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operations research

Designing Seasonal Initial Attack Resource Deployment and Dispatch Rules Using a Two-Stage Stochastic Programming Procedure

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Initial attack dispatch rules can help shorten fire suppression response times by providing easy-to-follow recommendations based on fire weather, discovery time, location, and other factors that may influence fire behavior and the appropriate response. A new procedure is combined with a stochastic programming model and tested in this study for designing initial attack dispatch rules integrated with development of seasonal suppression resource deployment decisions to support initial attack. Historical fires are spatially simulated according to historical weather and actual fire locations to provide fire samples that capture the stochastic nature of this problem. Constraints are added to a two-stage stochastic programming resource deployment and dispatch model to enforce a requirement that the same combination of initial attack resources be dispatched to all fires in any given dispatch category. A postoptimization procedure is used to check the resulting solution, potentially leading to refinements of candidate solutions before a model solution is accepted. Our test results indicate that not accounting for the use of standard response dispatch rules where they are typically implemented could lead planners to underestimate initial attack resource requirements and costs.

Keywords: suppression, dispatch rule, stochastic programming, two-stage model

Initial attack (IA) includes suppression actions within the first several hours of fire discovery (Martell 1982, Ntaimo et al. 2012) and is considered an efficient way to control a fire before it grows large (Parks 1964, Cumming 2005, Martell 2007). The US Department of Agriculture (USDA) Forest Service suppressed approximately 98% of fires reported between 1970 and 2002 before fire sizes exceeded 121 ha (Calkin et al. 2005). Notably, the small percentage of fires that escaped IA and grew into large fires caused the most damage (Petrovic et al. 2012). Those USDA Forest Service fires that did escape IA resulted in >97% of the total burned area (Calkin et al. 2005). Land management agencies with wildfire management responsibilities are continuously seeking more efficient suppression strategies, including IA, to control fires (Venn and Calkin 2011, Petrovic et al. 2012).

Martell (1982) divided fire suppression decisions into four subsections, the first three of which address IA needs: resource acquisition and strategic deployment, resource mobilization to meet current and future needs, IA dispatching, and extended attack management. MacLellan and Martell (1996) addressed the first two subsections by combining a subjective daily airtanker deployment model with a higher level seasonal deployment model. A number of other researchers have developed two-stage stochastic programming models for addressing Martell's first and third subsections, in which resource acquisition and deployment are addressed in the first stage and IA dispatching requirements are addressed in the second stage (Haight and Fried 2007, Hu and Ntaimo 2009, Ntaimo et al. 2012, 2013, Lee et al. 2013, Arrubla et al. 2014, Wei et al. 2015). The primary goal of modeling IA dispatching as second-stage decisions in these studies has been to support more robust first-stage resource acquisition and deployment decisions.

Representative fire locations (RFLs) have been used in stochastic programming IA models to group fires in the same geographic areas and sharing similar fuel types, with representative fires simulated in each RFL under low, moderate, high, and extreme weather scenarios. For example, Haight and Fried (2007) and Lee et al. (2013) constructed 100 representative fire days with 4 or more fires occurring each day within 46 modeled RFLs to reflect competing demand for suppression resources between fires reported on the same day. Similarly, Ntaimo et al. (2012, 2013) grouped representative fires from 46 RFLs by fire day for dispatching purposes and selected 756

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fire days to reflect unique daily ignition patterns. Arrubla et al. (2014) later organized these fire days into fire scenarios to further reflect seasonal ignition patterns. Using historical fire samples rather than representative scenarios, Wei et al. (2015) used FARSITE to parameterize a stochastic programming model with 1,655 historical fires on 935 fire days from 1993 to 2010 at their original locations on heterogeneous fuels and terrain according to the hourly historical weather conditions associated with each specific fire for second-stage dispatch decisions.

Like other mathematical programming methods, stochastic programming models use objective functions to identify solutions of interest to managers. For example, Haight and Fried (2007) and Lee et al. (2013) minimize the weighted sum of two performance measures: the number of resources deployed at stations in stage one, and the number of fires that do not receive a predefined standard response in stage two. Tradeoffs between the two objectives were used to create an efficient frontier through a series of model runs. While their objective function helps simplify the problem, minimizing the expected number of fires not receiving a standard response may produce solutions that allocate scarce resources to those fires requiring the fewest resources for containment. Ntaimo et al. (2012, 2013) and Arrubla et al. (2014) minimize the sum of the fixed cost of deploying available resources to operations bases, the total travel cost for relocating resources between bases, the total resource operating costs, and the total expected net value change using a constant net fire damage per hectare burned. Arrubla et al. (2014) and Wei et al. (2015) both include chance constraints to address decisionmakers' risk preferences. Wei et al. (2015) further suggest a proactive approach to modeling risk preference by employing a predefined deployment cost exceedance probability enforced using a chance constraint that partitions fire days into two sets: an IA set that reflects those fire days an IA organization is expected to handle without supplemental resources and the remaining set of more challenging fire days expected to require supplemental resources. Their model can be solved for a number of different exceedance probabilities to develop a cumulative probability curve of IA organization deployment costs for full containment to assist decisionmaking.

Dispatchers often use predefined "standard IA response" rules (Marianov and Revelle 1991). In Greece, response rules have been designed by fire experts based on management experiences supplemented by test results from IA models (Xanthopoulos 2002). Such rules are often documented as "dispatch rules" (synonymous terminology—preplanned dispatch plans, dispatch procedures, dispatch cards or "run cards"—based on the *National Interagency Fire Center Redbook* [National Interagency Fire Center 2002]) at fire dispatch centers in the United States. Dispatch rules use fire weather indicators and other factors that classify fires into dispatch categories. Managers define dispatch rules to provide standard responses for dispatchers to initiate upon discovery of fires in a given category. For example, according to the Black Hills National Forest Fire Management Plan (Berger et al. 2006), the energy release component (ERC) or burning index (Bradshaw et al. 1983) for each fire response zone is used to determine the dispatch rules for that zone in a given fire day. In the Black Hills "Deerfield" fire response zone, for example, dispatch rules indicate that if a fire occurred on a fire day with an ERC measurement of no more than 29 BTU/ft^2 (measured at the nearby weather station), a type 6 engine would be dispatched to the fire, if the ERC is between 29 and 43 BTU/ft^2, two type 6 engines would be dispatched to the fire, and if the ERC is >43, three type 6 engines would be dispatched to the fire (Berger et al. 2006).

In previous studies, researchers have defined standard response in various ways to reflect dispatch rules when modeling second-stage dispatch decisions. Haight and Fried (2007) and Lee et al. (2013) model standard response as a predefined combination of resources that varies by the maximum burning index of a given fire day. Their approach simplifies second-stage decisions because fire containment is not modeled explicitly; instead, the second-stage decisions focus on minimizing the number of fires that cannot receive standard responses within given travel time limitations subject to an upper bound on limited resources. Because standard responses are exogenously predefined and fires receiving standard responses might still escape, the resulting resource deployment plans are evaluated using a simulation model (Fried and Gilless 1999) to estimate how many fires would escape despite receiving standard response combinations.

Standard response has also been modeled in the form of a requirement that line production rates meet or exceed precalculated thresholds (Ntaimo et al. 2012). This approach differs from traditional dispatch practices because it does not specify the types and quantities of resources by fire dispatch categories. Simulation modeling is first used to calculate the potential length that each fire perimeter could grow within an IA time limit. This precalculated perimeter is used to establish a fireline construction threshold necessary to contain each fire in the second stage. A stochastic programming model is then used to optimize the deployment and dispatch of resources to meet the line construction requirement for each fire within an IA time limit. This approach to standard response assumes that managers have the ability to anticipate fire-specific line construction requirements and to optimally coordinate the dispatching of resources from multiple fire stations to meet those requirements. These models do not account for the interaction between line construction and fire perimeter, which may retard fire growth over the course of the fire (Fried and Fried 1996).

Other stochastic programming models do not use standard response either as predefined combinations of resources or predetermined line construction requirements; instead containment is modeled by directly comparing constructed fireline length to fire perimeter over several discrete periods of fire growth. For example, Ntaimo et al. (2013) used an "explicit fire growth response model" to compare fireline construction and fire perimeter for each fire growth period, declaring containment if the constructed fireline attains a user-defined percentage of the free-burning fire perimeter during any period before the IA time limit. Again, this model does not account for the interaction between line construction and fire perimeter. Wei et al. (2015) also compare constructed lines with fire perimeter in discrete fire growth periods. Rather than declaring containment based on a user-defined percentage of the free-burning fire perimeter, their model tracks how fireline constructed during earlier periods reduce fire growth in later periods to prevent overestimation of fire growth when second-stage dispatch decisions are made. An important issue with existing stochastic programming models that compare line production with fire perimeter to establish fire containment is that second-stage IA dispatch decisions are made with perfect knowledge of the fewest resources required to achieve containment on each fire.

The models introduced above either use exogenously generated dispatch rules (Haight and Fried 2007, Lee et al. 2013) or assume that resources are optimally dispatched from multiple stations to fires in the second stage to meet fireline construction requirements (Ntaimo et al. 2012, 2013, Arrubla et al. 2014, Wei et al. 2015). Exogenously generated run card-based dispatch rules may lead to suboptimal first-stage deployment decisions whenever resource combinations based on dispatch rules are larger or smaller than actually required to meet IA objectives. Similarly, models without such dispatch rules may miscalculate resource requirements by assuming dispatchers have perfect knowledge of the fewest resources required to achieve containment on each fire. Additional dispatch restrictions, such as 30/60-minute response time limits (Haight and Fried 2007, Ntaimo et al. 2012, 2013, Lee et al. 2013), reduce the potential for overoptimistic dispatching in these models but cannot eliminate this potential because resources within the response time limits are still optimally dispatched to all known fires. In addition, these restrictions do not allow for the possibility of dispatching from greater distances in times of greater need, potentially resulting in overestimation of resource requirements.

This study addresses the issues identified above by integrating endogenously designed dispatch rules with an IA resource deployment planning model. We revise the two-stage stochastic integer programming (SIP) model developed by Wei et al. (2015) to test a procedure that integrates three types of IA resource deployment and dispatch decisions simultaneously for a fire planning unit (FPU): the number of resources to be allocated to a FPU for IA; a plan for deploying resources to fire stations for a fire season; and a set of model-selected dispatch rules corresponding to predefined fire dispatch categories. To our knowledge, this is the first mathematical programming model that integrates IA dispatch rule designs into resource acquisition and deployment decisions. Our test results indicate that this integration is important because not accounting for the use of dispatch rules where they are typically implemented could lead planners to underestimate IA resource requirements and cost.

Methods

We designed, populated, and solved a set of two-stage SIP models to test five steps for integrating dispatch rules into IA resource deployment and dispatch decisions:

- Step 1: Select and organize a set of fires, either random fire samples or systematically selected representative fires with probabilities, to capture the variation of local fire situations in a FPU.
- Step 2: Define fire dispatch categories and partition the set of fires from step 1 into those categories.
- Step 3: Revise and parameterize the SIP model to deploy and dispatch local resources to successfully contain the selected set of fires from step 1 through IA using additional constraints to ensure the implementation of IA dispatch rules. This requires that all fires within a dispatch category defined from step 2 receive the same combination of IA resources.
- Step 4: Solve the model from step 3. Models of this type can grow large quickly and may require flexible and efficient solution algorithms.
- Step 5: Evaluate the solution from step 4 using postoptimization analyses, potentially refining the candidate solutions or returning to an earlier step.

As described in the Introduction, previous studies have implemented a number of these steps in various ways to build and solve different forms of two-stage SIP models for IA planning. This article streamlines and expands these analysis steps and enhances our previous two-stage SIP model so it can be used to create comprehensive deployment plans to efficiently station resources that support IA dispatching to a set of targeted fire ignitions using endogenously designed dispatch rules.

Our Implementation of the Procedure

We tested the above procedure by revising the model from Wei et al. (2015) for federal land in the Black Hills Fire Planning Unit (BHFPU). The original model does not include endogenously designed dispatch rules, so we will refer to it as the "fire-specific-dispatch" SIP model. In this study, we revise that model to incorporate dispatch rule decisions and call this revised model the "dispatch-rule" SIP model. BHFPU is located in western South Dakota and northeastern Wyoming, covering an area approximately 200 km long and 105 km wide. Figure 1A shows a map of the BHFPU including the FPU boundary and available fire station locations. We design dispatch rules and plan the deployment and dispatching of suppression resources using these rules for the FPU.

Data Preparation

Hand crews, fire engines, and water tenders are the three types of suppression resources included in this study. We modeled two types of fire engines using data collected for the Fire Program Analysis (FPA) system[1] developed by the USDA Forest Service and the US Department of Interior for modeling federal budget allocation strategies. In our models, each small engine, type 5 or type 6 (as described in Federal Fire and Aviation Task Group[2]), dispatches with three crew members; each large engine, type 3 or type 4, dispatches with four crew members. Water tenders transport water from a water source (i.e., lake, stream, or well) to the engines at a fire scene. For simplicity, we allow water tenders to be paired as an option only with the large fire engines to maintain a higher line production rate for this engine type. We assume that the small fire engines will run out of water after 1 hour of use, and the large fire engines will run out of water every 2 hours without support from a water tender. When an engine runs out of water, we assume that one crew member has to drive it to a water source for refilling, while the remaining crew members continue working on the fire at a hand crew rate of line productivity. For example, when a small engine without a water tender is dispatched to a fire in a location with fuel type 121 (Low Load, Dry Climate Grass-Shrub; based on Scott and Burgan 2005), the hourly line production rate would be set to 13.5 chains per hour for odd hours (1, 3, 5,...) after arrival at the fire, reflecting work periods with water available, and would be set to 5.4 chains per hour for even hours (2, 4, 6,...), reflecting the line production rate of a two-person hand crew. When a large engine is dispatched to the same fire without a water tender, the hourly line production rate would be set to 18.9 chains per hour for hours (1, 2, 4, 5, 7, 8,...) following arrival at the fire, reflecting work periods with water available, and would be set to 8.1 chains per hour every third hour (3, 6, 9,...), reflecting the line production rate of a three-person hand crew. If a large engine is operated together with a water tender, the line production rate would be maintained at the higher level of 18.9 chains per hour as we assume that the water tender would be able to provide a continuous water supply for this engine. We based these fireline production rates on the average of the resource productivity data found in the FPA system. The fireline production rates used here were collected for FPA modeling purposes and are calibrated specifically for the BHFPU. Other estimates of fireline production rates are available, including a recent national study by Broyles (2011).

In our analysis, suppression resources can be dispatched from any fire station to any fire in the planning unit. For simplicity, we chose not to constrain the numbers of resources that can be located at any fire station. Likewise, we chose in these tests to calculate travel times

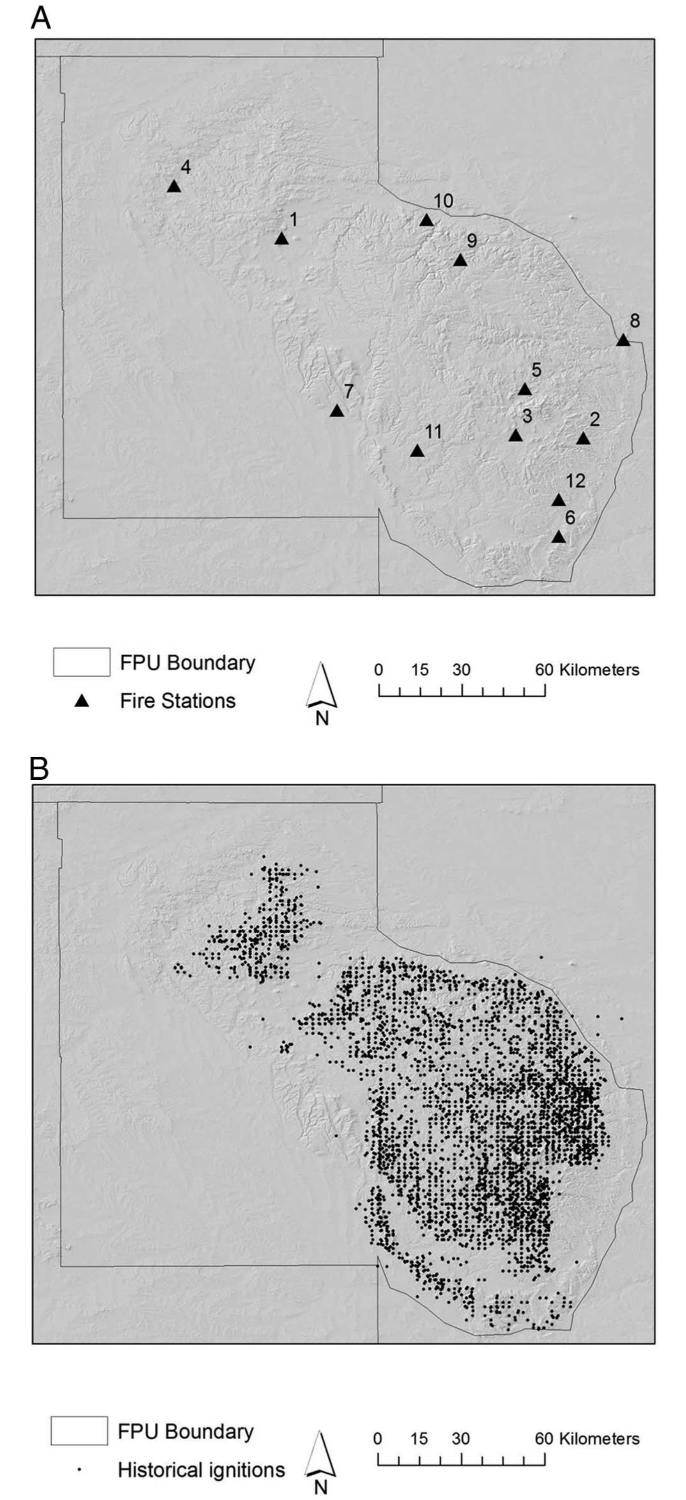

Figure 1. A. The locations of fire dispatch stations. B. The ignition locations of 1,655 historical fires from years 1993 through 2010.

from fire stations to fire locations simply as the distance between those points divided by a travel rate from the BHFPU FPA data of 56 km/hour. Modeled average costs per day for deploying each resource type in the planning unit for the fire season (also from FPA) are shown in Table 1. We also assume that resources cannot be dispatched to multiple fires in the same day.

To facilitate the summarization and comparison of the overall line productivity rates for the IA dispatch rules selected by the models in our test cases, we calculated the average hourly line production rate of a one-person crew, a small engine, a large engine, and "a large engine plus a water tender" across all fuel types for a 6-hour suppression duration (Table 1). Using a 6-hour average provides a common denominator across the different water availability cycles between the two modeled engine types, i.e., a 2-hour cycle for small engines and a 3-hour cycle for large engines. Note that these averaged hourly line production rates are used only to simplify presentation of results. During the model parameterization process, we used the fuel-specific and hourly-specific line production rate of each resource type to calculate the length of fireline constructed to contain each fire.

Table 1. Daily deployment cost for the four types of resources modeled in the BHFPU.

Resource name	Average production rate (m/hr)	Daily deployment cost ($)
Hand crew (per person)	39	146
Engine 5/6 (small engine)	180	601
Engine 3/4 (large engine)	317	1,108
Large engine + water tender	416	1,300

We downloaded BHFPU fire and weather records for years 1993 through 2010 from FireFamilyPlus (Bradshaw and McCormick 2000). From these records, we selected all federal fire records with sufficient data for our simulations. This process produced records for 1,655 ignitions (Figure 1B) occurring in 935 fire days. The fire discovery time for each fire is used to approximate the fire ignition time. We used FARSITE (Finney 2004) to simulate the hourly growth of each fire on raster landscapes with elevation and fuel types downloaded from LANDFIRE (Rollins and Frame 2006). Hourly weather data from seven Remote Automated Weather Stations (Red Canyon, Elk Mountain, Custer, Custer State Park, Mount Rushmore, Baker Park, and Nemo) were used to support the calculation of spatially varying hourly wind fields (direction and speed), using a "point initialization option" in WindNinja (Forthofer et al. 2009). Perimeters of these simulated free-burning fires were collected for each hour over a 24-hour period to support parameter calculations for our two-stage SIP models. We grouped the simulated historical fires into fire days to reflect resource drawdown due to simultaneous fires occurring in the same day.

Step 1: Select and Organize a Set of Fires to Model

In our procedure, we use estimated deployment budget exceedance probabilities implemented through a chance constraint (Equation A13 in the Appendix) to ensure the conditional probability of one or more fire escapes on days with ignitions is below a predefined threshold. Starting with a large sample of fire days, our goal is to contain all fires in K out of N ordered fire days where K is chosen to reflect an estimated exceedance probability α (refer to Wei et al. 2015) where $\alpha = [1 - K/(N + 1)$ (Gumbel 1958, Makkonen 2008). Selected sets include fire days in which the local IA organization is expected to contain all fires without outside support.

To enforce the exceedance probability α, we identify the K out of N ordered fire days to set up the corresponding chance constraint. We first run the two-stage fire-specific-dispatch SIP model for each of the 935 fire days (described in the Data Preparation section). Each run finds a minimum daily resource deployment budget required to contain all fires on the corresponding fire day by IA without implementing any predefined run card style dispatch rules and

Table 2. Dispatch category identification and the associated ERC range, elevation range, and ignition time of the corresponding fire samples.

Dispatch category identification	ERC	Elevation Low	Elevation High	Ignition time
		. . . . . .(m).		
1		0	1,200	Night
2		0	1,200	Day
3	≤20	1,200	1,900	Night
4		1,200	1,900	Day
5		1,900	Infinity	Night
6		1,900	Infinity	Day
7		0	1,200	Night
8		0	1,200	Day
9	(20, 40)	1,200	1,900	Night
10		1,200	1,900	Day
11		1,900	Infinity	Night
12		1,900	Infinity	Day
13		0	1,200	Night
14		0	1,200	Day
15	>40	1,200	1,900	Night
16		1,200	1,900	Day
17		1,900	Infinity	Night
18		1,900	Infinity	Day

assuming perfect knowledge of the resource requirements for containment of every fire. All fire days then were sorted by the required daily resource deployment budget from low to high, using the deployment budget as an indicator of IA complexity. Using these reported costs, we select two sets of fire days as possible IA planning targets. The first set includes all 935 fire days ($K = 935$, $\alpha = 0.002$); the second set is a subset of the first set consisting of the 889 less severe fire days ($K = 889$, $\alpha = 0.05$). More IA resources probably would be required to contain all fires in the 935 fire days; therefore, we refer to this set of fire days and its corresponding test case as the "level I" fire days and the level I test case. The second set and its corresponding test case are referred as "level II." The level II set of fire days probably requires a lower resource deployment budget than the budget needed to contain all fires in level I fire days. Modeling of level II fire days reflects an assumption that deploying IA resources at a local FPU to contain all possible fire ignitions within the FPU probably is too expensive to be practical in many cases. We compare these level I and II costs in our test cases.

Step 2: Delineate Dispatch Categories

For this procedure, our sample fires must be grouped first into predefined dispatch categories based on observable attributes that influence IA resource requirements. The intent is that all fires in the same dispatch category will receive the same combination of IA resources. For our test cases, we ran the fire-specific-dispatch SIP model again with one run for each fire. Note that in these runs, the suppression of each fire is optimized as if it were the only fire. These fire-specific runs calculate the minimum daily cost of deploying enough suppression resources to contain each of the 1,655 individual fire samples through IA. We then used the resource deployment cost associated with each fire as an indicator for the IA complexity of that fire. Based on an observation of relationships between the estimated IA complexity of fires and their corresponding ERC measurements, locations, and ignition times, we arbitrarily classified the 1,655 simulated fires into a set of 18 nonoverlapping dispatch categories (listed in Table 2). Although these dispatch categories do not reflect values at risk or other attributes that also probably influence categories in actual use, they are useful for testing purposes.

Step 3: Revise and Parameterize the SIP Model to Form Dispatch Constraints by Category

After the level I and II fire days have been selected in step 1 and the 18 dispatch categories have been delineated in step 2, a set of dispatch rule constraints are added to the fire-specific-dispatch SIP model to formulate the dispatch-rule SIP model. Equation 1 enforces that every fire classified in the same dispatch category will receive the same combination of IA resources

$$\sum_i y_{r,i,g} = S_{r,h}(g) \qquad \forall \ r,g \tag{1}$$

where i is the index of fire stations, $y_{r,i,g}$ is an integer variable denoting how many resources of type r are dispatched from fire station i to fire g, and $S_{r,h}(g)$ is an integer variable denoting the number of resources of type r to be dispatched according to the dispatch rule applied to fire g that belongs to dispatch category h.

Other dispatch requirements can also be added into this dispatch-rule SIP model (using Equation 2)

$$\sum_r C_r S_{r,h} \geq \sum_r C_r S_{r,h'} \qquad \forall \ (h,h') \tag{2}$$

where $S_{r,h}{}'$ is an integer variable denoting the number of resources of type r to be dispatched according to the dispatch rule in fire dispatch category h'. Dispatch category h is assumed to require at least as many resources as h' (measured by the sum of their average daily resource deployment costs). C_r denotes the cost of deploying 1 unit of resource r in the FPU (Table 1). For testing purposes, we modeled three arbitrarily selected additional requirements: for fires ignited within the same elevation and time ranges, at least as many suppression resources will be dispatched to fires ignited in a higher ERC category; for fires ignited within the same ERC and elevation ranges, at least as many resources will be dispatched to a fire ignited during daytime as at nighttime; and for fires ignited with the same time and ERC ranges, at least as many resources will be dispatched to a fire ignited in the midelevation category (mostly forest fuel types) as in the higher (and wetter) or lower elevation categories (mostly grass/shrub fuel types). When the number of historical fire samples is small in some dispatch categories, dispatch rules built on the small sample sizes may not fully represent the IA resource demands in those dispatch categories. Extra dispatch constraints in the model can be used to lessen the impact of small sample sizes and to enforce intuitive dispatch logic based on expert opinion.

Step 4: Solve the Dispatch-Rule SIP Model

If computing power was not a concern, we could build all targeted fire days (either level I or level II) into the two-stage dispatch-rule SIP model and solve it to find the corresponding optimal deployment and dispatch solution. However, when the number of sample fire days is large, computing time and the demand for computer memory hinder finding optimal solutions. Wei et al. (2015) adopted an iterative approach to solve the fire-specific-dispatch SIP model. In that case, a challenging subset of fire days is first used to build the SIP model. Solving that model provides a candidate resource deployment and dispatch solution. This candidate solution is then tested against the remaining sample fire days. If any fire day has any fire that escapes IA using the candidate solution, that fire day is added to the two-stage SIP model, and the revised model is solved again to find an updated candidate deployment and dispatch solution. That process continues until we find a subset of fire days leading to a deployment solution that can successfully contain all fires in all targeted fire days. This iterative approach allows us to use only a portion of the level I or II fire days to identify optimal IA deployment solutions for all targeted fire days.

We revised the iterative solution approach described above for use in this study to solve the two-stage dispatch-rule SIP model with an additional task of designing efficient dispatch rules for each of the 18 fire dispatch categories in Table 2. First, we select a subset of challenging fire days from all level I fire days ($K = 935$, $\alpha = 0.002$) or all level II fire days ($K = 889$, $\alpha = 0.05$) with that subset of fire days containing at least one fire in every dispatch category. We build this subset of fire days into the two-stage dispatch-rule SIP model so that the model can create a dispatch rule for every dispatch category. In addition, we solve two SIP models during each iteration with different objective functions and adjustment of constraints. For the first model run, we use an objective function (Equation 3) to minimize the overall FPU level IA resource deployment budget

$$\text{Min } u = \sum_r \sum_i C_r x_{r,i} \tag{3}$$

As in the Appendix, $x_{r,i}$ is an integer variable denoting the number of resources of type r to be stationed at fire station i. After the minimum deployment budget u^* is identified, we set that budget as an upper bound (Equation 5) in the second model run with Equation 4 as the new objective function to minimize the sum of resource deployment costs for all dispatch rules

$$\text{Min } \sum_r \sum_h C_r s_{r,h} \tag{4}$$

$$\text{Subject to: } \sum_r \sum_i C_r x_{r,i} \le u^* \tag{5}$$

Solving the second model is necessary because there may be alternative optimal solutions for configuring dispatch rules under a minimum deployment budget u^* from the first model run. For example, if dispatching one or two small engines to each fire in dispatch category h does not change the resource deployment budget u^*, Equation 3 would not provide incentive to choose the one-engine dispatch rule. Thus, to further reduce the cost of individual resource dispatch rules, we need to solve the dispatch-rule SIP model with Equation 4 as the objective function to minimize the number of resources in each dispatch category weighted by the corresponding resource deployment costs subject to the minimum FPU level suppression resource deployment budget u^*. The solution obtained after each iteration also needs to be tested against all of the remaining level I or level II fire days, depending on the exceedance probability α to prove the feasibility of the solution on all level I or II fire days. If a deployment plan and the associated dispatch rules based on a subset of fire days can contain all fires in the remaining level I or level II fire days, we conclude that the current solution is feasible and optimal; otherwise, the fire days with escapes are included in the next iteration and the solution process is repeated. We note, however, that such a solution is optimal only with respect to requirements included in the model. We continue to treat this solution as a candidate solution going into step 5.

Step 5: Solution Evaluation

Solutions identified from step 4 include a minimum FPU resource deployment budget to contain all fires in level I ($\alpha = 0.002$) or level II ($\alpha = 0.05$) fire days through IA, the corresponding resource deployment plans, and the set of endogenously generated standard dispatch rules covering all dispatch categories. We evaluate these solutions further using simulations to better reflect IA suppression realities.

Although the current version of our dispatch-rule SIP model enforces standard dispatch rules, it still assumes that a dispatcher could anticipate all the fire locations and their attributes before dispatching any resources each day. This allows the model to dispatch IA resources from multiple stations to multiple fires more efficiently than is really possible and, consequently, can lead to an underestimation of resources required to contain all modeled IA fires. A more realistic dispatch strategy is to dispatch the closest resources to each fire according to the temporal sequence of fire occurrence. Formulating and solving the closest-first dispatch requirement in a SIP model can be challenging. For example, one approach is to build a large set of logical constraints that explicitly track which resources are available at each hour and which are closest to the next fire ignition. To manage model size, we did not build this requirement directly in the dispatch-rule SIP model; instead we test this dispatch requirement using postoptimization simulations, leaving the exact formulation of and solution methods for this problem to future research.

To simulate the closest-first dispatching requirement, we repeatedly run the dispatch-rule SIP model with constraints added to enforce the dispatch rules discovered in step 4. Each run dispatches resources to each fire following the temporal sequence of fire ignitions in each modeled fire day. To provide incentive for the model to send resources from the closest fire station, we again revise the objective function of the dispatch-rule SIP model to minimize the sum of travel distances of all resources dispatched to each modeled fire. After resources are dispatched to a fire, we subsequently update the resource availability information at the corresponding fire stations. Then, when the next model run is used to dispatch resources to the next fire ignition, it can only use the updated set of resources available at each fire station.

Using these postoptimization analyses, we learn whether any targeted fires (in level I or level II fire days) would escape by implementing the closest-first suppression requirement under a candidate resource deployment and dispatching plan. If all targeted fires can be contained within the predefined IA time limit employing the candidate plan, we accept this plan as feasible and optimal for IA deployment and dispatching. If, instead, some targeted fires escape IA, managers might choose to revise the deployment plan to add resources at fire stations near the escaped fires. The feasibility of this new deployment plan could then be reevaluated against all targeted fires. Although this approach could produce a suboptimal deployment plan, fire managers may find this approach useful until further research more fully addresses this issue.

Results

We built a set of test cases with different parameter values for testing purposes. These three parameter values are as follows: IA time limits set to $T = 24$ hours or $T = 18$ hours; a 1-hour delay between fire ignition and dispatch; and line construction adjustment factor $\beta_D = 1$. The dispatch-rule SIP model used in this study uses the same formulation as the fire-specific-dispatch model (refer to Equation A3.1 in the Appendix) to model the interactions between fireline construction and fire perimeter growth. This method assumes that firelines are built along and across multiple free-burning fire perimeters at different hours of fire growth. β_D is a parameter

Table 3. Resource deployment with and without implementation of dispatch rules to contain all fires on level I fire days with IA time limit *T* set to 24 hours.

Fire station identification	With dispatch rules (T = 24 hours)				Without dispatch rules (T = 24 hours)			
	CREW	Small EN	Large EN	Large EN + WT	CREW	Small EN	Large EN	Large EN + WT
1	0	0	0	4	2	0	0	0
2	0	0	0	3	10	2	0	1
3	4	0	0	2	4	1	1	1
4	0	0	0	3	0	0	0	0
5	0	0	0	2	0	0	0	0
6	0	0	0	2	0	0	1	0
7	0	0	0	1	2	4	0	0
8	0	0	0	3	4	0	0	0
9	0	0	0	1	0	0	0	0
10	0	0	0	4	0	0	0	0
11	4	0	0	7	0	0	0	0
12	0	0	0	2	0	2	0	0
Sum	8	0	0	34	22	9	2	2
Budget			$45,368				$13,437	

With dispatch rules, the same combination of resources would be dispatched to each category of fires; without dispatch rules, the model can dispatch any combination of resources to each fire to meet the fireline construction requirement (perfect knowledge). EN, engine; WT, water tender.

Table 4. Resource deployment with and without implementation of dispatch rules to contain all fires on level II fire days with IA time limit *T* set to 24 hours.

Fire station identification	With dispatch rules (T = 24 hours)				Without dispatch rules (T = 24 hours)			
	CREW	Small EN	Large EN	Large EN + WT	CREW	Small EN	Large EN	Large EN + WT
1	0	0	0	1	0	0	0	0
2	4	0	0	1	4	1	0	0
3	2	0	0	1	2	0	0	0
4	2	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0
6	2	0	0	1	2	0	0	0
7	2	0	0	0	2	0	0	0
8	0	0	0	0	0	0	0	0
9	0	0	0	0	2	0	0	0
10	2	0	0	0	0	0	0	0
11	2	0	0	1	0	0	0	0
12	2	0	0	1	0	0	0	0
Sum	18	0	0	6	12	1	0	0
Budget			$10,428				$2,353	

EN, engine; WT, water tender.

reflecting how fireline can be built to connect these free-burning fire perimeters. A larger β_D value implies that longer firelines would be necessary to connect free-burning fire perimeters (details are presented in Wei et al. 2015). All test cases in this study assume $\beta_D = 1$, indicating that firelines are built to connect two adjacent free-burning fire perimeters with perpendicular line segments (or their equivalents in length). Under these assumptions, we tested the five analysis steps introduced in the Methods section to deploy resources and design dispatch rules to contain fires in either level I or level II fire days. We also ran the fire-specific-dispatch SIP model without using dispatch rules for level I and level II fire days with $T = 24$ hours to compare the rule-based dispatching results with results from dispatching under the perfect knowledge assumption.

Test results show that different modeling objectives and assumptions can lead to substantially different BHFPU IA resource deployment plans and dispatch rules. For example, if the planning objective is to contain fires on all level I fire days within a 24-hour IA time limit, results from the step 4 analysis using dispatch rules suggest that we should station 4 two-person hand crews and 34 large engines paired with water tenders in the FPU. The average daily deployment cost for this set of resources is $45,368 (Table 3). We did a comparison run that contains all fires in the level I fire days without using any dispatch rules, which resulted in the average daily resource deployment budget decreasing to $13,437 (Table 3). Using dispatch rules in this FPU while requiring containment of all level I fires more than triples the daily resource deployment budget. In addition, the resource deployment configuration when the model has perfect knowledge for dispatching is substantially different and includes 11 two-person hand crews, 9 small engines, 4 large engines, and 2 water tenders across the FPU (see Table 3).

We conducted a similar comparison using the level II IA target to contain all fires within 24 hours. When dispatch rules are enforced, the candidate solution suggests deploying six large engines paired with water tenders, plus nine two-person hand crews, with an average daily deployment budget of $10,428 (Table 4). Using perfect knowledge, this model would station only six two-person hand crews and one small engine within the FPU, with an average daily deployment budget of only $2,353 (less than one-fourth of the cost with dispatch rules). Clearly, the perfect knowledge assumption regarding dispatch capability can lead to a substantial underestimation of resource deployment costs in a FPU. As expected, daily resource deployment costs are also much lower in level II than in level I.

Table 5. Comparison of dispatch rules constructed under the 24-hour and 18-hour IA time limits to contain all fires in the level I fire day samples.

Dispatch category identification	24-hour IA limitation						18-hour IA limitation					
	CREW	Small EN	Large EN	Large EN + WT	Cost ($)	ALPR (m/hr)	CREW	Small EN	Large EN	Large EN + WT	Cost ($)	ALPR (m/hr)
1	2	0	0	0	292	78	0	1	0	0	601	180
2	2	0	0	0	292	78	0	1	0	0	601	180
3	4	0	0	0	584	156	0	1	0	0	601	180
4	0	0	0	2	2,600	832	0	1	0	1	1,901	596
5	2	0	0	0	292	78	0	1	0	0	601	180
6	0	0	0	1	1,300	416	0	1	0	0	601	180
7	2	0	0	0	292	78	0	1	0	0	601	180
8	0	0	0	1	1,300	416	0	1	0	0	601	180
9	0	0	0	1	1,300	416	0	0	0	1	1,300	416
10	0	0	0	2	2,600	832	0	1	0	1	1,901	596
11	4	0	0	0	584	156	0	1	0	0	601	180
12	0	0	0	1	1,300	416	0	1	0	0	601	180
13	0	0	0	1	1,300	416	0	2	0	0	1,202	360
14	4	0	0	2	3,184	988	0	6	0	0	3,606	1,080
15	0	0	0	2	2,600	832	0	1	0	1	1,901	596
16	0	0	0	3	3,900	1,248	0	1	0	3	4,501	1,428
17	4	0	0	0	584	156	0	2	0	0	1,202	360
18	0	0	0	1	1,300	416	0	2	0	0	1,202	360

ALPR, average line production rate; EN, engine; WT, water tender.

Table 6. Comparison of dispatch rules constructed under the 24-hour and 18-hour IA time limits to contain all fires in the level II fire day samples.

Dispatch category identification	24-hour IA limitation						18-hour IA limitation					
	CREW	Small EN	Large EN	Large EN + WT	Cost ($)	ALPR (m/hr)	CREW	Small EN	Large EN	Large EN + WT	Cost ($)	ALPR (m/hr)
1	2	0	0	0	292	78	0	1	0	0	601	180
2	2	0	0	0	292	78	0	1	0	0	601	180
3	4	0	0	0	584	156	0	1	0	0	601	180
4	0	0	0	1	1,300	416	0	0	1	0	1,108	317
5	2	0	0	0	292	78	0	1	0	0	601	180
6	4	0	0	0	584	156	0	1	0	0	601	180
7	2	0	0	0	292	78	0	1	0	0	601	180
8	6	0	0	0	876	234	0	1	0	0	601	180
9	0	0	0	1	1,300	416	0	1	1	0	1,709	497
10	0	0	0	1	1,300	416	0	1	1	0	1,709	497
11	4	0	0	0	584	156	0	1	0	0	601	180
12	4	0	0	0	584	156	0	1	0	0	601	180
13	0	0	0	1	1,300	416	0	0	1	0	1,108	317
14	2	0	0	1	1,592	494	0	1	1	0	1,709	497
15	0	0	0	1	1,300	416	0	1	1	0	1,709	497
16	2	0	0	1	1,592	494	0	1	1	0	1,709	497
17	4	0	0	0	584	156	0	0	1	0	1,108	317
18	6	0	0	0	876	234	0	0	1	0	1,108	317

ALPR, average line production rate; EN, engine; WT, water tender.

We also tested how candidate solutions are affected by altering the IA time limit (T). When we changed T from 24 hours to 18 hours while examining the level I fire days, the daily deployment budget increased by about 11% from $45,368 to $50,517. In concert with the budget change, the set of standard dispatch rules in the candidate plan was also altered: instead of employing hand crews and large engines + water tenders the candidate plan chooses to dispatch combinations of small engines and large engines + water tenders (Table 5). In contrast, when we target IA at level II fire days, changing T from 24 hours to 18 hours only slightly increased the average daily deployment budget in this FPU from $10,428 to $10,855. In this case, the 4-hour difference in T only increased the total deployment budget by 4%. The set of standard dispatch rules identified by the model changed significantly, however, employing different combinations of small and large engines rather than using either hand crews or large engine + water tender (Table 6). This change in deployment plans may seem odd given the similarity of the budgets, but because of the discrete nature of the problem, small budget changes can cause significant changes to deployment plans and dispatch rules.

Comparing the dispatch rules produced by the 18-hour and the 24-hour IA limits also helps reveal the impact of the configuration of the resource deployment plan on the design of the dispatch rules. By using the level I fire days with $T = 24$ hours, 8 of the 18 dispatch rule combinations in the candidate plan contain resources with a higher total daily deployment cost and higher average hourly line production rate than the corresponding dispatch combinations in the candidate plan produced using $T = 18$ hours (Table 5). For

Table 7. Postoptimization cross-evaluation of the deployment plans and corresponding dispatch rules by enforcing the "closest-first" dispatch requirement.

Assumptions used to acquire solutions	No. of fire days with escapes by testing against the same level of fire days under the "closest-first" dispatch requirement	
	T = 24 hours	T = 18 hours
Using level I fire days		
T = 24 hours	0	2 out of 935 days
T = 18 hours	0	0
Using level II fire days		
T = 24 hours	0	1 out of 889 days
T = 18 hours	0	0

example, for dispatch category 4 the candidate plan suggests dispatching two pairs of large engines + water tenders using a T = 24-hour IA time limit; however, it only dispatches one small engine and one pair of large engine + water tender if T is set to 18 hours. Similarly, for level II fire days, 3 of 18 dispatch combinations suggested by the candidate plan contain resources with a higher total daily deployment cost and higher average hourly line production rate for T = 24 hours (Table 6). These results may seem counterintuitive because containing a fire faster (i.e., T = 18 hours) should require a resource combination with a higher total line production rate. However, in this model dispatch rules are created in concert with corresponding deployment plans; thus, small changes in model parameters may create different deployment plans and unique dispatch rules. For example, if a small engine is not included in the least-cost deployment plan in a FPU, we cannot use it in any standard dispatch rules, which may create more expensive resource combination requirements for certain dispatch categories. Although an individual dispatch rule may seem to be more expensive than the same dispatch category in a different candidate plan, the comprehensive set of the 18 rules together create an IA deployment plan with the minimum overall resource deployment cost in a FPU for each set of parameters tested. These subtleties also highlight the inefficiencies that may be caused by using exogenously generated dispatch rules to form a resource deployment plan.

After identifying the four deployment plans and associated dispatch rules for level I and level II fire days within either the T = 24-hour or T = 18-hour IA time limits, we reevaluated these solutions using postoptimization analyses to simulate the "closest-first" dispatch requirement previously described in step 5 in the Methods section. Under this requirement, we always dispatch the closest resources to each fire according to the corresponding dispatch rule following the temporal sequence of fire occurrence in each fire day. In our test cases, postoptimization evaluations indicated that when the closest-first dispatch requirement is implemented, all fires in level I or level II fire days can still be contained within the corresponding 24-hour or 18-hour IA time limit using the dispatch rules and the corresponding deployment plans suggested by the candidate solutions (Table 7). Therefore, we accept these solutions as optimal. We also found that for both level I and level II fire days, the candidate plans identified for the shorter 18-hour IA time limit are capable of containing all fires when the IA time limit is extended to 24 hours (Table 7), as we would expect. However, the IA candidate plans identified for the 24-hour IA time limit cannot contain all fires on the corresponding fire days for the 18-hour IA time limit, i.e., fires escaped on 2 of the 935 level I fire days and on 1 of the 889 level II fire days when we tightened the IA time limit to 18 hours but used the candidate plan and dispatch rules identified for the 24-hour IA time limit (Table 7).

Discussion

Uncertainties regarding future fire situations play important roles in determining IA resource deployment and dispatching plans. These uncertainties include fire weather, fire behavior, resource values, operational effectiveness, and other factors (Thompson and Calkin 2011), which may include location and timing of ignitions. The number and locations of fires in each fire day have a particularly strong influence on resource deployment and dispatching decisions. Deterministic models often cannot reflect these uncertainties. This study proposes and tests an analysis method using a two-stage SIP model to deploy fire suppression resources and to design IA dispatch rules together using fire day samples constructed from historical fires.

We built a set of test cases to examine the potential influence of implementing endogenously designed dispatch rules on the overall FPU level IA deployment plan and budget. Our results indicated that an assumption of perfect knowledge in second-stage resource dispatching decisions can cause substantial underestimation of the required deployment budget. Other modeling assumptions can also influence the estimation of deployment budget. For example, deploying seasonal resources in home bases using exogenously designed dispatch rules may cause overestimation of the deployment budget if these rules are not designed efficiently; this may also cause underestimation of the deployment budget if deployment is configured using dispatch rules that cannot contain all fires in the corresponding dispatch category.

Most of the existing two-stage stochastic integer programming models for seasonal suppression resource acquisition and deployment (i.e., Haight and Fried 2007, Hu and Ntaimo 2009, Ntaimo et al. 2012, 2013, Lee et al. 2013, Arrubla et al. 2014, Wei et al. 2015) do not model the daily resource mobilization decisions, implicitly assuming that suppression resources will not be relocated on a daily basis to accommodate ongoing predictions of fire and resource situations. This represents a simplification of the real-world decisionmaking process because suppression resources can be prepositioned in response to weather predictions such as storm tracks and associated lightning strikes. Adding the daily resource mobilization stage into the current two-stage model would require us to collect daily weather forecasting data and understand how managers respond to those forecasts. Besides the daily resource mobilization stage, other decision stages during IA may also influence seasonal IA resource deployment. For example, dispatch rules are often used when a wildfire is first reported. After incident commanders arrive at fires, they may adjust the IA response as needed either by canceling dispatched resources or by ordering additional resources (Moab Interagency Fire Center 2014). The adjustment of IA responses by incident commanders can be treated as another stage of suppression decisions beyond the four stages suggested by Martell (1982). Skipping any decision stage in an optimization model probably would result in some degree of error in the estimation of required resources and deployment cost. Further studies to test multistage systems for seasonal suppression resource acquisition and deployment might prove useful.

The discrete nature of this model can make it sensitive to parameter values such as line production rates and fire growth rates, suggesting a need for sensitivity analysis. Although the main purpose of this article is to test a methodology, implementation of this method may carry additional issues. For example, past research suggests that crew productivity is inversely correlated with fire intensity (Hirsch et al. 1998). The data we collected from BHFPU only include suppression resource productivities based on fuel types; the impact of fire intensity on line production is not explicitly modeled.

This study focuses on FPU level IA resource deployment and dispatching. We recognize that resources deployed within an FPU are also an integrated component of regional or national fire planning. Whereas the methods tested here can be used to help identify external IA resources required to supplement local FPU resources during times of severe fire danger (as in Wei et al. 2015), we do not address resource needs for escaped fires or the coordination of resources required across FPUs. Examining the coordination between FPU level resources and regional and national resources presents an interesting future study.

This model groups fires into fire days to reflect the situation that multiple fires occurring in the same fire day will compete for the same set of IA resources. A limitation of this grouping method is it may not fully reflect the IA resource requirements from an episode of fires occurring over a sequence of multiple fire days. The most direct solution to this concern is to use such fire episodes to replace fire days. This could necessitate more complex modeling techniques because we would need to track the return of resources to fire stations during the middle of a fire episode, as well as the possible need for rest periods. In this study, we developed a postoptimization analysis procedure to test the "closest-first" dispatch requirement. This procedure can also be revised to evaluate how resource deployment plans and dispatch rules identified through a SIP model would perform when dealing with more complicated real-world situations such as episodes of fires. For example, fires can first be sorted based on their ignition times, resources would be dispatched to each fire according to the predefined dispatch rules from the closest stations, and the number of resources in each fire station would be updated by tracking the number of resources dispatched to each fire and those resources returned to fire stations after a fire is contained. Additional data and assumptions such as the duration of shifts of different types of resources are needed to support this type of episode-based postoptimization analysis. For cases in which a deployment plan or a set of dispatch rules cannot meet the IA containment target, further research is needed to address finding useful solutions. Nonetheless, with model and procedural revisions to accommodate endogenous decisions for dispatch rules, our two-stage stochastic programming model provides a substantial advancement in this approach to IA planning.

Endnotes

1. For more information, see www.forestsandrangelands.gov/FPA/index.shtml.
2. Please see www.nifc.gov/PUBLICATIONS/redbook/2014/RedBookAll.pdf.

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Appendix: A Fire-Specific-Dispatch Two-Stage Stochastic Integer Programming Model

The following model is described in detail in Wei et al. (2015).
Indices:

- g index of all sampled fires included in the model.
- k index of fire days. More than one fire could ignite during a fire day.
- i index of fire stations.
- r index of suppression resource types.
- t index of time steps (periods) since the start of a fire.

Sets:

- G_k a set of fire ignitions in the same fire day k.
- A the set of fire days (indexed by k) included in the model.

Variables:

- $x_{r\,i}$ general integer variables denoting how many resources of type r should be stationed at fire station i for the fire season. These indicate the first-stage decision.
- $y_{r,i,g}$ general integer variables denoting how many resources of type r are dispatched from fire station i to fire g. These indicate the second-stage decision.
- $l_{g,t}$ continuous variables denoting the length of new fireline that can be constructed during period t to suppress fire g. We assume that fireline produced during period t decreases the uncontained perimeter of fire g at the end of period t.
- $f_{g,t}$ binary variables denoting whether fire g will be contained at the end of period t. $f_{g,t} = 1$ denotes containment of fire g at the end of period t; otherwise $f_{g,t} = 0$.
- $v_{g,t}$ binary variables denoting whether fireline is built to contain fire g in period t. $v_{g,t} = 1$ denotes that fireline is built in period t for fire g.
- $w_{g,t}$ binary variables working as a switch; $w_{g,t-1} = 1$ denotes that the adjusted distance ($\beta_D D_{g,t}$) between two free-burning fire perimeters at periods $(t - 1)$ and t will be added into the uncontained perimeter of fire g at the end of period t.
- $p_{g,t}$ continuous bookkeeping variables used to track the uncontained perimeter of fire g at the end of period t before subtracting the new fireline constructed during period t.
- ρ_g bookkeeping variables tracking the uncontained perimeter of fire g after the T-period IA time frame. ρ_g is set to 0 if fire g was contained before or at the end of period T.
- ρ^{Total} bookkeeping variables tracking the total uncontained fire perimeters for all fires in set A after the IA time limit.
- u a bookkeeping variable tracking the total IA resources deployment budget in a FPU.

Parameters:

- C_r the cost of deploying resource r.
- $L_{r,i,g,t}$ the length of fireline constructed by each resource of type r dispatched from station i to suppress fire g during period t.
- $P_{g,t}$ the free-burning perimeter of fire g at the end of period t without suppression.
- β_D a parameter that reflects the possible line construction paths between two consecutive fire spread periods $(t - 1)$ and t.
- $D_{g,t}$ the average distance between free-burning fire perimeters at the end of period $(t - 1)$ and t.
- M a large positive number used to set the value of logic (switch) variables.

$$Min\ Z = u \tag{A1}$$

subject to

$$\sum_{g \in G_k} y_{r,i,g} \le x_{r,i} \quad \forall\ r,i,k \in A \tag{A2}$$

$$\begin{cases} p_{g,t} \ge \dfrac{P_{g,t}}{P_{g,t-1}}(p_{g,t-1} - l_{g,t-1}) + 2\beta_D D_{g,t} w_{g,t-1} \\ \qquad\qquad \forall\ g,t \mid P_{g,t-1} \ne 0 & \text{(A3.1)} \\ p_{g,t} \ge P_{g,t} \quad \forall\ g,t \mid P_{g,t-1} = 0 & \text{(A3.2)} \end{cases}$$

$$l_{g,t} \le \sum_r \sum_i L_{r,i,g,t} y_{r,i,g} \quad \forall\ g,t \tag{A4}$$

$$\begin{cases} l_{g,t} \le M v_{g,t} \quad \forall\ g,t & \text{(A5.1)} \\ v_{g,t} \ge v_{g,t-1} \quad \forall\ g,t \ge 2 & \text{(A5.2)} \end{cases}$$

$$p_{g,t} - l_{g,t} \le M(1 - f_{g,t}) \quad \forall\ g,t \tag{A6}$$

$$l_{g,t} - p_{g,t} \le M f_{g,t} \quad \forall\ g,t \tag{A7}$$

$$w_{g,t} \ge v_{g,t} - f_{g,t} \quad \forall\ g,t \tag{A8}$$

$$p_{g,T} - l_{g,T} \le \rho_g \quad \forall\ g \tag{A9}$$

$$\sum_g \rho_g \le \rho^{Total} \tag{A10}$$

$$\rho^{Total} \le 0 \tag{A11}$$

$$\sum_r \sum_i C_r x_{r,i} \le u \tag{A12}$$

Objective Function A1 minimizes the total resource deployment budget u. Constraint A2 enforces that the number of resources of type r dispatched from station i to all fires within any modeled fire day cannot be more than the total number of resources of type r available from station i. This reflects an assumption that any resource which has already been dispatched to a fire cannot be dispatched to another fire within the same day. Resources are assumed to go back to their assigned stations, ready to be dispatched again the next fire day. Constraint A3.1 calculates the length of uncontained fire perimeter of fire g at the end of period t. It assumes that fireline constructed in earlier periods will halt fire spread at those locations. Whereas the FARSITE simulations used to parameterize our model are run on a spatially defined raster landscape, fire growth in our model is not. Instead, we use the length of the free-burning fire perimeters calculated in FARSITE to calculate a discrete-time linear approximation of perimeter growth reduced by line construction. $P_t/(P_t - 1)$ is the ratio between the length of the free-burning fire perimeters at the ends of period t and $(t - 1)$. It reflects the rate of fire perimeter expansion during period t and is used to approximate how much fireline constructed in period $(t - 1)$ can reduce the expansion of fire perimeter during period t. We built Constraint A3.2 in place of A3.1 for time steps for which FARSITE reported fire perimeter lengths of 0 in the preceding time step.

We do not model the exact line construction paths in Constraint A3.1. Instead, the value of β_D is set to mimic different fireline construction paths, providing a calibration option in the model. Lower values of β_D represent assumptions of more efficient line construction when we connect the free-burning fire perimeter. Constraint A4 tracks the new fireline constructed during period t by all resources dispatched from all stations to a fire g. Constraint A5.1 sets the value of binary variable $v_{g,t}$ to 1 when fireline is first built in period t, and it remains 1 until the end of the IA time limit T (Constraint A5.2) to ensure the continuity of fireline. Constraints A6 and A7 set the binary variable $f_{g,t}$ to indicate whether fire g is contained at the end of period t. If and only if the amount of new fireline constructed during period t is as long as or longer than the uncontained fire perimeter at the end of period t, $f_{g,t}$ is set to 1 to declare containment of this fire. $f_{g,t}$ remains 1 for the time steps after fire containment (e.g., for periods $t + 1$, $t + 2 \ldots$ after the fire is contained at period t) because the fire perimeter lower bound (set by Constraint A3.1) remains 0 afterwards. Constraint A8 sets $w_{g,t}$ to 0 before suppression starts (when $v_{g,t} = 0$). Constraint A8 also sets $w_{g,t}$ to 0 in period t when fire g is contained ($v_{g,t} = 1$ *and* $f_{g,t} = 1$). If $w_{g,t} = 0$, the model excludes $\beta_D D_{g,t}$ from the next period fire perimeter growth in Constraint A3.1.

Constraint A9 calculates the value of ρ_g, the perimeter (if any) for fire g remaining after the T-period IA time frame. Constraint A10 sums the total uncontained fire perimeter for all fires after the T-period IA time frame. Constraint A11 enforces the full containment of all modeled fires. Constraint A12 tracks the total resource deployment budget (the preparedness budget). This budget is minimized in the objective function. The variable cost (suppression cost) of dispatching a resource to a fire is not counted in this study.

This model minimizes the total IA resources deployment budget u and identifies fire station assignments for IA resources so as to limit the probability that any day with fire ignitions will result in one or more IA containment failures. In the context of this model, this requires meeting the following chance constraint

$$P_k\left(\sum_{g \in G_k (1-f_{g,T})>0}\right) \leq \alpha \qquad \text{(A13)}$$

where the probability that IA fails to contain one or more fires within T time periods on any random fire day k is no greater than a prespecified exceedance probability α (e.g., $\alpha = 0.05$) (Gumbel 1958, Makkonen 2008). G_k is the set of fires in fire day k; $f_{g,T} = 1$ denotes that fire g is contained within T time periods. A is the set of fire days included in the model for IA containment.