Resource Sharing for Control of Wildland Fires

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Abstract

Wildland fires (or wildfires) occur on all continents except for Antarctica. These fires threaten communities, change ecosystems, destroy vast quantities of natural resources and the cost estimates of the damage done annually is in the billions of dollars. Controlling wildland fires is resource-intensive and there are numerous examples where the resource demand has outstripped resource availability. Trends in changing climates, fire occurrence and the expansion of the wildland-urban interface all point to increased resource shortages in the future. One approach for coping with these shortages has been the sharing of resources across different wildland-fire agencies. This introduces new issues as agencies have to balance their own needs and risk-management with their desire to help fellow agencies in need. Using ideas from the field of multiagent systems, we conduct the first analysis of strategic issues arising in resource-sharing for wildland-fire control. We also argue that the wildland-fire domain has numerous features that make it attractive to researchers in artificial intelligence and computational sustainability.

Introduction

A wildland fire (also referred to as a wildfire, bushfire, veldfire, *etc.*) is typically defined as an unplanned non-structural fire burning in forested, grass, scrub-covered *etc.* areas. All continents, except for Antarctica, regularly experience wildland fires which threaten communities, change ecosystems destroy vast amounts of natural resources, and the cost estimates of the damage done annually is in the billions of dollars. For example, in the beginning of January 2013 alone, wildland fires in Tasmania, Australia destroyed at least 80 homes, left thousands of people stranded and resulted in over 42 million USD in insurance claims (AUS 2013; Henshaw 2013). Changing climate is leading to both increased fire-occurence in areas already prone to wildland fires (Westerling et al. 2006), as well as large fires occurring in areas previously not considered to be at significant risk (Jones et al. 2009; Mack et al. 2011).

Controlling and combating wildland fires is resource intensive, requiring specialized equipment, aircraft and highly trained personnel. For example, during the summer of 2003 in British Columbia, Canada, over 10,000 firefighters and support personnel were involved in fire suppression. Two air tanker crew members and a helicopter pilot were killed and it has been estimated that the cost of control and suppression alone was close to one billion CAD (BC 2013). Determining the right level of resources for wildland fire agencies is challenging. It is not financially feasible to maintain resource levels so as to handle situations like seen in British Columbia in 2003, since most seasons are not that severe. Relying on historical averages may also not be appropriate due to the unpredictability and variability of wildland fires. For example, in Canada during 2011, the number of wildland fires was two thirds that of the previous ten year average and the area burned was 15% lower. However, these numbers do not show the entire picture since 2011 was also the year of the Slave Lake fire in northern Alberta, which burned into the community of Slave Lake, destroying over 400 homes and causing $700 million CAD in insurable losses (CIF 2011).

Agencies responsible for wildland fire control and suppression are faced with the challenge of maintaining their resource establishment levels while also requiring the flexibility to access additional resources during peak demand. *Resource sharing* across agencies is one approach that is used to this end. The idea is very simple. An agency in need contacts other agencies, who lend any resources they are not currently using. Resource sharing mechanisms are in place in a number of countries including the US, Canada, and Australia, and there are international agreements which also support resource-sharing across international borders.

In this paper we study the strategic issues which arise when wildland fire agencies share resources. We propose a model which highlights some of the key features of resource sharing in this domain, including the problem of balancing the desire to help another agency against taking on additional risk in a highly uncertain environment, and the difficulty of determining whether excess resources are available in the first place. Given our model, we show that lending decisions are strategic; they depend both on the protocol being used to select and allocate offered resources and on the decisions of other agencies. We conclude the paper with a discussion of future work related to resource sharing for wildland fire control, and an argument that this is an interesting domain for AI researchers and practitioners.

Resource Sharing in Canada

Our model and analysis is based on the Canadian system as overseen by the Canadian Interagency Forest Fire Centre (CIFFC). CIFFC's primary mandate is to facilitate the exchange of wildland fire fighting resources inside Canada, and it has been doing this for over 25 years. In Canada, wildland fire control is the responsibility of the provinces and territories. Each province or territory has its own agency and resources, and is responsible for fires inside its borders. In times of need, an agency contacts CIFFC, and requests additional resources. CIFFC sends these requests to all other agencies across the country, who each check their resource availability and report back to CIFFC. CIFFC is responsible for deciding which of the offered resources will be used, arranging the logistics for transporting the resources to the agency in need (and returning them). Details on the formal sharing arrangements are specified in the Mutual Aid Resources Sharing (MARS) Agreement which outlines the terms under which resources can be legally shared, how resources will be made available, what costs will be involved and the conditions for their return.

Model

In this section we describe our model of resource-sharing for wildland fire.[1] There are three key components in the model: the distressed agency, the broker responsible for resource allocation, and the lending agencies.

The Distressed Agency The distressed agency, D, finds itself in a situation where its current level of resources is inadequate. It submits a request for additional resources, R_D, to the central broker. We assume D is non-strategic, that its request for resources represents its actual needs, and that all other participants are aware of this.[2]

The Broker The broker, B, is responsible for receiving the resource request from D, broadcasting the request to the lending agencies, receiving the offers of resources, O_i, from each lending agency, and then selecting which resources will be used. In particular, we assume B follows a protocol, S_B, that specifies how resources will be selected. If lending agencies announce resource availability $(r_1, \ldots, r_n)$ where r_i is the set of resources agency i can share, then $S_B(r_1, \ldots, r_n) = (c_1, \ldots, c_n)$ where $c_i \subseteq r_i$ is the set of resources the broker selects and allocates to D. This protocol is common knowledge. Finally, the broker is also responsible for setting the payment, $\text{pay}(r)$, agencies receive for sharing r resources. This payment function is fixed, set in advance, and common knowledge.

[1]The model was developed through a series of consultations with wildland fire-control agencies and CIFFC which took place between October 2011 and March 2012.

[2]Our interviews seemed to indicate that if there was any strategizing by distressed agencies, it was more likely to be *under-reporting* their needs instead of over-reporting. While the phenomena contributing to this are very interesting, it is beyond the scope of this study.

Lending Agencies Once the broker announces that R_D resources are needed, the lending agencies are faced with a difficult decision. They need to balance their own resource needs with the benefits and costs of lending some of their resources to the distressed agency. A lending agency benefits both from monetary payments it receives as well as the *social goodwill* generated by helping a fellow agency in their time of need.

The costs of lending are two-fold. First, if an agency lends resources then it has less resources available for its own use in case of wildfires. This additional risk depends on future fire events, which are difficult to predict in advance. Abusing terminology somewhat, we say *fireload*, ω, is the amount of resources required to successfully control a fire event (this could include multiple wildfires). We let Ω be the set of all possible fireloads, and assume during the lending period (*i.e.* after the lending decision has been made, but before the lent resources have been returned) the fireload of agency i is drawn from Ω with cdf F_i and pdf f_i and that this is common knowledge. The second challenge faced by agencies is that they need to determine whether they have resources they can lend, and have to ensure that their remaining resources are deployed effectively. This typically involves solving complex allocation and logistic problems in times of pressure.

We define a lending agency as follows.

Definition 1 *A lending agency, i, is defined by its type*

$$\theta_i = \langle R_i, F_i, \text{damage}_i(\cdot,\cdot), \text{goodwill}_i(\cdot), \text{search}_i(\cdot)\rangle$$

where:

- R_i *is the total resources controlled by agency* i*,*
- F_i *is the cdf over* Ω*,*
- $\text{damage}_i : \Omega \times R_i \mapsto \mathbb{R}$ *where* $\text{damage}_i(\omega, r)$ *is the fire damage* i *would sustain if it had* r *resources available under fireload threshold* ω*. If* $r \geq \omega$ *then* $\text{damage}(\omega, r) = 0$*, but for* $r < \omega$*,* $\text{damage}(\omega, r)$ *is convex.*[3]
- $\text{goodwill}_i : R_i \mapsto \mathbb{R}$ *is the social goodwill that* i *experiences. We assume that* $\text{goodwill}_i(r) \geq 0$ *for all* $r \geq 0$*.*
- $\text{search}_i : R_i \mapsto \mathbb{R}$ *is the cost that* i *incurs when determining its resource availability. This search cost captures the effort and overhead of finding available resources and making the decision to lend them. This includes generating alternative plans to cover situations which might arise once those resources are gone. We assume that* $\text{search}_i(\cdot)$ *is convex so as to capture diminishing marginal returns of searching for additional resources.*

The *actions* available to an agency consist of selecting a subset of its resources to make available for the broker to send to the distressed agency. We use the notation $O_i \in 2^{R_i}$ to represent the action or *offer* made by agency i. We further make the assumption that resources across agencies are comparable and substitutable.[4]

[3]This captures the increasing severity of the consequences as the shortfall of resources increases for a given fireload.

[4]This assumption is not unrealistic given the setting. Either resources are completely incomparable (*i.e.* airtankers *vs* axes) and so can be treated as separate categories or are standardized across all agencies and so are truly interchangeable.

The utility of agency i with fireload ω_i which offers resources O_i and is selected by the broker to contribute $C_i \subseteq O_i$ resources is

$$\begin{aligned} u_i(\theta_i, O_i, C_i, \omega_i) &= \text{pay}(C_i) + \text{goodwill}_i(C_i) \\ &\quad -\text{damage}_i(\omega_i, R_i \setminus C_i) \\ &\quad -\text{search}_i(O_i). \end{aligned}$$

We define $u_i(\theta_i, O_i, C_i) = E_{\omega_i \in \Omega_i}[u_i(\theta_i, O_i, C_i, \omega_i)]$.

Analysis of Resource Sharing

There is a clear interdependency between a particular agency's utility and the actions taken by others. An agency's utility depends on both the resources it offers to lend (O_i) and the resources it actually contributes (C_i), where the latter may depend on the offers of others. Thus, ideas from multiagent systems and game theory are appropriate analysis tools for this setting.

A key feature of the lending-agency model is that it falls into the general *deliberative agent* framework studied in the multiagent systems literature (*e.g.* (Larson and Sandholm 2001; 2005; Thompson and Leyton-Brown 2007; 2011)). In this framework, agents are uncertain about their true preferences or valuations for outcomes, but can invoke *costly effort* or deliberation to remove this uncertainty. In our resource-sharing model, a problem faced by the agencies is determining how much resources they actually have available to lend and balancing the effort or cost required to determine their resource availability becomes a key strategic decision.

A strategy for an agency is a mapping from its type to the effort it exerts to determine its resource availability and the amount that it declares to the broker. We let resource levels represent the effort involved in determining the availability of those resources. This is without loss of generality due to the existence of the function $\text{search}_i(\cdot)$ which provides a mapping from resources to cost or effort. The formal definition of a strategy is as follows.

Definition 2 *A (pure)* strategy *for agency i with type $\theta_i = \langle R_i, F_i, \text{damage}(\cdot,\cdot), \text{goodwill}(\cdot), \text{search}(\cdot)\rangle$, when the broker is using protocol S_B, is*

$$\sigma_i^{S_B} : \theta_i \times \Omega \mapsto \left(O_i, \hat{O}_i\right)$$

where O_i is the resources i determines to be available and $\hat{O}_i$ is the resources i reports to the broker.

In the rest of the paper we make the assumption that $O_i = \hat{O}_i$ and so will write $\sigma_i^{S_B}(\theta_i, \omega) = O_i$. There are two reasons for making this assumption, First, it simplifies the strategy space and allows us to focus on the issue of agencies searching for available resources. Second, while it is possible that there are scenarios where an agency may have incentive to report a different resource-value than their true availability, both back-of-the-envelope calculations and consultations with actual agencies indicate that these tend to be pathological cases. While it might be interesting to characterize, for example, how extreme risk attitudes could lead to misreporting of resource availability, we leave this to future work.

Given a strategy profile $\sigma^{S_B} = (\sigma_i^{S_B}, \sigma_{-i}^{S_B})$ where $\sigma_{-i}^{S_B} = (\sigma_1^{S_B}, \ldots, \sigma_{i-1}^{S_B}, \sigma_{i+1}^{S_B}, \ldots, \sigma_n^{S_B})$, the utility of agency i with type θ_i under fireload ω_i is $u_i(\sigma_i^{S_B}(\theta_i, \omega_i), \sigma_{-i}^{S_B}) = u_i(\theta_i, \sigma_i^{S_B}(\theta_i), S_B(\sigma_i^{S_B}(\theta_i), \sigma_{-i}^{S_B}), \omega_i)$. The solution concept used in the analysis is the *Bayes-Nash equilibrium*. A strategy profile $\sigma^* = (\sigma_i^*, \sigma_{-i}^*)$ is a Bayes-Nash equilibrium if for all i and for all θ_i, $E[u_i(\sigma_i^*, \sigma_{-i}^*)|\theta_i] \geq E[u_i(\sigma_i, \sigma_{-i}^*)|\theta_i]$ for all $\sigma_i \neq \sigma_i^*$.

The Broker's Protocol, S_B: Prioritizing *a priori* The protocol used by the broker to select resources to send to D is key since it influences the strategies of the lending agencies significantly. While the broker's main interest is collecting enough resources for the distressed agency, it also has certain preferences as to where those resources come from. For example, the broker is responsible for handling the logistics of moving the resources from the lending agencies to the distressed agency and so the desire to minimize this overhead can play a role in how resources are selected. In the rest of this section, we assume the broker ranks agencies before they make any resource offers, and that this ranking is fixed and is common knowledge. We also analyse in detail the case where there are two agencies and then explain how the analysis can be extended to the n-agency case.

Definition 3 *Assume there are two agencies, i and j. Assume that the broker uses* priority scheme protocol *S_B where $i \succ j$. Then $S_B(O_i, O_j) = (C_i, C_j)$ where*

- *If $R_D \subseteq O_i$ then $C_i = R_D$ and $C_j = \emptyset$.*
- *If $O_i \subset R_D$ and $R_D \subseteq O_j$ then $C_i = \emptyset$ and $C_j = R_D$.*
- *If $O_i \subset R_D$ and $O_j \subset R_D$ then $C_i = O_i$ and $C_j = (R_D \setminus O_i) \cap O_j$.*

That is, the broker prefers to fill R_D by using a single agency (with i preferred to j), but if no single agency can fulfill R_D, B will select i's resources before j's. This protocol allows us to partition the strategies of agencies into different classes. We say that if agency i submits $O_i \supseteq R_D$ then it makes a *full* offer. If it submits O_i such that $\emptyset \subset O_i \subset R_D$ then it makes a *partial* offer, and if it submits $O_i = \emptyset$ then it makes no offer. Table 1 captures the possible outcomes and utilities for the different classes of strategies.

Analysis of the 2-Agency Case There are certain observations that can be made directly from Table 1.

Observation 1 *If $u_i(\theta_i, R_D, R_D) \geq u_i(\theta_i, O_i, O_i)$ for all $O_i \subset R_D$ then the dominant strategy of i is to offer R_D, and j's best response is to search (and offer) nothing. The equilibrium is $\sigma^* = (R_D, 0)$.*

Observation 2 *If $u_i(\theta_i, O_i, O_i) \leq 0$ for all $O_i \supset \emptyset$ then i's dominant strategy is to offer nothing. Agency j's best response is to offer $O_j^* = \arg\max_{O_j} u_j(\theta_j, O_j, O_j)$.*

What is more interesting is what happens if agencies make *partial* offers of resources. Since, according to the protocol, S_B, agency i has priority, as long as agency j does not make a full offer, the best strategy for i is to find

$$O_i^* = \arg\max_{O_i} u_i(\theta_i, O_i, O_i, \omega_i).$$

$i \setminus j$	Full (R_D)	Partial ($O_j \subset R_D$)	Nothing ($\emptyset$)
Full (R_D)	$u_i(\theta_i, R_D, R_D)$, $-\text{search}_j(R_D)$	$u_i(\theta_i, R_D, R_D)$, $-\text{search}_j(O_j)$	$u_i(\theta_i, R_D, R_D)$,0
Partial ($O_i \subset R_D$)	$-\text{search}_i(O_i)$, $u_j(\theta_j, R_D, R_D)$	$u_i(\theta_i, O_i, O_i)$, $u_j(\theta_j, O_j, (R_D \setminus O_i) \cap O_j)$	$u_i(\theta_i, O_i, O_i)$,0
Nothing ($\emptyset$)	0,$u_j(\theta_j, R_D, R_D)$	0, $u_j(\theta_j, O_j, O_j)$	0,0

Table 1: *The outcomes when two agencies compete to fullfill a request of resources. We assume that agency i has priority over agency j. Note that this is not the real normal form game representation since there are muliple partial O_i.*

Since ω_i may be unknown, agency i will typically maximize its expected utility.

For a given O_i^*, if agency j finds and offers O_j resources, then the maximum set of resources in which it will actually lend is

$$E_j = (R_D \setminus O_i^*) \cap O_j.$$

Agency j's utility is

$$\begin{aligned} u_j(\theta_j, O_j, E_j, \omega_j) &= \text{pay}(E_j) + \text{goodwill}_j(E_j) \\ &\quad -\text{damage}_j(\omega_j, E_j) \\ &\quad -\text{search}_j(O_j). \end{aligned}$$

There are two cases.

Case 1 (unconstrained), $O_j \subset R_D \setminus O_i^*$**:** Agency j's export is limited by its own capacity. Thus, $E_j = O_j$. The utility of agency j is

$$u_j^{(1)} = u_j(\theta_j, O_j, O_j, \omega_j). \tag{1}$$

Case 2 (constrained) $O_j \supset R_D \setminus O_i^*$**:** Agency j's export is limited by the size of the outstanding request. Thus, $E_j = R_D \setminus O_i^*$. The utility of agency j is

$$u_j^{(2)} = u_j(\theta_j, O_j, R_D \setminus O_i, \omega_j). \tag{2}$$

Note that as O_i^* or O_j increases, it is more likely that the utility of agency j is constrained. Figure 1 illustrates the effect the above constraints have on the utility of agency j. The x-axis is the resources found and offered by agency j and the y-axis is the utility. We show the case where j is unconstrained in that whatever it finds and offers is used (solid, blue line), the case where the amount lent by j is constrained to be at most 50 resources (the dashed, red line) and the case where the amount lent by j is constrained to be at most 30 resources (the dotted green line). We set the fireload, $\omega_j = 70$, and assume that all other things being equal, the social goodwill and payments received from lending resources is higher than the cost incurred by searching for their ability. Figure 1 show that under these assumptions, if any offer made by agency j is accepted, then it is best off by offering the maximum amount before fire-damage becomes an issue. Offering any additional resources beyond the threshold results in significant utility loss. For the constrained cases, the utility of j increases as it approaches the maximum possible accepted amount of resources, subject to the offer of i. After this point, its utility decreases, but not in the same dramatic rate as for the unconstrained case. This is because, while the agency has incurred additional search costs for finding resources which will not be used, the amount lent never drains

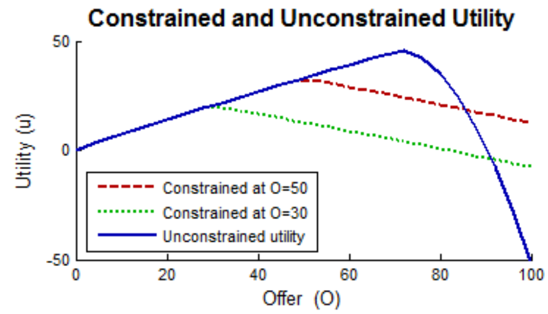

Figure 1: *Constrained and Unconstrained Utility Curves.*

its own resources to the extent that fire-damage becomes an issue.

For agency j to determine its optimal resource offer, it must reason about the offer made by i, O_i^*, as this determines whether its utility falls into the constrained or unconstrained case. To this end, we assume that j maintains a set of *beliefs* about O_i^*. These beliefs incorporate information about other agencies' resources and capabilities, and the information about expected future fireload as captured by F_j. We let $p(r)$ be the probability with which j believes i has made an offer $O_i^* = r$ and let $P(r)$ be the associated cdf. As new information becomes available, j updates its beliefs using Bayes' Rule. The utility for j with fireload threshold ω_j when it makes an offer O_j depends on whether it is constrained by O_i^* or not. Recall that if $O_j \subseteq R_D \setminus O_i^*$ then j is unconstrained, while if $O_j \supset R_D \setminus O_i^*$ then it is constrained. These conditions are, equivalently, $O_i^* \subseteq R_D \setminus O_j$ and $O_i^* \supset R_D \setminus O_j$. The expected utility of j is thus

$$\begin{aligned} E[u_j|O_j, \omega_j] &= u_j(\theta_j, O_j, O_j, \omega_j)P(R_D \setminus O_j) \\ &\quad + \sum_{R_D \setminus O_j \subseteq r \subseteq R_D} u_j(\theta_j, O_j, R_D \setminus r)p(r). \end{aligned}$$

The optimal resources to be found and offered by j (*i.e.* its best response) is $O_j^* = \arg\max_{O_j} E[u_j|O_j, \omega_j]$.

Extending to Many Agencies So far we have assumed that there are only two lending agencies. However, the protocol used by the broker can be extended to multiple agencies in a natural way. The broker generates a list of agencies in decreasing order of priority. An agency j treats the preceding agencies $1, 2, \ldots, j-1$ as a single meta-agency, and maintains a belief about the amount of resources still required. The same reasoning is required, as described earlier, to incorporate the fact that an agency from $j+1,\ldots,n$ might offer R_D, pre-empting all previous offers.

Empirical Examples

In this section we instantiate our model and illustrate how different parameters influence the behavior and utility of agency j. We emphasize that the contribution of this section is to highlight *qualitative properties* and that no quantitative conclusions should be drawn. Obtaining precise quantitative results is beyond the scope of this paper and falls into future work.

Unless stated otherwise, we used the following instantiation of the model. Let $R_D = 100$ and assume that the benefits of lending resources is linear in the amount of resources. That is, $\text{pay}(r) + \text{goodwill}(r) = v \cdot r$ for some constant $v \geq 1$. For search costs, we use the convex function $\text{search}(r) = c \cdot r^{\alpha}$ with $c > 0$ and $\alpha > 1$. Unless stated otherwise, we set $c = 0.2$ and $\alpha = 1.136$. The $\text{damage}(\cdot,\cdot)$ has the following form:

$$\text{damage}_j(\omega_j, r) = \begin{cases} 0 & \text{if } r \geq \omega_j \\ k(\omega_j - r)^{\beta} & \text{otherwise} \end{cases}$$

with $\beta > 1$ and $k > 0$. Unless otherwise noted, we set $\beta = 1.8$, and $k = 0.25$. Finally, while we experimented across numerous settings of ω_j in all shown graphs we have set $\omega_j = 50$. Our qualitative conclusions did not change when varying ω_j and so we keep it constant here so as to serve as a consistent benchmark.

Agency j's utility depends critically on how much agency i has offered to export. Because O_i^* depends strongly on the fire-load of i, and wildland fireload is typically modeled using Poisson distributions (see, for example (Witala 1999; Alvarado, Dansberg, and Pickford 1998; Jiang, Zhuang, and Mandallaz 2012)), we make the assumption that the maximum contribution possible for j (which depends on i's contribution), C_j^*, is distributed according to a Poisson distribution where $Pr(C_j^*) = \frac{\lambda^{C_j^*} e^{-\lambda}}{C_j^*!}$.[5] We initially set $\lambda = 50$.

Figure 2 shows the expected utility for agency j under our initial parameters. This figure depicts both the expected utility of agency j if it was not competing with another agency (the unconstrained utility), and the expected utility after accounting for the other agency. In this case, there is an apparent advantage of having the second agency in the system. While the optimal offer made to the broker is the same, by constraining the amount that j will actually lend, it is potentially protected from severe extreme fire damage as it has extra resources available.

In Figure 3 we show the utility of agency i when $\lambda = 20$. This corresponds to a situation where i has made a large contribution of resources, constraining the amount that will be accepted from j. The optimal offer of j is shifted accordingly, and we observe that if j tries to over-contribute, its

[5]This assumption can be interpreted as j having a fairly clear understanding of i's capabilities and resources, but is uncertain as to the fireload i is experiencing. This uncertainty is informing j's beliefs about i's contribution.

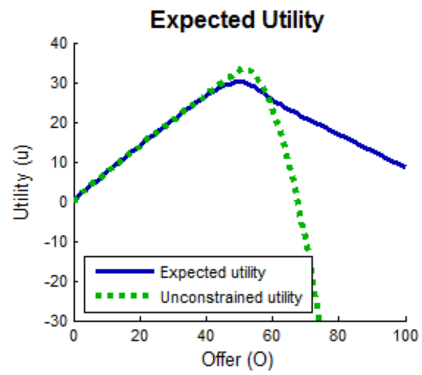

Figure 2: *Expected utility under default parameters.*

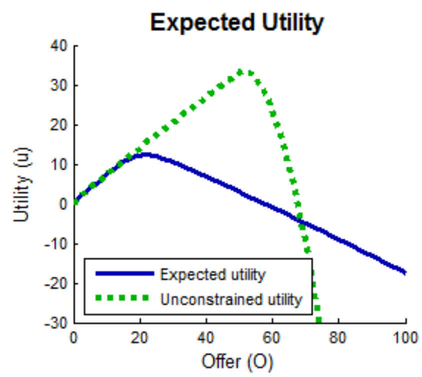

Figure 3: *The expected utility of agency j in both constrained and unconstrained settings when $\lambda = 20$.*

utility decreases due to search costs. However, the magnitude in the utility loss is less than that of the fire damage when it contributes in full (unconstrained curve).

In Figure 4 we adjusted the $\text{search}(r)$ function by increasing the exponent, α, to 1.4. As search costs increase, they begin to outweigh the social goodwill and payments derived from lending resources. Thus, there is little benefit to offering significant resources, irrespective of the contributions of the other agencies. We also experimented with increasing the coefficient in the search function and observed similar trends.

Protocol S'_B: Highest-Offer First So far our analysis has focused on the case where the broker assigns different priorities to the agencies, before they even offer any resources. In this section, we empirically compare the utility of agency j under this protocol with an alternate one which selects resources depending on the amounts offered. We assume that each agency submits their offers, and then the broker orders the agencies based on the size of the offer. That is, if $O_i \supset O_j$ then $i > j$. The broker then begins filling R_D based on this ordering. This policy could be advantageous to the broker since it minimizes the number of agencies lending resources (and potentially reducing the logistical overhead of the broker when coordinating transportation of resources). Figures 5 and 6 compare the expected utility of

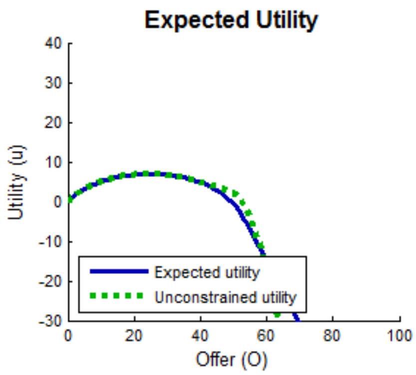

Figure 4: *The expected utility of agency j in both constrained and unconstrained settings when* $\text{search}(r) = 0.2r^{1.4}$.

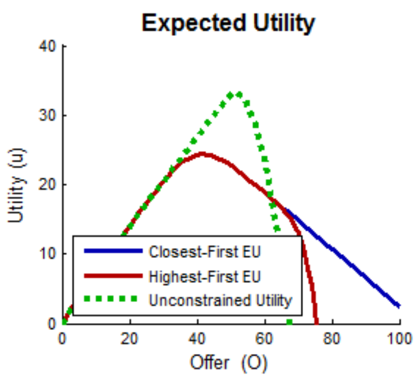

Figure 5: *Expected utility of agency j under different allocation protocols ($\lambda = 40$ and $R_D = 120$).*

agency j under both protocols and we include the unconstrained utility for reference. Note that the different protocols do lead to different best-responses for agency j, given agency i's expected offer. The highest–offer first policy encourages agency j to search for and offer larger bundles of resources than the prioritization scheme. However, this can also lead to the agency taking on more risk, and thus suffer increased losses due to fire damage.

Discussion

We introduced the first model for wildland fire resource sharing. Using ideas and analysis techniques from the multiagent systems and game theory literature, we highlighted the strategic issues which arise in this domain, investigated best-response strategies for agencies under various resource-sharing protocols, and illustrated how these strategies are sensitive to different parameters.

There are several points we want to highlight from our analysis. First, agencies must be strategic when reasoning about the resources they make available. Even though there are benefits from sharing resources, agencies need to mitigate their own risk and account for added difficulties they face when some of their resources are sent abroad. Second, there are inefficiencies in the system, and these inefficiencies

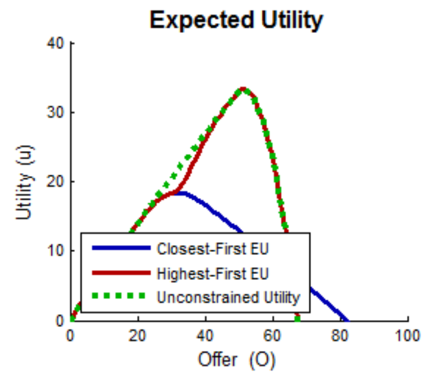

Figure 6: *Expected utility of agency j under different allocation protocols ($\lambda = 30$ and $R_D = 60$).*

are mainly due to uncertainty. If agencies better understood the types of the other agencies and had more accurate information about fireloads overall, then better lending decisions could be made. Finally, the protocol used by the broker for selecting amongst offered resources is important. It changes agencies' strategies and affects their utilities.

There are a number of future directions this work can take. First, while our model is based on a series of consultations with experts in the field and, we believe, captures the key aspects of wildland fire resource sharing, it can be made richer. Ideas developed in the preference elicitation literature could be used fine-tune aspects like the goodwill function (Boutilier 2013), techniques from machine learning could be used to develop better models of fire damage (Cortez and Morais 2007), while the planning problems faced by agencies when searching for resources is well suited for constraint programming techniques (Coffrin and Hentenryck 2012). Second, we studied two protocols that the broker might use when selecting resources. It would be interesting to characterize the optimal protocol in terms of different constraints. While in practice an optimal protocol may not be adopted due to a variety of reasons, it would still be interesting to see what the limits are in terms of resource-sharing. Finally, while our model and analysis was based on the Canadian method of wildland-fire resource sharing, we believe that the ideas and techniques presented are applicable to other wildland-fire resource sharing protocols, and may be useful for researchers studying resource allocation in other domains.

We also wanted to introduce the general wildland fire domain to the broader Artificial Intelligence community. There are a number of features of the domain which make it appealing for AI research in general: there are challenging planning and logistic problems which are time critical, decisions need to be made under highly dynamic and uncertain circumstances, risks need to be carefully controlled, and there are interesting issues balancing cooperative and competitive interests. Finally, the problems caused by wildland fires are global, have great impact on both ecosystems and economies, and, due to climate change, are expected to become more severe in the future.

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