Optimizing firefighter allocation for wildfire response

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Problem statement

Each year, wildfires cause a total annual economic burden of at least \$400B in the US. Suppression resources have an estimated budget of \$100B to protect communities, infrastructures and the environment.

Wildfire management represents a complex challenge due to the unpredictable nature of fire spread and varying effectiveness of suppression efforts. Current allocation methods often rely on experience and local heuristic approaches, which may not efficiently utilize available data and predictive models.

In this research project, we investigate the allocation of fire crews to different incidents at different days that ensures timely responses to more costly fires while minimizing transportation costs. More precisely, our goal is to maximize the total surface area of wildfires treated over a three-day period, with a prioritization of larger fires, while minimizing firefighters travel costs.

Methodology

Our work covers the preprocessing of the real-world data, the elaboration of different methods and experiments, and various interpretations of formulations and results. We think it is important to keep in mind that we are trying to tackle an operational management problem, and that each of the proposed formulation has benefits and drawbacks that are insightful from a wildfire management point of view.

Data

This project leverages three datasets collected from https://www.wildfire.gov/application/sit209 for years 2015 to 2018. The dataset contains 38 491 timestamped reports, covering 5892 fires. To run our experiments, this real-world dataset required methodical preprocessing.
Our goal was to "capture" the dataset at a particular day. We obtained a cleaned dataset of the 51 reported fires that were happening August 1st, 2018, containing the area of the fire on this day, the number of the total amount firefighters sent, and the maximum amount of fire crew sent during any day.

We also computed the distances between these fires using both Haversine and Euclidean formulas.

Approach

Our first method studies the problem of suppression allocation at the level of the fire crew. This natural approach offers information at the most granular level, which is helpful for operational management. With this method, the wildfire manager has a plan for each firecrew, which allows him to easily share this planning to the resources concerned.

We denote $k = 1, \dots, n$ each distinct fire, $i = 1, \dots, m$ the individual firefighters, $t = 1, \dots, 3$ the time in days, S_k the surface area of fire k in hectares, and $d \in \mathbb{R}^{n \times n}$ where $d_{k_1 k_2}$ is the distance between fire $k_1 \in [\![1, \dots, n]\!]$ and $k_2 \in [\![1, \dots, n]\!]$.

Decision variables:

$$X_{itk} \in \{0,1\} \text{ such that } X_{itk} = \begin{cases} 1 & \text{if firefighter } i \text{ is assigned to fire } k \text{ at time } t, \\ 0 & \text{else.} \end{cases}$$

$$Y_{itk_1k_2} \in \{0,1\} \text{ such that } Y_{itk_1k_2} = \begin{cases} 1 & \text{if firefighter } i \text{ has moved from fire } k_1 \text{ to fire } k_2 \text{ at time } t, \\ 0 & \text{else.} \end{cases}$$

1.1 Baseline model: Treating fires in descending order of area

We built a baseline model that prioritizes the allocation of crews by addressing the largest fires first. Once the biggest fire has been ”solved”, the crews move to the second, and then to third one. The new allocation happens 3 times. The allocation is ”easy” to solve after sorting the fires by size.

1.2 First model: fire-area agnostic

We implement a first model that treat fires without the consideration of varying area. In other words, the cost of a fire is simulated by the demand in fire crew headcount, and this demand does not depend on the size of the fire.
We define the demand for a fire k as:

$$\text{demand}_k = \sum_{t=1,2,3} (\text{maximum crews sent to fire k})$$

We define the treatment of fire k at time t as the sum of all crews allocated between the first day and now:

$$\sum_{i=1}^{m} \sum_{t' \leq t} X_{ik}^{t'}$$

We define the cost at time t of fire k as the demand that is not treated:

$$max(0, \text{demand}_k - \sum_{i=1}^{m} \sum_{t' \leq t} X_{ik}^{t'})$$

Objective Function:

$$min \sum_{t=1}^{3} \sum_{k}^{n} max(0, \text{demand}_k - \sum_{i} \sum_{t'<t} X_{ik}^{t'}) + \alpha \times \sum_{t=1}^{3} \sum_{k_1,k_2} \sum_{i=1}^{m} Y_{ik_1k_2}^{t} \times \text{distance}_{k_1k_2}$$

where α is a parameter for controlling the trade-off between penalizing the area treated versus the distance traveled.
Constraints:

1. Firefighter Availability: Each firefighter can be assigned to only one fire at any given time.

$$\sum_{k} X_{itk} = 1 \ , \forall t \in [\![1, \ldots, 3]\!], \forall i \in [\![1, \ldots, m]\!]$$

2. Binary variable Y:

$$X_{i(t-1)k_1} + X_{itk_2} - 1 \leq Y_{itk_1k_2} \text{ , } \forall t \in [\![1,\ldots,3]\!], \forall k \in [\![1,\ldots,n]\!], \forall i \in [\![1,\ldots,m]\!]$$

For computational time matters, we look at the firefighters as crews of 34 firefighters, obtaining a total of 523 crews of 34 firefighters.

1.3 Area-dependent model: encouraging crews towards larger fires

The first approach does not consider the cost of the routing. The second approach lacks the crucial information of the cost of a fire. We propose an MIO formulation that incorporates both these information and try to minimize the total cost.

Before prioritizing bigger fires, we have to model a demand that is a function of the initial area. We don't take into account the prediction uncertainty and we suppose that we have a prediction power: by looking the fire at time t, we know exactly how much fire crews could be sent to take the economic cost to zero.

To emulate the priority of bigger fire, we formulate important assumptions in our model : first we assume a linear scaling between cost and fire surface. Second, we will assume a sublinear relationship in the numbers of needed firecrews against the area of the fire, that we observed in the data. In economic terms, this could be interpreted means that a firecrew marginal revenue is thus higher in bigger fires.

Objective Function:

$$\begin{aligned}\text{Min } \sum_{t=1}^{3} \sum_{k}^{n} \max(0, S_k - \sum_{i} \sum_{t' \leq t} X_{ik}^{t'} \times \frac{1}{\Gamma(S_k)}) \\ + \alpha \times \sum_{t=1}^{3} \sum_{k_1,k_2} \sum_{i=1}^{m} Y_{ik_1k_2}^{t} \times \text{distance}_{k_1k_2}\end{aligned}$$

where $\Gamma(S_k) = e^6 \times s^{0.3}$

Constraints:

1. Firefighter Availability: Each firefighter can be assigned to only one fire at any given time.

$$\sum_{k} X_{itk} = 1 \text{ , } \forall t \in [\![1,\ldots,3]\!], \forall i \in [\![1,\ldots,m]\!]$$

2. Binary variable Y:

$$X_{i(t-1)k_1} + X_{itk_2} - 1 \leq Y_{itk_1k_2} \text{ , } \forall t \in [\![1,\ldots,3]\!], \forall k \in [\![1,\ldots,n]\!], \forall i \in [\![1,\ldots,m]\!]$$

In Gurobi, it is easy to linearize the max operator by taking a positive upperbound of the right side of the max. For computational time matters, we look at the firefighters as crews of 34 firefighters, obtaining a total of 523 crews of 34 firefighters

1.3.1 Timed network formulation

The MIO captures the information at the level of a single fire crew, or group of fire crews. Such method is very interesting in terms of management because it allows to allocate groups of persons to a certain sequences and fires, which greatly helps the operational planing. However, the optimization problem has a large search space, with an amount of binary variables quadratic in the number of fires and linear in the number of fire crews, which is greater than 10 billion binary parameters in our case. Therefore, to make the problem tractable, we had to implement teams of firecrews, which limits the advantage of being able to manage fire units individually.

To speed up the solution to this problem, we believe we can leave a bit of local information, and come up with a different approach. Instead of having the information of which fire crew was allocated to which fire, we can count the number of fire crews per fire and the number of units that transits from fire k_1 to fire k_2 during any time step.

Dynamic graph interpretation

We tried to gain intuition about this approach that represents a spatial graph, dynamic throughout discrete time steps.

Such a formulation has similitude with the structure of a directed network flow problem. We can gain visualize the network as a sequential set of nodes, each one representing the set of fires at a certain time step t. Between two layers, the nodes are fully connected, with the direction of the edges collinear to the arrow of time : the nodes at time t have a directed edge towards each of the nodes of time t+1. The cost of the edge between two nodes is the distance between the two associated fires, and such edge has infinite capacity.

After this, the analogy with a network flow problem ends. Each node in this scenario represents a fire and has a cost based on the demand from the fire's area. The total cost comes from the total unmet demand. A key challenge is that each node, which corresponds to a fire at a certain time, must not only account for resources allocated to it at that moment but also remember all resources allocated to that particular fire in the past, in order to correctly count the treated percentage. To manage this, we could introduce a new layer of nodes, one for each fire, where each node tracks the total resources allocated to a specific fire over time, by being added between any time transitions.

The problem could also be viewed as a finite state automaton where all fire nodes are interconnected, each transition between nodes has a cost representing the distance, and self-transitions for a node are cost 0. The automaton can synchronously fire its transitions 4 times. Each node can keep track of the number of fire crew that has visited it.

Management science interpretation

Regardless of this intuition, this formulation has the benefit of having a much smaller search space than the previous MIO approach. Further, the problem can easily be relaxed and we could be satisfied of the non-integral result. Rounding at one unit does not seem much of a problem giving that there are way fewer fires than fire units.

However, while being tractable and conceptually attractive, this formulation lacks the local information of the MIO, and this tradeoff should not to be underestimated. Here, the fire management department is only aware of the macro-planning : they know how many units they should send from fire i to fire j at each day, but they don't know who to send. Not knowing the states of the fire crew is problematic. In real life, there are more constraints than what our model reflects, and lots of them happen at the level of a unit. For instance, a practical constraint would be that a unit can only move with its firecrew team. Thus, such a formulation seems to be limited in real-life, and should be complemented by local optimization. This double sided optimization would certainly lead to sequence of exchanges between the central management, and the local fire crew teams, until a reasonable plan is found.

Formulation

Decision variables:

$Y^t_{k_1 k_2}$ the number of fire crews that moved from fire k_1 to k_2 before day t.

In this formulation, the number of fire crews at fire k at time t is given by $\sum_{k_1} Y^t_{k_1 k}$

Objective Function:

$$\text{Min} \sum_{t=1}^{3} \sum_{k}^{n} max(0, \text{demand}_k - \sum_{t' \leq t} \sum_{k_1} Y^{t'}_{k_1 k}) + \alpha \times \sum_{t=1}^{3} \sum_{k_1 k_2} Y^t_{k_1 k_2} \times \text{distance}_{k_1 k_2}$$

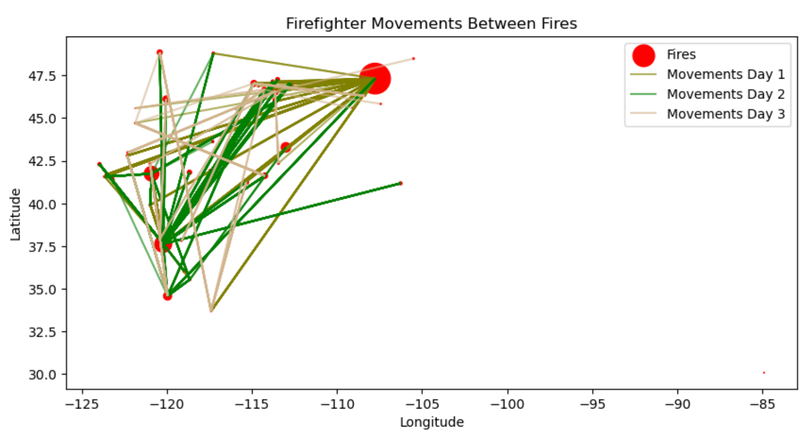
Constraints:

1. Conservation of matter throughout time : what enters node k at time t leaves (or stays) at time t+1 :
   $\sum_{k_1} Y^k_{k_1,k} = \sum_{k_2} Y^{t+1}_{k,k_2}$, $\forall t \in [\![1, 2]\!]$

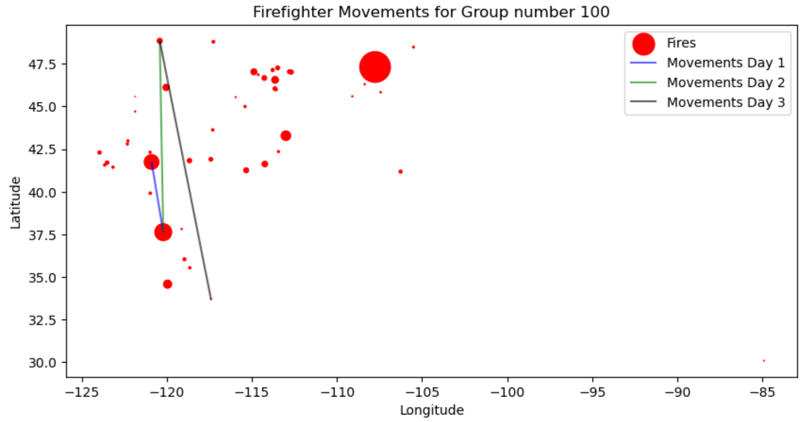
This problem is linear, after accordingly regularizing the max operator.

Results

1. **Baseline model**
   The optimal solution to this problem is attained for **Optimal Cost** = 69826.
   We visualize the assignments and movements of firefighters:

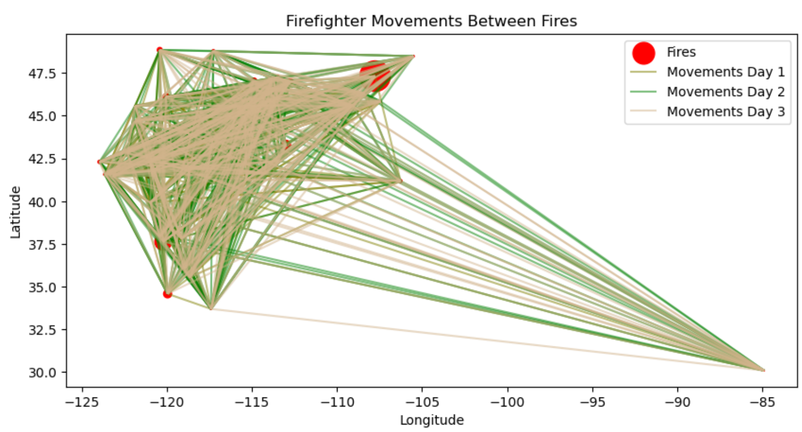


It can be interesting to focus on one unique fire crew, and observe its movements over the three days.



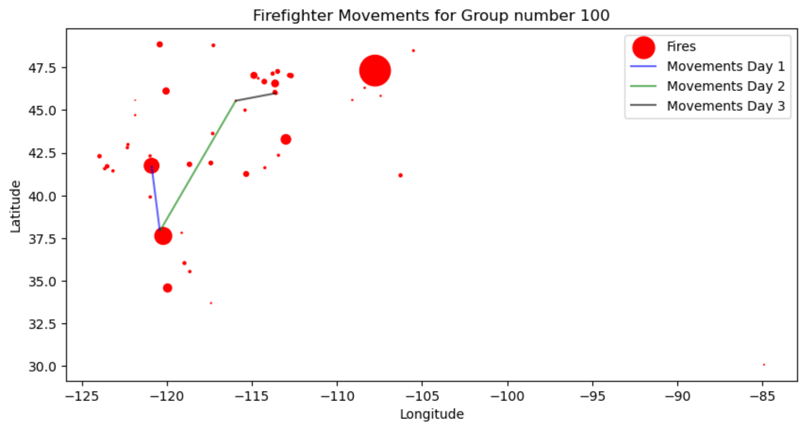
We observe that the crew travels from the second largest fire to the third, then fourth largest fire (the first largest fire at coordinates $(-107, 47)$ is not adressed by the crew because it was already adressed by other crews on day 1).
Notice that the crew travels from day 2 to day 3 a significant distance, hence clearly not accounting for costs.

2. **Area-agnostic model**
The optimal solution to this problem is attained for **Optimal Cost** $= 2032$.
We visualize the assignments and movements of firefighters:



We observe that the crews travel far more than the baseline model, adressing a higher number of fires. This translates the fact that a crew does not wait for a fire to be entirely taken care of before addressing others. All-in-all, this strategy minimizes the cost associated with damages.

It can be interesting to focus on one unique fire crew, and observe its movements over the three days.



We observe that the crew's displacements sum up to less distance than the baseline model.

3. **Dynamic network**: The solution is found immediately, with an **Optimal Cost** $= 876$.

Impact

Our study covers a wildfire management problem, balancing prioritization of dangerous fires against human logistics cost. Formulating different problems and developing problems, we focused on both the theoretical and the practical aspects of the problem, while keeping in mind the important operational interpretation. Notably, the MIO formulation, while being computationally expensive, offers rich decision-making information allowing wildfire management more flexibility in real life. The linear dynamic graph formulation offers a very tractable method, allowing to quickly experiment and adapt to real life operations at a higher frequency. However, the information given by the solution be limiting compared to the granularity of information needed to manage operations. Such tradeoff between information level, economic performance, and computational tractability is particularly interesting and seems to be at the core of the philosophy of complex operational research problems.

References

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