Modelling and Simulation Analysis of Drones Allocation for Bushfires

Junxu Wang†, Haisong Weng†, Yuxin Yan† and Congduan Li*
School of Electronics and Communication Engineering, Sun Yat-sen University, Shenzhen, China
†All authors contributed equally

*Corresponding author email: licongd@mail.sysu.edu.cn

Abstract. Recent years, bushfire has been more and more frequent because of climate changes. At the scene of fires, firefighters have used drones for surveillance. In this paper, a model is designed to determine the optimal number of drones needed for a bushfire based on the data from satellites. We design a greedy algorithm to plan the cruise lines with the minimal number of drones, covering the fire region. We divide a region (take Victoria, Australia as an example) into blocks, and analysed each block to get the average number of drones needed. We also model the fire probability distribution and finally determine the total number of drones that should be reserved. The simulation (The simulation code is publicly available via https://github.com/WRangers/msadab) results and analysis show the model is effective and can adapt to a real-time changing large-scale bushfire situation, adjusting the cruise scheme dynamically. The algorithm is helpful to make a budget on purchasing equipment, and also helps the fire department deploy drones in bushfires.

Keywords: Bushfire; Drone allocation; Greedy algorithm; Cruise planning.

1. Introduction
Australia was hit hard by bushfires during summer 2019-record-breaking temperatures and months of severe drought have fuelled the most catastrophic bushfire season ever experienced in the country’s history, with the worst impact in New South Wales and eastern Victoria [1]. There are a variety of models about fire spread, among which mathematical modelling is most general. Most of them are reaction-diffusion systems based on parameter of terrain, fuel type, fuel state heat, et al. [2-6]. Some model the bushfire activity using a decision tree [7-8], and there are other methods like cellular automata modelling [9-10]. Those approaches are effective for small-scale bushfire. As for the bushfire has the same scale with the bushfire that mentioned above in Australia, they mostly failed because the parameter changing as time passes [1, 4]. Moreover, we do not know the exact parameters most of cases. It is hard for them to adapt to the complex environment. Therefore, it is necessary to establish a model that qualifies to cope with large-scale bushfire in real time.

On the frontline of bushfire, firefighters have used drones and other wearable equipment for surveillance [11]. Inspired by the thought of wireless network [12-14], we build a model that makes full use of drones to surveil bushfire, based on a dynamic network driven by the data form satellites. Because the model is based on the data from satellite initially, it is more actuary than those based on fire spread model. The model gives a scheme that how drones cruise to cover the fireplaces. The drone scheme is also supposed to be capable of disposing of frequent bushfire, especially when multiple places on fire simultaneously. We use the greedy algorithm we designed to plan the least cruise lines that cover all the fireplaces within a specific area, thus the number of drones used is minimal.
Victoria, Australia as an example, and also achieve the total number of drones that should be reserved through statistic methods [15].

The contributions of this paper include: a) a model planning cruise lines of drones for bushfire; b) a detailed simulation with robustness analysis of the model shows that the model is able to adjust the cruising strategy of drones according to the real-time situation and satellite data which is overwhelming to other traditional methods that cannot achieve; c) the results can help related divisions of government make a budget and also help determine the number of drones to deploy.

The remaining of this paper is organized as follows. Section 2 first illustrates the format of data from satellite, implicating the fire situation. Then explains the construction of the model for planning drone cruise lines, and statistic methods to determine number of drones needed. And the simulation results and analysis are shown in section 4. Finally, we make the conclusions of this paper in section 5.

2. Model

2.1. Data

The data we used come from NASA EARTHDATA, including bushfire data in Australia from 2001-19. The databases were recorded by the instrument MODIS in the satellite Terra. Each data item includes the GPS location, the brightness implying fire behaviour, approximate fire area, and confidence coefficient.

We divide the area of Victoria into $11 \times 18$ regions. Each region's area is $50 \times 50 \text{ km}^2$, and we call such a region as a block. We eliminate the data whose confidence less than 50 which is up to 100. Then divide them into groups by acquired time. Each group of data represents a bushfire event (Here, a group of data represents a bushfire event, but not a fire. Namely, an event may involve more than a fire-a few different places are at fire at the same time.), and we consider the mean position of a group of data as the origin of a fire, as shown in Figure 1. The data out of the region of Victoria have been picked out.

2.2. Overview

When a bushfire occurs, we get the data from the satellite (an example is shown in Figure 2), our objective is to use the fewest drones to cruise all these fireplaces. The model will design optimal cruise lines using the greedy algorithm [16], considering about fire size, drones' working time, et al. Then, we can surveil the fireplaces and adjust the cruise scheme whenever necessary.

2.3. Model Construction

The satellite processes the observation data of bushfires in some way, acquiring a few fire pixels

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**Figure 1.** The fireplaces in different blocks during 2019 in Victoria, Austria. Each small red rectangle represents a bushfire event, and its size implies the area of fire.

**Figure 2.** An example of a fire event within a block, there are serval places on fire at the same time.
(small rectangles as shown in Figure 2). The centre of each pixel is approximately the fire location, and the size of each pixel implies the fire size. Because the centre cannot represent the fire position precisely, it is necessary to cruise over the area of the pixel using drones [17]. To simplify the analysis, we assume the cruising time over each pixel is proportional to its circumference. Naturally, its centre position is our target observation point and the circumference is the cruise journey.

The working time of a drone is limited. To make sure the drone can come back, we should estimate whether the drone can return before it flies to the next target observation point. Thus, we can make sure that the drone can always return to its starting point before it runs out of power. The fire is not still but spreads [3, 5]. To get information from the frontline in time, the drones should spy on every observation point as frequent as possible. So, we set the maximum allowable observation interval as $T_0$.

Constructing a graph for a drone, representing the cruising line. The vertex set $V$ stands for positions on the cruising line, denoted as $P_i \in V \ (i = 0, 1, \ldots, n)$, where $P_0$ and $P_i (i \neq 0)$ represent the take-off and observation points, respectively. Let us say the number of drones $m$, the velocity of drones $v$ (We assume that all the drones work at maximum flight speed which we set to be 20 m/s), then

1. The time of the journey $y_{ij}$: the time it takes a drone to get from one target observation point to another

$$y_{ij} = \frac{\|P_i - P_j\|}{v}, \quad i, j \in \{0, 1, \ldots, n\}. \quad (1)$$

2. The time of observation $x_i$: in order to observe the fire situation, the time required for the drone to circle the edge of the flame pixel of the target point $P_i$. Particularly, we set the time required at the take-off point to 0, namely $x_0 = 0$. We definition $x_i$ as follow:

$$x_i = l_i / v, \quad (2)$$

where $l_i$ is the observation journey at $P_i$. Considering the effect of different terrains, we correct the equation (2) to be

$$x_i = \exp\left(\frac{|\nabla H_i|}{\alpha}\right) \cdot \frac{l_i}{v}, \quad (3)$$

where $|\nabla H_i|$ represents the absolute value of the gradient of the target observation point's altitude, indicating the extent of complexity nearby; $\alpha$ is a constant coefficient depending on the terrain.

3. Flight period $T_k$: the time of a drone, with the serial number of $k$, taking off until it returns. The constraint conditions of $T_k$ are list as below:

i. $T_k = \sum_{i=0}^{n} \sum_{j=0}^{n} (y_{ij} + x_j) d_{ij}^{(k)}, \quad \forall k, T_k, T_0, \quad k = 0, 1, \ldots, m, \quad (4)$

where $d_{ij}^{(k)} = \begin{cases} 1, & \text{the drone numbered } k \text{ passes the edge from } P_i \text{ to } P_j, \\ 0, & \text{others.} \end{cases}$

ii. To balance capability and safety with economics, the selected take-off point $P_0$ subjects to

$$P_0 = \arg \min_m \sum_k T_k. \quad (5)$$
Namely, the model should minimize the number of drones $m$ and also the sum of flight period of all the drones.

### 2.4. The Algorithm

The algorithm is illustrated below [18-19]:

**Step 1.** Initialize. Let the number of drones $n$ as 1, and the working time of the drone $T$ as 0. All the vertexes belong to the set $V = \{ P_0, P_1, \ldots, P_n \}$. A set of accessed vertexes is denoted as $S_i = \emptyset$ and the serial number of the current vertex $a_i = 0, i = 0$;

**Step 2.** Calculate the set of reachable and accessible vertices, namely

$$Q = \{ P_j \mid P_j \notin S_i, T + y_{a_j} + x_j + y_j, T_0 \};$$

**Step 3.** If the set $Q$ is empty, let $n = n + 1, T = 0$ and then repeat Step 2. If the set $Q$ is non-empty, calculate $\min_{\alpha \in Q} y_{a_j} + x_j$, denoting the vertex that makes it reach the minimum value as $P_{a_i}$, as well as letting $S_{i+1} = S_i \cup \{ P_{a_i} \}$;

**Step 4.** If $i = n$, stop the algorithm, or replace $i + 1$ with $i$ and then repeat Step 2.

### 2.5. Determining the Total Number of Drones Needed within a Region

With the model, we calculate the average number of drones in each block and get a fire probability distribution; thus, we can get the expected number of the drones to determine how many drones to reserve. We denote the following symbols:

- Fire probability matrix $B_p$: recording the fire probability in each block.
- The average number of drones matrix $D_p$: the average number of drones for each block.

The working time of a drone is limited but normally bushfires last for more than the max working time. Assuming that recharge time needed for the built-in battery of a drone is less than the max working time. Multiplying the total number of drones calculated by two, we can respond to fire events that last longer than the max working time. Therefore, the store of drones is enough for most of the cases. However, there may be more than a place which is on fire, the drones needed indeed should be more. Therefore, the total numbers of drones needed at least is

$$N = 2 \sum_j \sum_{\theta \in \theta} B_{pj} B_{d\theta}. \ (6)$$

### 3. Simulation and Analysis

We simulate the algorithm via the software MATLAB® 2021a. The velocity of drones $v$ is set at 20 m/s. The maximum working time of a drone is set at 2.5 h. We calculate the number of bushfire events of each block in year 2019, getting the $B_p$, i.e., the fire probability distribution [15], which is shown in Figure 3. The darker the colour, the higher the probability of fire. Based on the data in Figure 2, we give the simulation results in Figure 4, where there are 3 cruise lines, i.e., we need three drones. Line in different colour represent different cruise lines. The blue rectangle in Figures means the take-off location of drones. That is the initial cruise scheme. We can set a time interval to update the cruise scheme according the real time data from both drones and satellites, achieving the goal that adapting to large-scale bushfire with dynamic scheme. For example, in Figure 5 and 6, the updating interval is 30 minutes. The former shows the case of the bushfire abates, while the latter one shows that of aggravating. The results prove that the model qualifies to adapt to changing bushfire situations. Hence, it is more flexible than models with traditional reaction-diffusion systems which do not considerate the occasion where there are multiple places on fire at the same time and the progress of fire suppression.

For the bushfire that lasts for days or even weeks and the area involved quite large, the model is
efficient because we can adjust our deployment according to the bushfire, making best of material and manpower resources.

Figure 3. The fire probability distribution of Victoria’s blocks in the year 2019.

Figure 4. The three cruise lines of the example bushfire event and three drones are needed. The blue rectangle means the take-off position.

Figure 5. We set the updating interval at 30 minutes. (a) The updated cruise scheme after 30 minutes. (b) The updated cruise scheme after an hour. We can see that the bushfire abates the number of drones decreases to two after an hour.

Figure 6. The case where the bushfire abates. (a)-(c) The cruise schemes from initial to after an hour with the interval of 30 minutes. The bushfire aggravates and the number of drones increases to 5.

4. Conclusion
This paper first introduces a model to determine the optimal number of drones needed for a bushfire, where we design the least cruise lines based on the data obtained from the satellite. Within the blocks divided in a region, we can get the number of drones of every bushfire event, thus also the average number. Through the fire probability distribution and statistical methods, it is easy to determine how many drones in total needed for a region to cope with bushfires.

We make the simulation based on the data of the year 2019 in Victoria, Australia. The results show that the algorithm is effective to large-scale bushfire which adapts to changing situation. The results are helpful to relative divisions of government to make decisions about budget when purchasing drone equipment, and also help the fire department deploy drones in bushfires.
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