number of firefighting personnel (F) and engines with hoses (H), we would find the average crew size hose (F/H) and interpolate. For example, for crews of size 3.2 (personnel), the interpolated hose lay rate would be 37.83 ft. (11.5 m) per minute for each crew of that size. Data are from Rahn (2010) and Hemme and Cox (2018).

Table A.4. Los Angeles County Average Productions Rates

Brush type	Number of RAWS subareas	Number of personnel			
		1	2	3	4+
Brush-5	14	3.3	6.6	13.2	17.6
Chap-4A	4	2.2	3.3	8.8	16.5
Grass-1A	3	6.6	13.2	26.4	38.5
Weighted average		3.6	6.9	14.2	20.4

Notes. Each RAWS subarea is classified in one of three vegetation (brush) types. In the four subareas classified as having Chaparral-4A vegetation, three firefighters can clear 8.8 ft. (2.7 m) of firebreak per minute. Data are from Hemme and Cox (2018). In our initial modeling, we use a rate of 3.3 for participating CAs and 3.6 for other firefighters. Chap-4A, Chaparral-4A.

Table A.5. Examples of LACoFD Resource Types, Capacities, and Relocation Costs

Firefighting resource	Type I engine, three-person	Type III engine, four-person	Fourth FF on Type I engine	Type VI engine (patrol), one-person	CA on Type VI engine	WT
Resource type (r)	T I	T III	4FF	T VI	CA	WT
Resource composition	Type I engine (three-person)	Type III engine	Second FF added to Type I engine	Type VI engine (one-person)	CA added to Type VI engine	Water tender
Vehicles in LACoFD	218	8		37		12
Firefighters (f_r)	3	4	1	1	1	0
100 ft. hoses	8	8		4		0
Water capacity (ω) (gallons)	500	750		250		3,000
Production rate (ρ) (feet/minute-person)				3.6	3.3	
Fuel mileage (miles/gallon)	4.5	7		9		4.5
Transport cost ($/mile at $4/gallon)	0.89	0.57		0.44		0.89

Notes. A Type III engine carries four firefighters, eight hoses, and 750 gallons (2,839 L) of water and drives with fuel consumption of 7 mi. per gallon (3 km/L), thus costing $0.57 per mile to reposition. Only Type_VI personnel (FFs and CAs, if any) can be used for clearing lines (other line-clearing personnel include camp crews, not listed here). WT, water tender.

Table A.6. December 6, 2017, LACoFD and AOM Augmentation Plans

RAWS subarea	T_I_3 (Type I, 3 staff)	T_III (Type III)	T_I_4 (Type I, 4 staff)	T_VI (Type VI)	T_VI_CA (Type VI with CA)	WT (Water tender)	BI > BIT	Fire (ac)	Pop. dens. (p/ac)	Prob. fire
Santa Fe Dam	**14 | −1 | 0**	**1 | 0 | 0**	**5 | 0 | 0**	**2 | 1 | 0**	**0 | 3 | 0**	**0 | 1 | 0**	**Yes**	**1**	**3.92**	**0.15**
Henninger Flats	3 | 1 | 0	2 | 0 | 0	2 | −1 | 0	0 | 2 | 0	0 | 1 | 0	0 | 0 | 0	Yes	—	7.16	0.03
Claremont	11 | 0 | −3	0 | 0 | 0	0 | 0 | 0	0 | 3 | 0	0 | 0 | 0	0 | 0 | 0		—	2.47	0.10
Whittier	30 | 19 | 10	0 | 0 | 0	24 | −20 | −23	2 | 25 | −1	1 | 1 | −1	0 | 0 | 0		—	10.90	0.38
San Rafael	2 | 0 | 0	0 | 0 | 0	0 | 2 | 0	1 | −1 | 0	0 | 1 | 0	0 | 0 | 0	Yes	—	13.18	0.05
Tonner Canyon	**7 | −2 | −7**	**0 | 0 | 0**	**0 | 2 | 12**	**1 | 1 | 5**	**0 | 1 | 0**	**1 | 1 | 1**	**Yes**	**1.42**	**5.98**	**0.08**
Cheseboro	2 | 0 | 3	1 | 0 | 0	0 | 3 | 0	1 | 2 | 0	0 | 2 | 0	1 | 1 | 0	Yes	—	0.44	0.06
Malibu	2 | −1 | 0	0 | 0 | 0	1 | 1 | 0	1 | 1 | 0	0 | 1 | 0	1 | 1 | 0	Yes	—	0.49	0.04
Beverly Hills	**10 | 3 | 0**	**0 | 0 | 0**	**4 | −3 | 0**	**1 | 2 | 0**	**0 | 0 | 0**	**0 | 0 | 0**	**Yes**	**422**	**12.90**	**0.14**
Leo Carrillo	1 | −1 | 1	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0	Yes	—	0.20	0.03
Malibu Canyon	4 | −3 | 0	0 | 0 | 0	1 | 3 | 0	0 | 1 | 0	0 | 4 | 0	0 | 0 | 0	Yes	—	1.23	0.02
Topanga	1 | 6 | 0	0 | 0 | 0	0 | 0 | 0	0 | 7 | 0	0 | 0 | 0	0 | 0 | 0	Yes	—	6.64	0.01
Saugus	**6 | 2 | −6**	**1 | 0 | 0**	**1 | 1 | 11**	**0 | 6 | 7**	**0 | 2 | 1**	**2 | 1 | 1**	**Yes**	**0.12**	**1.48**	**0.25**
Acton	2 | −2 | 0	0 | 0 | 0	0 | 2 | 0	1 | −1 | −1	0 | 2 | 0	1 | 1 | −1		—	0.12	0.03
Del Valle	1 | 0 | 0	0 | 0 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0	0 | 0 | 0	Yes	—	0.34	0.07
Newhall Pass	6 | −5 | −6	0 | 0 | 0	0 | 4 | 12	2 | −3 | 5	0 | 2 | 0	1 | 1 | 1	Yes	—	5.06	0.19
Camp-9	2 | −2 | −1	0 | 0 | 0	0 | 2 | 0	0 | 0 | 0	0 | 2 | 0	0 | 0 | 0		—	0.01	0.04
Whitaker	1 | −1 | 0	0 | 0 | 0	1 | 0 | 0	0 | 1 | 0	0 | 1 | 0	0 | 0 | 0	Yes	—	0.07	0.02
Poppy Park	2 | −1 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0		—	0.11	0.07
Saddleback Butte	3 | −3 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0	0 | 1 | 0	0 | 0 | 0		—	0.09	0.03
Lake Palmdale	6 | 5 | 3	0 | 0 | 0	6 | −6 | -6	0 | 6 | 0	0 | 0 | 0	2 | −2 | −2		—	1.07	0.23
Totals	116 | 14 | −6	5 | 0 | 0	45 | −7 | 6	12 | 54 | 15	1 | 26 | 0	9 | 5 | 0				

Notes. Each resource column indicates the total number prepositioned within the RAWS subarea row. A pipe-separated three-tuple of numbers indicates the LACoFD base, followed by the change induced by LACoFD augmentation and then that of AOM. The BI > BIT column indicates whether the RAWS subarea had a forecasted BI above its corresponding BIT. Following that are the actual burned acreage (a bold row signifies that a fire occurred), if any; the population density; and the estimated probability of fire. The augmentations of LACoFD and AOM focus on similar subareas, but LACoFD augmentation this day cost $267,000 and augmented in every RAWS subarea whether the BIT was exceeded or not. AOM only augments when the BIT is exceeded and suggests $29,110 out of a $30,000 budget. This does not mean that AOM was more effective, but merely that it chose not to augment as many reserve forces as LACoFD. ac, acres; p/ac, people per acre; Pop. dens., population density; Prob. fire, probability of fire.

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Verification Letter

Derek Alkonis, Assistant Fire Chief, Air & Wildland Division, County of Los Angeles Fire Department, Los Angeles, California 90063, writes:

"We are excited to hear the NPS AOM research may appear in INFORMS. Please accept this updated communique in support of NPS' work.

The County of Los Angeles Fire Department (LAC) responds to over 600 wildland fires annually on average. During late Summer and through Fall, these fires become more challenging with the arrival of the Santa Ana winds. Protecting a population of 10 million when large fast-moving fires ignite is challenging with finite resources and personnel.

To optimize resource staffing and placement during periods of high fire danger, faculty members and graduate students from the Naval Postgraduate School (NPS), Operations Research (OR) Department have created an Augmented Optimization Model (AOM). The AOM provides planners with cost-effective options for augmenting staffing in preparation for wildfire when fire weather is forecasted.

For the 2019 fire season, LAC planners used the legacy augmented staffing process while also reviewing AOM staffing recommendations. This was to allow planners to become familiar with AOM output reports, to compare AOM staffing recommendations to legacy process, and to find where improvements to AOM could be made. A more thorough comparative review of the two processes performed post-2019 fire season indicates AOM can provide more cost-effective augmented staffing solutions than the legacy process.

The 2020 fire season was our biggest ever, and AOM was right there with us providing staffing recommendations. For the 2021 fire season, we anticipate AOM playing a larger role in providing cost effective staffing decisions to match our persistent wildfire threat.

Please do not hesitate to contact me for additional information at derek.alkonis@fire.lacounty.gov."

Gerald G. Brown is a distinguished professor of operations research at the Naval Postgraduate School, where he has taught and conducted research in optimization and

optimization-based decision support since 1973. He is a member of the National Academy of Engineering, recipient of two U.S. Navy Distinguished Civilian Service Medals, and an INFORMS fellow.

Robert A. Koyak is an associate professor of operations research at the Naval Postgraduate School. He obtained his PhD in statistics from the University of California, Berkeley, in 1985 and joined the faculty of the Naval Postgraduate School in 1998. His research focuses on statistical applications of graph theory and the use of machine learning for motion and destination prediction of aircraft and ships. He is a recipient of the Wayne E. Meyer Award for teaching excellence in systems engineering and a publications award from the International Test and Evaluation Association.

Javier Salmerón is a professor of operations research at the Naval Postgraduate School. He obtained his PhD in mathematics from Polytechnic University of Madrid, Spain. His research focuses in the area of applied optimization, where he has developed multiple decision support systems for private industry, government agencies, and the military. Areas of interest include network interdiction, stochastic optimization, decomposition methods, and applications of simulation-optimization. He has won the Military Operations Research Society Barchi Prize.

Zachary Scholz commissioned with distinction from the U.S. Naval Academy in 2018, earning a BS in nuclear and mechanical engineering, and was accepted by the Naval Postgraduate School as part of the Bowman Scholar Program. He has published, proposing novel configurations for highly enriched uranium surrogate sources. He graduated with distinction from the Naval Postgraduate School with an MS in applied science (operations research), earning the Chief of Naval Operations Award for Excellence in Operations Research for his master's thesis. He now serves on *SSN721 Chicago*.