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Dynamic decision making model for wildfire containment

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ABSTRACT

Wildfires are severe natural disasters and environmental problems. This paper describes a methodology for constructing a dynamic decision model which aims to support the human expert's decision making in fire containment. The main idea is based on Markov decision processes (MDP) which can handle the uncertainty and dynamic features of decision making problems. In order to apply MDP to large scale real world problems, we use a factored manner to describe and formulate the dynamic decision model. This helps the problem expression and solution, and the policy generated by the model is explicit and specific actions of wildfire suppression measures which is easily understood by human decision makers. Furthermore, we simulate two scenarios and verify the decision effects solved by the model. The results reveal that our model has prominent performance on wildfire containment and deals with multi-objective decision problems easily and intrinsically.

KEYWORDS

Wildfire containment; Dynamic decision making; Markov decision processes.

INTRODUCTION

Wildfire is one of the severest natural disasters on the planet, which cause significant loss of life and property and have enormous environmental effects on ecosystems. In recent years, wildfire activities are increasing due to global climate change, requiring more effective containment of wildfires to protect the society and public safety.

It is quite difficult to predict wildfires in space and time, which makes efficient decision about mitigation efforts a great challenge, particularly during the dynamic response period to the wildfires[1]. Therefore, the ability to predict wildfire location and behavior is the key point for an effective wildfire initial response. Furthermore, faster and precisely prediction of fire behavior and suppression measures would help fire containment planning and limit the damage of wildfires.

The most effective way of predicting fire spread and reducing risk is through modeling and simulation[2]. There are extensive literatures on wildfire modeling and simulation, including mathematical models of fire spread[3], fire simulation on a specific region[4, 5], firefighting resources allocation[1]. However, most of the existing researches are rarely relevant to dynamic response to wildfires in a unified and mathematical framework.

In this article, we apply Markov decision process (MDP) to model the Dynamic response process of wildfire containment, combining fire spread simulation and suppression measure in a unified, dynamic, and mathematical framework. First, we describe the states of the wildfire in a factored manner. Then we map the fire spread law into a transition function probabilistically. Moreover, we define abstract fire suppression measures and design reward function according to decision objectives. Finally, we apply the dynamic decision model to specific scenarios representing wildfire fighting decision situations, and verify the decision effectiveness of the model.

METHODOLOGY

MDP provides a mathematical framework for modeling dynamic and probabilistic decision making problems. An MDP can be defined as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R})$[6], where

$\mathcal{S}$ is a set of states.

$\mathcal{A}$ is a set of actions.

$\mathcal{T}$ is a transition function, a mapping specifying the probability $\mathcal{T}(s_i, a_i, s_j)$ of going into state s_j if action a_i is executed when the current state is s_i.

$\mathcal{R}$ is a reward function that gives a finite numeric reward value $\mathcal{R}(s_i, a_i, s_j)$ obtained when the system goes from state s_i to state s_j as a result of executing action a_i.

Here, it should be noted that the time element is implicit in this kind of expression. Since most of wildfires response would be finished at fixed time, we can enumerate the time steps as $t=1,2,\ldots,T_{end}$.

In order to apply MDP framework to wildfire containment, we need to specify each element of MDP according to the knowledge of wildfires spread and suppression. Although defining an MDP takes just a few lines of text, describing an MDP instance in enumerative way would require exponential space with the increasing magnitude of problems[7]. Therefore, we use a more compact way, factoring the state space into constituent variables, to describe our model. The steps for building a dynamic decision model for wildfire containment are listed as below.

Define the states

A wild land region can be represented as a two-dimensional cell space composed of cells of dimensions $m \times n$, where m and n are the length and width of the region respectively. And each cell of the whole region can be identified by its location or coordination. For example, if we set two axes for the region as $\mathbf{x} = (x_1, \ldots, x_m)$ and $\mathbf{y} = (y_1, \ldots, y_n)$, then any cell of the region is marked with (x_i, y_j), where $1 \leq i \leq m$ and $1 \leq j \leq n$. Each cell can be associated with one of three states: unburned, burning, and burned. An unburned cell can catch fire to enter the burning state and will eventually die out, becoming burned. The decision situation here does not allow for regrowth of a burned cell, so these state transitions proceed in one direction only. We use two binary variables, which are whether a cell is on fire (defined by $o(x_i, y_j)$) and whether the combustible materials of a cell has burned down (defined by $b(x_i, y_j)$), together to represent the above three states (see Table 1).

TABLE 1: States representation

state	$o(x_i, y_j)$	$b(x_i, y_j)$
unburned	0	0
burning	1	1
burned	0	1

Determine the state transition function.

Wildfire progression is driven by inherently complex, interconnected, physical processes, involving a variety of factors, including weather, vegetation, and terrain[8, 9] To focus on our research essence- dynamic response to wildfire, we simply assume that each individual cell has uniform weather, vegetation, and topographical conditions, and different cells can have different factors.

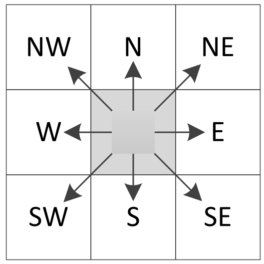


Figure 1: Moore neighborhood of a cell

To simulate the wildfire spread through the cells of the region, we define neighborhood of each cell. Here we use Moore neighbourhood (see figure 1.). Each cell has at most eight neighbors (except for cells on the corner or edge of the region). We describe this neighborhood in a factored manner as North($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), South($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), East($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), West($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Northeast($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Northwest($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Southeast($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Southwest($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), and then we have

$$\text{North}(x_{i_1}, y_{j_1}, x_{i_2}, y_{j_2}) = \begin{cases} 1 & \text{if } (x_{i_1}, y_{j_1}) \text{is on} \\ & \text{the north of} (x_{i_2}, y_{j_2}) \\ 0 & \text{others} \end{cases} .$$

Since the definitions of South, East, and other neighbor relationships are similar to the North definition, we do not enumerate them respectively.

The fire can spread from burning cells to unburned cells over the temporal progression of fire contagion. The state of a cell at time step *t+1* is determined by a function of the state itself and the states of its neighbor cells at time step *t*. To describe the state transition rule of each cell between consecutive time steps, we define a basic transmissibility *v*, to be the average probability that a burning cell will ignite the unburned cell in its neighborhood. Then the transition probability for an unburned cell is the sum over the transmissibility of all its neighbor cells. Since the diagonal cells are farther than adjacent ones to the central cell, the transmissibility is modified by a factor of $1/\sqrt{2}$. Moreover, we have to consider the influence factors of wildfires, including weather, vegetation, and terrain. The most important weather factor that affects forest fire spreading is the wind speed and direction[10]. We can incorporate wind factor by assigning a weight to the corresponding neighbor relationship due to the wind speed and direction. For example, if the wind is blowing from west to east, then the transmissibility for East($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), West($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Northeast($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), Southeast($x_{i1}, y_{j1}, x_{i2}, y_{j2}$), would be vK_W^E, vK_W^W, vK_W^{NE}, and vK_W^{SE}, where (x_i, y_j) is unburned cell, $K_W^E > K_W^{NE} = K_W^{SE} > 1$, and $K_W^W < 1$. The transmissibility for other neighbor relationships do not affect by the wind, so their weights are set to 1. Vegetation can be considered as fuel of each cell, and the speed of spread for cells varies with the different types of fuel. Each type of combustible material is assigned a weight to demonstrate how fast the fires spread across cells with different fuels, denoted as K_M. If the cell has no combustible material (like rocks), then $K_M = 0$. For terrain factor, the height differences between cells greatly affect the forest fire spreading. It is common that fires show a higher rate of spread when they climb up an upward slope, whereas fires show a smaller rate of spread when they descend a downward slope[11]. Referred to wind factor, we assign weights to the transmissibility about height for various neighbor relationships according to the topography of the wild land region, denoted as K_T^N, K_T^S, and etc. Finally, we have a comprehensive transition probability for unburned cell (x_i, y_j) by integrating all above factors,

$$\begin{aligned} p_{x_i,y_j} = v \cdot K_M [&o(x_{i2}, y_{j2})\text{North}(x_i, y_j, x_{i2}, y_{j2}) K_W^N K_T^N \\ &+ o(x_{i2}, y_{j2})\text{South}(x_i, y_j, x_{i2}, y_{j2}) K_W^S K_T^S \\ &+ o(x_{i2}, y_{j2})\text{East}(x_i, y_j, x_{i2}, y_{j2}) K_W^E K_T^E \\ &+ o(x_{i2}, y_{j2})\text{West}(x_i, y_j, x_{i2}, y_{j2}) K_W^W K_T^W \\ &+ \frac{1}{\sqrt{2}} o(x_{i2}, y_{j2})\text{Northeast}(x_i, y_j, x_{i2}, y_{j2}) K_W^{NE} K_T^{NE} \\ &+ \frac{1}{\sqrt{2}} o(x_{i2}, y_{j2})\text{Northwest}(x_i, y_j, x_{i2}, y_{j2}) K_W^{NW} K_T^{NW} \\ &+ \frac{1}{\sqrt{2}} o(x_{i2}, y_{j2})\text{Southeast}(x_i, y_j, x_{i2}, y_{j2}) K_W^{SE} K_T^{SE} \\ &+ \frac{1}{\sqrt{2}} o(x_{i2}, y_{j2})\text{Southwest}(x_i, y_j, x_{i2}, y_{j2}) K_W^{SW} K_T^{SW}] \end{aligned}$$

Intuitively, a small fire would have less possibility to escalate, so we turn down the basic transmissibility to a half when the number of burning cells in neighborhood is less or equal than 2.

Map the suppression measures into actions of MDP

There are three classes of measures of fire suppression, namely direct attack, parallel attack and indirect attack on fires[12]. Direct attack is made directly on the fire's edge or perimeter, knocking down the fire by dirt or water. Parallel attack is made by constructing a fireline parallel to, but further from, the fire edge than in direct attack. Indirect attack is accomplished by building a fireline some distance from the fire edge and backfiring the unburned fuel between the fireline and the fire edge. We can abstract two actions from these measures, one is put out the fire on a cell, and the other is cut off the fuel on a cell to prevent the fire spread across it. We use $\mathrm{Put}(x_i, y_j)$ to denote put out the fire on cell (x_i, y_j), and $\mathrm{Cut}(x_i, y_j)$ to denote cut out the fuel on cell (x_i, y_j). The outcome of the actions may not be deterministic, and each outcome is reached with some probability. The preconditions and effects of the actions are formulated (as Table 2).

TABLE 2: Preconditions and effects of action

Action	Precondition	Effect	Probability
$\mathrm{Put}(x_i, y_j)$	$o(x_i, y_j) = 1$	$o(x_i, y_j) = 0 \wedge b(x_i, y_j) = 1$	r_p
		$o(x_i, y_j) = 1$	$1 - r_p$
$\mathrm{Cut}(x_i, y_j)$	$b(x_i, y_j) = 0 \wedge o(x_i, y_j) = 0$	$b(x_i, y_j) = 1 \wedge o(x_i, y_j) \equiv 0$	r_c
		$b(x_i, y_j) = 0 \wedge o(x_i, y_j) = 0$	$1 - r_c$

Design reward function with respect to the goals of firefighting missions

In most wildfire containment situations, the prior goal of the decision makers (fire commanders) is to put out the fire as soon as possible. Therefore, we need to interpret this goal into reward function. We consider both the loss caused by the fire and the cost of fire suppression actions in reward function, letting C_{unit} be the loss of a burning cell at one time step, C_{put} and C_{cut} be the cost of taking put and cut action, respectively. Then, we have reward function,

$$\mathcal{R} = -C_{\mathrm{unit}} \cdot \sum_{\substack{1 \le i \le m \\ 1 \le j \le n}} o(x_i, y_j) - C_{\mathrm{Put}}(x_i, y_j) - C_{\mathrm{Cut}}(x_i, y_j).$$

Moreover, in some wildfire situations, there may be some important targets (like village or buildings) on the wildfire region. The decision makers not only consider the firefighting, but also the protection of such important targets. We can easily model this decision making problem by considering the value of the target in the reward function. For example, suppose that an important target lies on the cell (x_{goal}, y_{goal}), and a large weight is assigned to the target. Once it burned, it would cause a penalty of the weight. Then the reward function can be modified to

$$\mathcal{R} = -\, C_{\mathrm{unit}} \sum_{\substack{1 \le i \le m \\ 1 \le j \le n}} o(x_i, y_j) w \times o(x_{goal}, y_{goal}) - C_{\mathrm{Put}}(x_i, y_j) - C_{\mathrm{Cut}}(x_i, y_j)$$

RESULTS AND DISCUSSION

We use two scenarios to illustrate the application of our model and verify the fire containment effects. The first scenario is simply firefighting decision. The second one is multiple goals decision including firefighting and protecting an important target on the fire region.

Firefighting Scenario

In this scenario, we simply assume the wildfire region shares the same fire spread factors, such as homogeneous vegetation and flat terrain, no wind. Therefore, the weights of these factors are simply set to 1. Moreover, we assume the successful rate of put and cut actions are 100%, and then r_p=1, r_c=1. The other parameters of the decision model are m=10, n=10 , v=0.1, C_{unit}=1, C_{cut}=0, C_{put}=0. The initial state of the wildfire is shown in figure 2. There are five cells on fire at the beginning.

To verify the fire containment effects, we simulate six policies of fire control and compare their effects. The policies are no control policy (NCP), random putting out policy (RPP), dynamic decision making of putting out policy (DDMPP), random cutting off policy (RCP), dynamic decision making of cutting off policy (DDMCP), and dynamic decision making of mixture actions policy (DDMMP). NCP provides a pure simulation of the wildfire; random policies (RPP and RCP) are reference to the dynamic decision making policy (DDMPP and DDMCP); while the DDMMP is composed of both of put and cut actions calculated by the model.

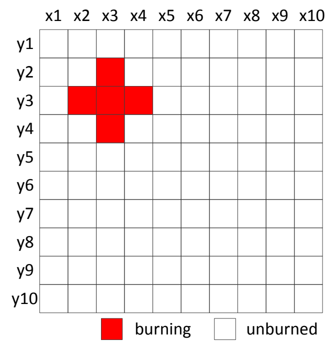
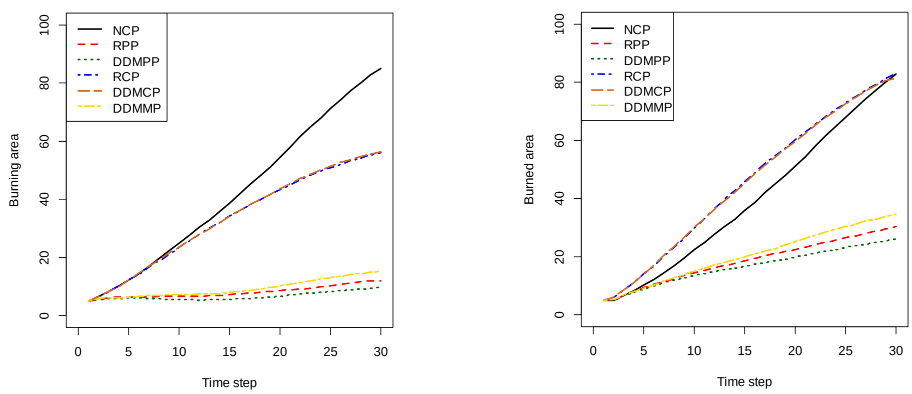


Figure 2: Firefighting scenario

For each policy, the simulation is executed 100 times, with a decision horizon of 30 time steps. The results (average of the 100 simulations) are shown in figure 3. Since the cut off action clears the vegetation on the cell, the number of cut off cells is also included in the burned area. We can see from figure 3(a), for NCP, the burning area is obviously the largest among the six policies since no control measures implemented in such policy. However, the burned area of RCP and DDMCP are even larger than NCP in most of the simulation times (see figure 3(b)). This reveals that although the burning area of RCP and DDMCP are smaller than NCP due to the amount of cleared cells, from the vegetation damage perspective, these two policies are worse. In addition, these two policies demonstrate no difference in burning area and burned area, and the dynamic decision making plays insignificant role during the response process. Therefore, the cut action is not an effective action in the context of our model. This is also reflected in DDMMP. Because of considering cut action, the DDMMP is even worse than RPP. On the contrary, the put action is quite effective in wildfire containment in the context of our model. All of the three policies considering put action demonstrate great advantages in both of burning area and burned area than the other policies. Additionally, DDMPP surpasses RPP, demonstrating effectiveness of dynamic decision making policy solved with our model.



(a) **(b)**

Figure 3: Firefighting scenario simulation results: a) Burning area, b) Burned area.

Important target protection scenario

Through above analysis, the cut action is not as effectiveness as put action. As a result, in this scenario, we only consider put action in the response to the wildfire. We also assume the fire spread affect factors are uniform and set to 1 as in the previous scenario. The other parameters of the decision model are *m*=10, *n*=10, *v*=0.1, r_p=1, C_{unit}=1, C_{put}=0, *w*=1000. The important target is near the initial burning cells at (x_5, y_5) (see figure 4).

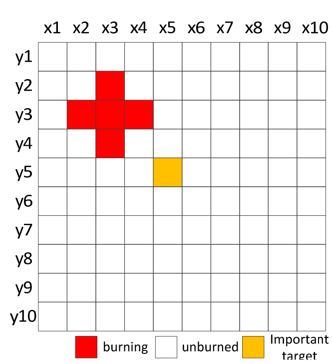


Figure 4: Important target protection scenario

We compare differences between two dynamic decision making rules, whether considering the important target in the decision. Each rule can be expressed with corresponding reward function as shown in Eq. (1) and Eq. (2). Eq. (1) is the rule without considering the important target; Eq. (2) is the rule considering the target and encourage executing put actions near the target by gaining award of 2 of each put action. Each was simulated 100 times, with a decision horizon of 30 time steps.

$$\mathcal{R} = -\sum_{\substack{1\le i\le 10\\ 1\le j\le 10}} o(x_i, y_j) \tag{1}$$

$$\mathcal{R} = -\sum_{\substack{1\le i\le 10\\ 1\le j\le 10}} o(x_i, y_j) + 2\sum_{\substack{3\le i\le 7\\ 3\le j\le 7}} \mathrm{Put}(x_i, y_j) - w\cdot o(x_5, y_5) \tag{2}$$

In order to evaluate the decision effect, we calculate the put action executed times of each cell, as well as burned times of each cell of both decision rules. The burned times are illustrated in figure 5 and figure 6. Under the rule of without considering target, the initial burning cells (x_2, y_3), (x_3, y_2), (x_3, y_3), (x_3, y_4), (x_4, y_3) are put out 96, 96, 97, 93, 97 times respectively, which are the most distributed cells of put actions. Their surrounding cells are less distributed uniformly. Then the put action times of the farther surrounding cells decrease in a uniform manner. The burned times of each cell display the same distribution as the put action taking times (see figure 5). Meanwhile, the put action taking times of the initial burning cells under the rule of considering target are not uniformly distributed. The topleft cells have a large number of put action times than the cells near the target. This shows the decision effect that during the response process, the cells near the target have a higher priority and thus are put out once they catch on fire before they transmit the fire to their neighbor cells; whereas the cells on the reverse direction near to the target are sometimes ignored and thus are put out late, which cause a larger spread to their neighbor cells. As a result, the less burned times lead to less put actions. We can see from figure 6, the burned times are sharply decrease approaching the target, and they are not uniformly distributed as circles like in figure 5. This proves our model remarkably reflect the goal of protecting important target.

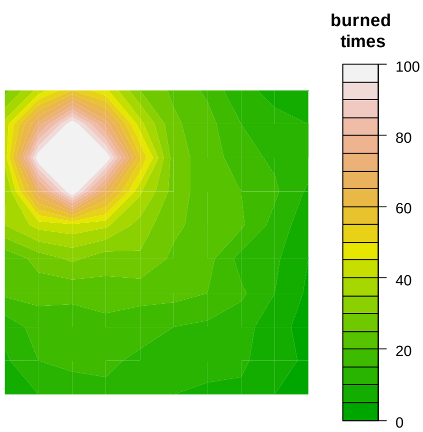


Figure 5: Cells burned times without considering the target

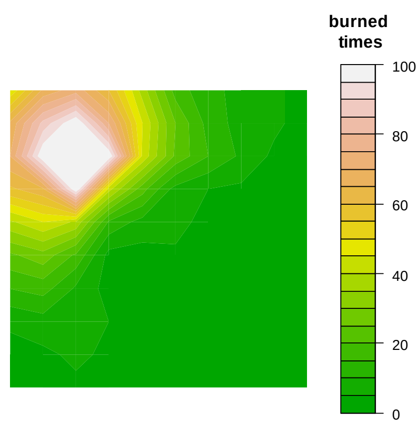


Figure 6: Cells burned times considering the target

CONCLUSIONS

We presented a framework for building a decision model which can dynamically control wildfires, a complex task during uncertainty and real time decision situation. It is important to include a formal model for wildfire suppression measures supporting human decision making for this complex task, since the problem involves urgency and dynamic feedback that make the plan exploration and evaluation very difficult for human experts. Our model based on MDP can serve as a basic tool to support the dynamic decision making of wildfire containment, and makes the decision problems quantitatively represented and computationally solved.

Moreover, our model can be adopted by wildfire management decision support systems. The model can be implemented as software or systems for real-time decisions support. Online algorithms[13] of MDP generate policies in an interactive manner, which is able to generate policies according to given states in real-time. As a result, the stress of the decision makers would be alleviated under time pressure and urgency with such decision support systems.

Last but not least, it should be noted that the dynamic decision model also captures essential features of related problems such as the spreading of infectious diseases, flooding, and hazardous chemical gas. Through expert analysis of such domains, the framework of this model can also be applied to these problems, and shed light on decision support for human experts in these related fields.

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