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Summary Sheet

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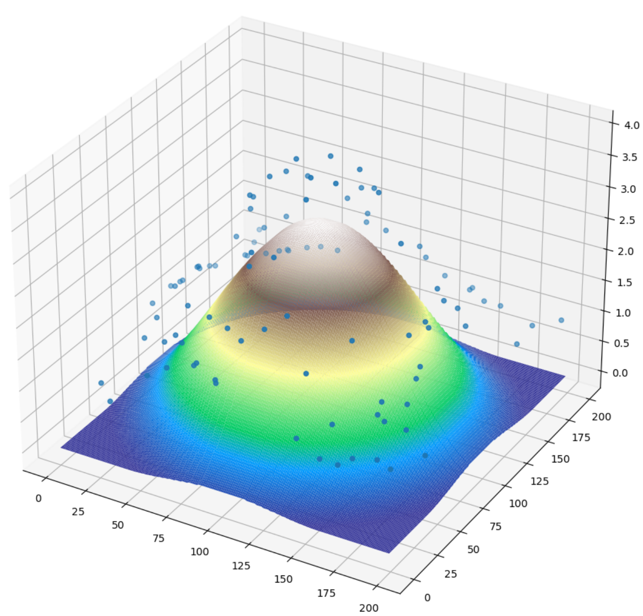
In our paper, we seek to resolve issues surrounding the mitigation of persisting wildfires in susceptible areas like Australia. We devise a optimization model for the utilization of drones in the process of firefighting to aid human efforts. The model we propose is based upon the Coverage Path Planning methods and the OTO Decentralization algorithm to achieve optimal pathways for aerial fire detection. We also use Optimal Transmission Distributions to simulate position reconfigurations of individual drones relative to the network of drones. Furthermore, we modify the aforementioned methods to establish the optimal position configuration (Lasso Configuration) around the area of the wildfire, with respect to the EOC and the grounded personnel. The model is inclusive of many parameters and metrics attainable for most locations on earth, such as environmental conditions, the FFDI Index, etc., along with with economic feasibility, making it adaptable to scenarios in the real world, given the resources are sufficient. We believe that with the exponential advancements in AI and UAV technology, the capabilities of our method can only be improved upon in the future.



Application and Advancement of Decentralized Coverage Path Planning Technique to Optimize Drone Utilization in Fighting Wildfires

Team 2125880

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Abstract

Optimizing drone usage in real-life wildfire scenarios for detection and communication purposes require coverage path planning when expenditure is taken into account. This study seeks to maximize surveillance and transceiver capabilities while minimizing expenditure by exploring efficient patterns for drone arrangement on a given area for establishing ranged communication link and adapting a modified version of the OTO Transmission Distribution Algorithm to optimize how each individual drone establishes itself in the broader network of drones.

Keywords : Surveillance drone, Radio repeated drone, Wildfires, Optimize, Decentralization, Coverage Path Planning

Contents

1 Introduction

The 2019 Australian wildfires are considered to be the worst wildlife disasters in modern history. The record-breaking temperatures and months of severe drought have caused a series of massive bushfires across Australia. New South Wales and Victoria have been worst affected by the wildfire. There are more than five million hectares is being affected in New south Wales, destroying more than 2,000 houses and forcing thousands to seek shelter elsewhere. [6] Although wildfires occur naturally in nature, the severity of the situation in Australia is unparalleled. [4] This is a pressing issue that needs to be resolved as it is concerning to many people and detrimental to the environment.

A wildfire is an unplanned fire occurring naturally in regions such as a forest and grassland. Due to climate change and other environmental factors, the manifestation of extremely dry conditions, such as drought and strong winds, are increasing the occurrence of wildfires in regions across the world. Natural disaster of such scale can have consequential effects on the basic living needs of many people, such as shortages in essential services like electricity and gas, the deterioration of air quality and water supply, and not to mention loss of property, agriculture, and human lives. We must recognize that in order to avoid such disasters, preventative measures must be taken by the means of detecting the wildfires at an early stage in order to mitigate the damage.

There are two common practices that firefighters used to find the wildfire location. The first practice is to use drones for surveillance and situational awareness (SSA) so that we can ensure the crew members have a clear information before they reach the fire site. The second is to use Repeater drone so transceivers using radio wave communication can relay the location information until the crew is able to reach the wildfire's location.

In this paper, we first provide a model that determine the optimal mixture in numbers of of SSA drones and Radio Repeater drones should working together so that we reach a balance in capability and safety with consideration to economical feasibility. We incorporate frequency, lifetime, and area coverage as parameters for the SSA drone, and fire event size and wind parameters are used for the radio Repeater drones. Secondly, we project the model to see how it can adapt to the changing likelihood of extreme fire events over the next decade and the potential increase in equipment cost. Thirdly, we provide another model that optimizes the locations of radio-Repeater drones based on the changing fire size and the altitude of fire location. Lastly, we make a budget request for our case study to the Victoria state government in Australia.

2 Definition of Terms

- **"Boots-on-the-ground" Forward Teams**: Front-line firefighters that are physically at the location of action who are trained to control a fire event and immediately respond in rapidly changing situations.
- **Emergency Operations Center (EOC)**: The central command and control point for emergency related operations and activities; requests for activation and deployment of resources (personnel or equipment). A mobile EOC can be deployed near the site of an emergency.
- **Repeater**: An unattended radio transceiver that automatically rebroadcasts a received signal at high power on a nearby frequency (±600kHz (0.6 MHz) for VHF and ±5MHz

for UHF) or on an adjacent channel.

- **Situational Awareness**: The perception of the current elements of an event, understanding their significance, and extrapolating their status to the near future; In other words, the knowledge and understanding of what is going on around you.
- **Surveillance**: The systematic collection and analysis of data, and the sharing of those data to others who can act upon that information.
- **Surveillance, Safety Awareness (SSA) Drones**: Drones used to monitor and report data from wearable devices (location beacons) on front-line personnel to the EOC. These drones are equipped with cameras capable of capturing thermal imaging and high resolution images as well as sensors that transmit information.
- **Repeater drones**:Hovering drones carrying repeaters and are used to dramatically extend the range of low power radios on the front lines.
- **Topography**:The topography of an area could refer to two qualities: the surface forms and features themselves as seen in our graphic replication of the Australian terrain in Figure 1.

3 Statement of Problem

Our effort here is aimed to aid the search of the wildfire by providing a concrete method to surveying an area of interest (AOI) so that we can detect the occurrence of a wildfire in an optimal time to optimize response time. This model focuses on detection of wildfire in a large region with an undefined shape. Once a wildfire region is detected and identified using a modified Decentralized Coverage Path Planning Method, the communication pathway is optimized by utilizing the transceiver capabilities of Repeater drones in this affected region. Additionally, factors such as: fire size, rate of growth and containment, frequency of wildfire events, susceptibility to wildfires, and topography play a role in the drone flight behavior. These factors, where integrated in our model in aims to optimally replicate a real-life flight path of an SSA and Repeater drones.

3.1 Assumptions

3.1.1 Regions Susceptibility to Wildfires

We have prior information about the wildfire prone locations in Victoria, Australia and so we will assign a unit of measure of susceptibility to wildfires to different regions, ρ. Such that $\rho \geq 0.7$, is considered very susceptible, $0.4 < \rho < 0.7$ is considered moderately susceptible, and $\rho \leq 0.4$ is low susceptibility to wildfires. Where $\rho = frequency/period$ with the assumption that it is an annual period with 365 days, and the frequency is the number of complete days with wildfires burning. Then, not all the positions into the area S should be monitored at the same minimum rate. Therefore we will apply this probability to our model.

3.1.2 Using Heterogeneous Drones

Besides the quantity of the drones being used in different frequency wildfire areas, the quality of the drones is also considered in our model. In high frequency areas, we will use drones with more speed and longer duration hour so that it can cover more area in the same given time to determine whether there is wildfire in the location.

3.1.3 Synchronization of SSA drone

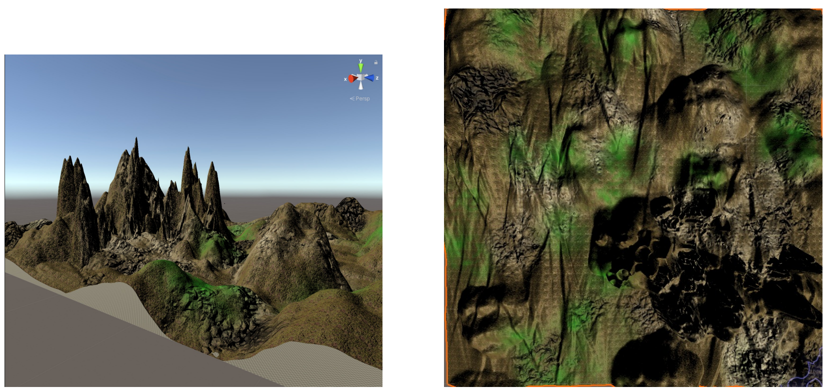
We note that the one-to-one (OTO) Decentralization algorithm uses the drones' proximity to one another to ensure the synchronization of a drone and its neighboring drone's movement so that they can pass on information when they meet. We make the assumption that the type of SSA drone used in a two given sub-regions of approximately similar ρ values is the same, since this model distributes a set of heterogeneous drones D randomly over a given area of interest (AOI).

3.1.4 Topography

For our model we assume the topography of the AOI to include two aspects:

1. Inclinations of the surface, such as mountains or buildings.
2. Features of the land, in particular, the susceptibility of wildfire occurrence ρ

Visual representation of the terrain in Victoria Australia to illustrate topographical factors affecting our model.



(a) Side View (b) Proximate Top View

Figure 1: Victoria, Australia Topographical Image

3.1.5 Heat Detection

Let ζ be the heat difference parameter of the SSA drone. We assume that $\zeta = 0$ is the case of no critical change in thermal signatures, while $\zeta > 0$ means that this threshold is surpassed.

3.1.6 Wildfire Surface Area

To account for the surface area of a given wildfire event, we assume the images sent to the EOC by the SSA drone will provide enough information for the EOC to quickly construct a formula for any surface area that will be used in our algorithm to determine locations of the Repeater drones.

3.1.7 Flight Pathway

For modeling the pathway of drones such as SSA drones, the take-off component of the pathway has been disregarded in this article. SSA and Repeater drones required for such missions are typically larger in comparison and require a runway [8]. We do not have information about the runway (incline, length), the time required takes to reach cruising altitude, or the point of cruising altitude. However, this portion of their flight is small in comparison to total flight distance, making it negligible. Lifetime Our model uses drone self-conditioned distribution. Thus, we assume that their data link will notify the EOC when a new drone is needed to replace another in the system when recharging is needed.

3.2 Outline of Our Approach

The general description of our model is as follows:

1. Construct the optimal pathway for the surveillance drone allocation in any given area using the CPP method. Hence we consider a heterogeneous case with factors including weather (wind in particular), topography elevation, and irregularity in the shape of the AOI.
2. Modify the OTO Decentralized Technique to minimize the response time for wildfire containment by optimizing the data linkage between the SSA drone in region with detected fire, which we will denote D_f, and the EOC.
3. Develop the initial value problem with the boundary conditions identified by the sub-area of the detected wildfire. This is to optimize the positioning of the Repeater drones on the boundary of the affected area with relation to the rate of fire spread and fire containment.
4. Modify the Decentralization Technique to optimize communication link through an optimized allocation of the Repeater drones by converting the allocation based on area occupied to a proximity measure along the surface area of the AOI.

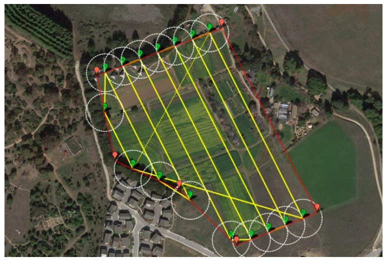
4 Constructing Optimal Pathway

In any given AOI, regular or irregular, the surveillance of the area needs to be optimized. This means that the sweeping pathway of the patrolling drones or in our case, the SSA drones. We optimally allocate the SSA drones to survey this AOI by using a discritization method.

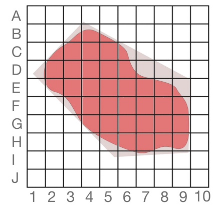
4.1 Coverage Path Planning (CPP) of Drones

Cabreira (et al.) devised the technique of Coverage Path Planning to optimize the routes for a drone to take while surveying within a target area. The target area is analyzed in pre-flight planning and decomposed into smaller cells varying in shapes.

The decomposed cell and its shape will have a direct impact on flight patterns. Methods in the decomposition techniques such as cellular decomposition, grid-based decomposition, etc. are applied to reduce the "concavities of complex areas" or to further subdivide the decomposed cells to improve survey efficiency and optimize coverage paths as seen in Figure 2a. 5. Using this concept of grid-based decomposition, we divided our AOI as seen in Figure 2b. **??** [9].



(a) Optimizing Drone Route Using a CPP Method [2]



(b) Using Grid-Based Decomposition For Subdivision of AOI

Figure 2: Decomposition of Area of Interest

4.2 One-To-One Decentralized CPP Technique

Acevedo (et al.) presented a decentralized algorithm for partitioning irregular areas during surveillance missions [1]. This method can be graphically represented, as seen in Figure 3. They used Homogeneous vehicles to distribute the sub-regions using a one-to-one coordination technique and explore adjacent areas. One-to-one coordination technique is beneficial because it helps the system to locate the information on location even when the coverage of the robots are not enough for the total coverage compared to total area. Moreover, because each drone can relay information from nearby neighbors, a decentralized approach has the edge over its robustness and dynamism, in a way that each drone can self-adapt to its sub-area efficiently. Thus, the system is able to complete the surveillance mission in the most effective manner.

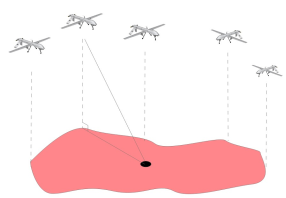


Figure 3: Area Optimization Through One-To-One Decentralization Method

The vehicles have a short range of communication and but must share information so the algorithm uses a sub-surface area method to equally distribute the paths over sub-region of equal range. This takes into consideration the area of the area of the surface and generates an interior subdivision scheme similar to it. In this way, the maximum area of each sub-region is less than or equal to the coverage range of the drones used.

When surveying, a frequency-based approach is used, where the objective implies to optimize the time of revolution of the area coverage of each drone.

4.2.1 Original Algorithm For OTO Decentralization

Algorithm

D_i receives the whole area to cover and its grid cell position
D_i computes the initial area division
D_i initializes its own variables
D_i generates its own coverage paths and starts to move
for all t **do**

D_i follows its own path
if D_i arrives to a link position **then**
if it is a link position without neighbor **then**
D_i recomputes the link position
D_i generates its own coverage path
else
if D_i does not meet its neighbor **then**
D_i waits a time T_w
D_i joins a portion of the neighbor D_j area to its own coverage area
D_i recomputes the link positions
D_i generates its own path
if Neighbor area size is zero **then**
D_i labels this link positions as without neighbor
end if
else
D_i receives information from neighbor D_j
D_i executes a share and divide function
else D_i
D_i recomputes the common link position
D_i generates its own coverage path
end if
end if
end if
end for

Where, T_w is the refresh time mentioned earlier.

5 Basic Model

Our model is an optimization model that aims to minimize the number of drones needed from each of the SSA and Repeater drones by utilizing the OTO Decentralized Method [1]. For the SSA drones, we determine the optimal area discritization for a set of heterogeneous SSA drones of a given area. For the Repeater drones, we modify the OTO decentralized method to determine the optimal discritization of the surface area of the sub-region that detected a wildfire. We can describe it simply as,

$$T_S = T_{ssa} + T_r \tag{1}$$

Where T_{SSA} is the minimized number of SSA drones and T_R is the minimized number of Repeater drone. Both values will be determined in the following sections with the appropriate constraints.

5.1 Modeling SSA Drone Flight

We consider an irregular area $S \in \mathbb{R}^2$ with a surface A which we want our SSA drones defined by $D := D_1, D_2, ..., D_N$ to survey in a recurrent system to detect changes in thermal radiations over S and identify wildfires as they happen.

At any given time t, our SSA drone D_i will be moving along the area S following a path with a ground speed $v_i(t)$ and the monitoring of an area defined by Jose Acevedo and her team [1], $C_i(t)$.

$$C_i(t) := r \in \mathbb{R}^2 : |r - r_i(t)| < c_i(t)$$

where $r_i(t) \in \mathbb{R}^2$ is the drone center projection on the plane $z = 0$ and $c_i(t) = z_i(t)tan(\theta_i)$ is the actual drone coverage range, with $z_i(t)$ as its altitude and θ_i as its angle of view. In our case we have differing $v_i(t)$s in relation to the probability of wildfire index ρ we defined earlier. In their model they define the coverage speed, a_i, as the area covered per second and approximated using:

$$a_i(t) \approx 2c_i(t)v_i(t) \tag{2}$$

We define our velocity function $v_i(t)$ by factoring in the wind speed and direction at a given time t [3].

$$v_i(t) = \rho(v_a(t)cos(arcsin(\beta sin(\psi_{WTA})) + (v_w(t)cos(\psi_{WTA}))), \tag{3}$$

where $\psi_{WTA} = \psi_s - \psi_w$ is the drone's heading relative to the wind and is the difference of the sweep direction angle, ψ_s and the wind direction angle, ψ_w. And ρ_i is the probability of susceptibility to wildfires of sub-region i. β is the ratio of wind speed to airspeed ($\frac{v_w(t)}{v_a(t)}$).

We then use this method to partition the area S into N many non-overlapping sub-areas: $S : S_1 + S_2 + ... + S_N$.

The general idea is to figure out the area of each sub-region the SSA drone will survey to optimize the data linkage as can be seen in Figure 3 and area division based on the capabilities of each drone of the set of heterogeneous drones D_i and there corresponding coverage areas A_i. Where A_i is initially described by:

$$A_i = a_i^{max} \frac{A}{\sum_{j=1}^{N} a_i^{max}}, \tag{4}$$

where $a_i^{max} = max\{a_i, i = 1, 2, ..., N\}$.

5.1.1 After Optimal Transmission Distribution

Each SSA drone then re-configures its area to optimize coverage while minimizing surveillance overlapping with its neighboring SSA drone: Where A_i is then described by:

$$A_i = a_i \frac{A(S_i + S_j)}{a_i + a_j}. \tag{5}$$

Such that once the difference between A_i at iteration t and iteration $t + 1$ is virtually zero the drone recognizes this region as its domain and terminates it change of path.

5.1.2 Total SSA Drones

Use the information for every SSA drone D_i to determine the total area coverage of all SSA drones, A_d:

$$A_d = \sum_{k=0}^{N} A_k, \tag{6}$$

where A_k is the area surveyed by drone D_k.

By this we can conclude that the number of SSA drones needed in a given area S is as follows:

$$T_{ssa} = \frac{S}{A_d} \tag{7}$$

5.2 Modeling Repeater Drone Flight

In order to minimize the location and number of Repeater drones used during the event of a fire in a given sub-region or group of sub-regions, we recognize the fact that response to wildfires has one main objective: to contain and distinguish the fire. This suggests that the Boots-on-the-ground forward team will align themselves around the fire. Therefore, the Repeater drones will also surround the fire. We will split the pathway into two parts:

1. a straight path between the EOC and the region of the fire since it is the shortest distance to the fire
2. over the surface area of the total region with fire. We can find this surface area SA_i by integrating the function describing surface A as follows:

$$\int \int_D \sqrt{f_x^2 + f_y^2 + 1} dA$$

Where $D := \left\{(x, y) \in \mathbb{R}^2 : x_0 \leq x \leq x_N, y_0 \leq y \leq y_N\right\}$. This model can be seen in Figure 4.

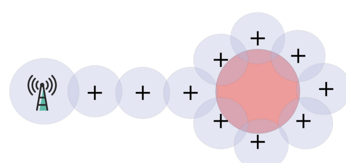


Figure 4: Two Pathway Decentralization Over AOI

5.2.1 Pathway 1

The first part of the pathway will use the distance formula:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \tag{8}$$

where the coordinates (x_1, y_1, z_1) and (x_2, y_2, z_2) are defined. The EOC is a fixed point since it is a fixed structure and the second coordinate is the point on the boundary of the fire such that it is the shortest distance to the EOC. We will assume that this coordinate is found using the SSA drone sensor since it will map the areas with increased thermal energy and the exact locations will be sent back to the EOC through our modified algorithm in section 5.2. This is the grid cell position being mapped by the SSA drone.

5.2.2 Pathway 2

The second pathway is an optimized positioning so as to ensure proximity of each other to transmit information along that path to the EOC. We design this path using our modified algorithm *Repeater Drone Lasso Distribution* in section 5.3 by the boundary value problem we developed using the surface area SA_i, fire growth rate r_g and fire containment rate r_c to construct the problem with boundary conditions of the rate of surface area growth $P_i'(t)$ and initial surface area. Dimensional analysis was also used to determined the problem P.

Note that$0 \leq SA_i \leq SA_p$. Hence, the minimum size of the fire is 0km where there is no fire, or SA_p which is the surface area of the entire AOI such that $SA = \{SA_1, SA_2, ..., SA_p\}$. The rate ratio $\frac{r_g}{r_c} = P_i'$.

We define our Boundary Value Problem (BVP) is as follows:

$$\begin{cases} SA_0' = \frac{SA_1}{SA_0} \\ SA_0 = 0, \quad SA_0' = 0 \end{cases} \tag{9}$$

This model would generate the first surface area. So we generalize this algorithm to:

$$\begin{cases} SA_{i-1}' = \frac{SA_i}{SA_{i-1}} \\ SA_{i-1} = SA_{i-1}, \quad SA_{i-1}' = SA_{i-1}' \end{cases} \tag{10}$$

Where the current surface area SA_i depends on previous SA_{i-1} and boundary conditions generated from SA_{i-2}. It would go through this algorithm until $SA_n = SA_p$.

- The solution to this BVP SA_i is the surface area size of which we want to place our Repeater drones along at.
- The SA_{i+1} only depends on SA_i hence our algorithm is really just following a Discrete-Time Markov Chain.
- The positions of the drones are constantly changing with the growth and decay of the size of the surface area to ensure they are always on the boundary of the given area.

5.2.3 After Repeater Drone Lasso Distribution

Each Repeater drone then re-configures its position to optimize communication buy maximizing surface area coverage of the region area surface area SA_i while minimizing surface area coverage overlapping with its neighboring Repeater drone: Where the point-coordinates of the position are then described by:

$$X_{i+1} = \frac{x_i + r_x}{SA(SA_i) + (SA_j + r_d))}.$$

$$Y_{i+1} = \frac{y_i + r_y}{SA(SA_i) + (SA_j + r_d))}.$$

- Where x_i and y_i are the initial coordinates chosen on the surface area boundary of the fire SA_i at time i. The x-coordinate uses the simple idea of horizontal stretches and compressions.
- Moreover, to ensure that the most efficient positioning of the Repeater drone is achieved, we place the drone's boundary at the boundary of the surface area by adding its radius to the previous coordinate that the algorithm locates on the boundary of the fire as seen in the simplified representations in 2-dimensional and 3-dimensional space in Figure **??**.

(a) 2-Dimensional Space with Perimeter Boundary

(b) 3-Dimensional Space with Surface Area Boundary

Figure 5: Optimizing Positioning of Drone on Boundary in 2D and 3D

- Note that the drone will move in a straight line inwards and outwards depending on the size of the fire to minimize time between each position change.

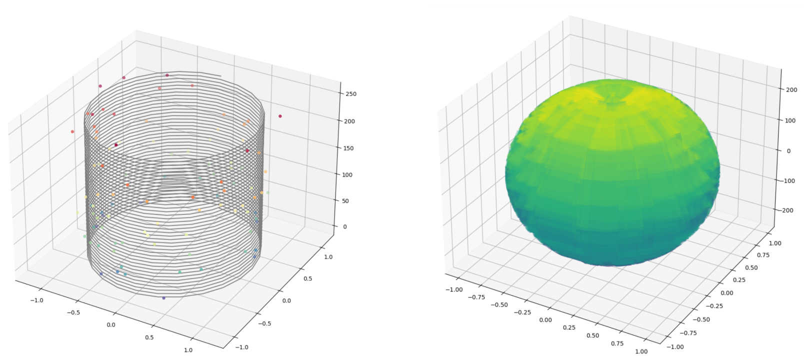
The optimal elevation at a given time $i+1$ is,

$$Z_{i+1} = tan_{i\gamma}$$

- We assume that the reference point $z = 0$ is the center plane of the surface area with z_i as its altitude of the terrain and $tan_{i\gamma}$ is the normalized gradient $||\nabla Z(X_i, Y_i)||$.

Once elevation and values of ρ are accounted for, we can visualize the distribution using our code and the Fire Danger Index Map ??. We generate the initial distribution of drones on the Boundary SA_0 as seen in Figure 6. Note that the intensity of the thermal energy present in a given region increases as you go down the spectrum to the right.

Furthermore, elevation of the ground affect the altitude of the drones. Thus, we represent the extent of its range capabilities in 3-Dimensional space in Figure 6 for a better visualization. Note that these figures are not to scale. The spherical coverage space demonstrated in Figure 6 is scaled up by a factor of 2.84×10^4.



(a) Repeater Drone Distribution in Surface Area of Pathway 2

(b) Spherical Representation of Drone D_i Range in 3-Dimensional Space

Figure 6: Illustration of Repeater Drone Distribution and Range Capabilities

5.2.4 Total Number of Repeater drones

Upon to determine the optimal locations depending on terrain and size of fire, we use information from our *Repeater Drone Lasso Distribution* algorithm to determine the optimal number of drones to fit the surface area of a fire. So we have:

$$T_r = \frac{D}{40} + \frac{SA_i}{\sum_{i=0}^{N} M_i} \tag{11}$$

Where M_i is the surface area coverage determined by our algorithm.

6 Modifying OTO Decentralized Technique

Although we modified the velocity function of the area coverage function to account for wind speed and direction. This model needs to also be modified to shorten the pathway from detection of fire to the EOC. Another modification will be made to the algorithm to use surface area of given region with detected fire, to optimize the distribution of the Repeater drones.

6.1 Optimal Transmission Distribution

When looking at the OTO Decentralized Algorithm, we noticed that it does not optimize the data link pathway when a given fire threat is detected. The transmission and receiving pathway needs to be optimized. Therefore, the algorithm needs to add a condition to direct all SSA drones to move in a straight line pathway of the shortest distance to the EOC when we have a D_f. This algorithm can then be extended for cases of multiple fire detections. However, for the purposes of our paper, will will not extend the algorithm as it will derail from our focus.
Therefore, once we have an AOI as in Figure **??** and we want to survey it, we will go through a modified decentralized method that takes into account fire detection and optimizes transmission of this information. We will refer to this algorithm as the *"Optimal Transmission Distribution"*.

Algorithm

D_i receives the whole area to cover and its grid cell position
D_i computes the initial area division
D_i initializes its own variables
D_i generates its own coverage paths and starts to move
for all t **do**
  D_i follows its own path
  if D_i arrives to a link position **then**
    if it is a link position without neighbor **then**
    if Rb_i coverage surface area overlaps with neighbor Rb_j surface area coverage of $\mu \leq 0.3$**then**
      D_i recomputes the link position
      D_i generates its own coverage path
    else
      if D_i does not meet its neighbor **then**
        D_i waits a time T_w
        D_i joins a portion of the neighbor D_j area to its own coverage area
        D_i recomputes the link positions
        D_i generates its own path
          if Neighbor area size is zero **then**
          D_i labels this link positions as without neighbor
          end if
      else
        D_i receives information from neighbor D_j
        D_i executes a share and divide function
          if $\zeta > 0$ **then** D_i generate shortest distance on its bound to the EOC
          else
          D_i

D_i recomputes the common link position
D_i generates its own coverage path
end if
end if
end if
end for

Where ζ is the difference of thermal energy.

6.2 Repeater Drone Lasso Distribution

Once the surface area information is received by D_f our Repeater drones will go through the modified OTO Decentralization method which we will refer to as the *"Repeater Drone Lasso Distribution"* and represented in Figure 4 and optimize its boundary in Figure 7.

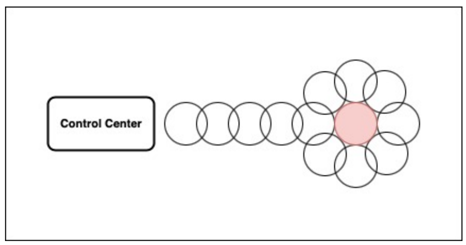


Figure 7: Repeater Drone Lasso Distribution with Optimally Positioned Repeater Drones

6.2.1 Key Factors

- **Surface Area Partition:** The surface area P is divided into non-overlapping lines/-pathways such that, $P : \{SA_1, SA_2, ..., SA_p\}$.
- **Repeater Drones in Surface Area:** The set $Rs : \{Rs_1, Rs_2, ..., Rs_m\}$ is used here to describe the Repeater drones in the surface area of fire.
- **Repeater Drones on D:** The set $Rd : \{Rd_1, Rd_2, ..., Rd_l\}$ is used here to describe the Repeater drones on the shortest distance D. With these repeater drones, we describe their pathway as a vector in the direction of (x_2, y_2, z_2), the point on the shortest path to the surface area plane. This is made with the assumption that the EOC is the reference point $(0, 0, 0)$.
- **Simultaneous Algorithms** Both "Algorithm for Rb_i" and "Algorithm for Rs_i occur simultaneously.
- **Less Movement:** Since Repeater drones only need to position themselves to allow for optimal communication link between Boots-on-the-ground forward team and EOC. Therefore, unlike SSA drones that need continuous surveillance, it does not move unless the surface area size changes.
- **Overlapping:** We want to ensure that the overlapping of coverage areas of Repeater drones Rs_i and Rd_i and their neighboring Repeater drones Rs_j and Rd_j, respectively, is low. Therefore we will assign the parameter μ_i to the degree of overlapping between two neighboring drones R_i and R_j.

- **Growing Surface Area:** We have modified the algorithm to consider the lasso distribution as a two part way of the OTO decentralized technique where it takes into account a growing surface area SA such that the distance D will eventually be covered by this growing area, thereby decreasing the number of drones on the vector (x_2i, y_2j, z_2k) as they shift SA to achieve a degree of overlapping $\mu \leq 0.3$
- **Elevation:** We note that the 5-Watts frequency of the handheld radios has a nominal range of 5 km over homogeneous terrain conditions; fairly flat and unobstructed land. However, drops to 2 km in heterogeneous terrain conditions; land with inconsistent and random increases and decreases in elevation. Therefore, we modify the algorithm to account for these heterogeneous conditions. There are three main cases:
  1. **Case 1 - Flat Terrain:** This would mean that the drone's maximum altitude is $5 + 20$
  2. **Case 2 - Elevated Terrain :** This would mean that the drone's maximum altitude is $2 + 20 + elevation$
  3. **Case 3 - Depressed Terrain :** This would mean that the drone's maximum altitude is $2 + 20 + depression$ where $depression$ is a negative quantity.

Repeater Drone Lasso Distribution Algorithm

Algorithm For Rb_i

for all i **do**
if $r_g > r_c$ and $SA_i > SA_r$ **then**
EOC releases $\frac{SA_i - SA_r)}{SA_r}$ many Rd drones
Rd_i receives the pathway vector (x_2i, y_2j, z_2k) and length D to cover
Rd_i computes the initial vector length division
Rd_i initializes its own variables
Rd_i generates position on vector and starts to move
for all t **do**
Rb_i follows a straight path
if Rb_i arrives to a link position **then** $\alpha = 1$
for all $\alpha = 1$ **do**
if $tan_{i\gamma} = 0$ **then**
$z_i = 20 + 5$
if $tan_{i\gamma} > 0$ **then**
$z_i = 20 + 2 + tan_{i\gamma}$
end if
if $tan_{i\gamma} < 0$
then
$z_i = 20 + 2 + tan_{i\gamma}$ **if** it is a link position without neighbor **then**
Rb_i generates new unvisited position on vector
else
if Rb_i coverage surface area overlaps with neighbor Rb_j surface area coverage of $\mu \leq 0.3$**then**
Rb_i recomputes the link positions into surface area SA_i
Rb_i generates position in surface area SA_i
else **if** Neighbor area size is zero **then**
Rb_i labels this link positions as without neighbor
end if
else
Rb_i receives information from neighbor Rb_j
Rb_i executes a share and divide function
Rb_i
Rb_i recomputes the common link position
Rb_i generates position
end if
end if
end if

Algorithm For Rs_i

Rs_i receives the whole surface area SA_0 to cover and its grid cell position
Rs_i computes the initial surface area division
Rs_i initializes its own variables
Rs_i generates position on surface area and starts to move to it
for all t **do**

Rs_i follows a straight path
if Rs_i arrives to a link position **then**
if it is a link position without neighbor **then**
Rs_i recomputes to generates new unvisited position on surface area
else
if Rs_i coverage surface area overlaps with neighbor Rs_j surface area coverage of $\mu \leq 0.3$ **then**
Rs_i recomputes to generates position
else **if** Neighbor area size is zero **then**
Rs_i labels this link positions as without neighbor
end if
else
Rs_i receives information from neighbor Rs_j
Rs_i executes a share and divide function
Rs_i
Rs_i recomputes the common link position
Rs_i generates position
end if
end if
end if
$SA_{new} = SA_i$ $SA_0 = SA_{new}$ **end for**
end for

- Where the degree of overlapping μ is set to 30% as the upper percentile accuracy with less computational expense overlapping degree is in the range of $30 - 40$.
- Where SA_new is the S_i found by our BVP. Therefore, the algorithm accepts an initial SA_0 which the Rb_i drone receives. Then the SA_0 become that which was found by our BVP.

7 Applying our Model to Victoria, Australia

7.1 Simulations

In simulating our model to the Victorian terrain and wildfire frequency:

1. **SSA Drones:** We defined the fixed and variable parameters as well as functions of the AOI:
   Fixed and Variable Parameters: $\rho, \zeta, \psi, \mu, \theta S$ and drone range radius. We also fixed their velocities for algorithm efficiency and simplicity.
   Functions: D_i, C_i, a_i, A_i.
2. **Repeater Drones:**We defined the fixed and variable parameters of the SA and D: We defined our algorithm over a polar coordinate system using our given θ. We then simulated the results over a predefined polar coordinate surface using a random S. This is illustrated below in Figure 8.

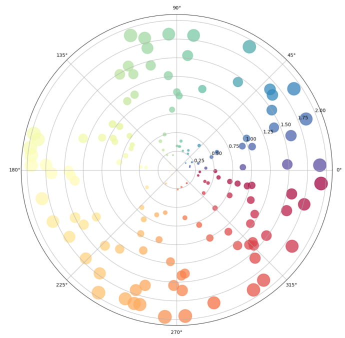
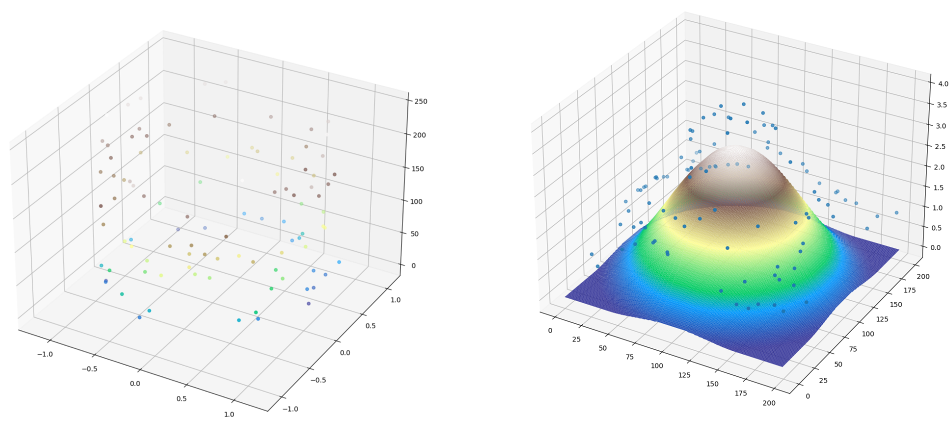


Figure 8: Simulated Optimal Transmission Distribution Over Polar Surface

Fixed and Variable Parameters:, ζ and drone range radius
Variable: $Z_i, C_i, a_i, A_i, X_{i+1}, Y_{i+1}, Z_{i+1}$.
We first examined the resulting distribution on a 3-D grid with no terrain as in Figure 9, we then utilized our algorithm algorithm and placed the position points it generated over a given mountainous terrain, and in particular, Mount Bogong's elevation of 1.986km as illustrated in Figure 9. Meanwhile maintaining a safe distance from a projected fire.



(a) Simulated Distribution of Repeater Drones

(b) Simulated Distribution of Repeater Drones Placed Over Mount Bogong

Figure 9: Drone Distribution Over a Heterogeneous Terrain Using Repeated Drone Lasso Method

8 Weaknesses and Proposed Improvements

8.1 Seasonal Optimization

Our model uses the frequency of fires occurring in a specific region over a year to determine degree of wildfire susceptibility ρ. This creates a slightly skewed approximation of the necessary number SSA drones with higher area coverage per second a_i, thereby increasing our cost. Different seasons will have different ρ values, allowing for a better approximation of drones per season. This would require a run-through of our *Optimal Transmission Distribution* algorithm for every significant change in ρ in every sub-region, not to mention the random overlapping of ρ values with the randomly generated set of sub-region A. This make it computationally expensive. Therefore, a future modification to the random generation of sub-regions or a seasonal algorithm would greatly improve results.

8.2 Optimal Communication Range

We define the parameter ξ as the threshold distance to flames before it is in a compromising altitude. However, to ensure Repeater drone is in range to ground at any given time i we constrain it to $tan_{i\gamma} + \xi \leq Z_i \leq 20$.

The boundary SA_i and R_{i_c} to be the center of a Repeater drone's communication range which is essentially (X_t, Y_t, Z_t). This would be optimal position of the drone such that the drone is centered on the edge of A_i and decreasing the data linkage pathway distance to the EOC as seen in Figure 7.

8.3 Area Partitioning For SSA Drones

Our model assumes that the EOCs will be located optimally to ensure full coverage of AOI is achieved. To be efficient it would limit the distance traveled by the SSA drone before it reaches any boundary of A_i is minimal to ensure it makes optimal use of it lifetime. Our model does not position the EOCs in these optimal locations. Therefore, a future modeling of this problem may include this factor with a gathering of route options, topography, and degree of wildfire susceptibility.
Although, placing the drones in such an arrangement would shorten the distance to the EOC (as the entire communication stream would be shifted towards the EOC by a factor of r, where r is the radius of the drones communication range), this would place the drone in positions where they would be susceptible to heat damage and other varying uncertainties. This poses a great risk to the entire operation. If a single drone is at risk, then the link of communication can be broken, which ultimately can induce greater risk for the personnel on the ground. Thus, taking this risk into account, it would in our best interest to place the drones outside A such that the circumference of the communication range is tangent to A.

9 Effects of Extreme Fire Events

The Australian wildfires of 2019 were nothing short of catastrophic with a burn coverage of approximately 19 million hectors [7]. There are many factors that caused the wildfire, but the main factor is global warming. Therefore, in developing the model, we ensured that the algorithm can be modified and extended to accommodate future extreme fire events occurring over the next decade. With rising temperatures, more moisture from the ground evaporates, causing an increased drying out the soil, making vegetation more flammable [4]. Due to Australia's long history with wildfires [7], it was only natural to assume wildfire events will happen more frequently with the rapid rise of temperatures. As a result, there will be a higher need for modeling drone surveillance and maximizing front-line communication range.

9.1 Change in Cost

- **SSA Drones**: As mentioned in the previous section, with the change in climate the state of our topography changes, the degree of wildfire susceptibility ρ increases. This would result in a higher demand for more frequent surveillance, and thus more capable SSA drone. Thereby, increasing our cost.
- **Repeater Drones**: Moreover, the events of wildfires are expected to be larger and more intense, covering more surface area . Additionally, when assuming that the fire containment methods remain constant while rate of growth increases, this will increase the fire size. Consequently, we will need a larger number of Repeater drones needed, which means cost will increase accordingly.

9.2 Change in Model

- **Multiple Simultaneous Fires**: The increased number of wildfires will suggest an increase in the number of needed Repeater drone systems. Furthermore, one of the major factors of rapid spread of wildfires in Australia is the dense and unreachable conservation areas with no accessible route options. This would suggest a need for an adapted version of our area partition to optimize sub-regions in a more accessible route. Consequently, this modification to the *Repeater Drone Lasso Distribution* algorithm will make the detection time to response time much smaller.

10 Annotated Budget Request

In order to optimize the expenditure of this project, the model constructed minimizes the number of drones Surveillance (SSA), Communication Enhancers (Repeater) while ensuring efficiency, safety and the utilization of drone capabilities. In the budget request, we provide an estimated number of drones need from each of the Repeater and SSA drones.

10.1 Factors Affecting Drone Choices

- **Price Based on Number of SSAs:** Due to our model's flexibility with regards to the type of SSA drones, we aimed to gauge a rough cost estimate by analyzing Victoria's data on Fire Index in different regions to develop a rough estimate of the number of higher, moderate, and lower (yet capable) quality SSA drones needed. Using our algorithm **??** we found a range of average area coverage by a set of random SSA drones with different capabilities. We used equation ref 7 to find this total number of SSA drones. As for the total price, we found quotes from online retailers/manufacturers for the highest to lowest(within capabilities) and applied that to the number found.
- **Price Based on Number of Repeater Drones:** To roughly estimate the number of Repeater drones needed to cover a wildfire event at a given time throughout the year to ensure the optimal response efforts are met, we used the highest degree of susceptibility as well as the maximum wildfire coverage of the average wildfire event. Moreover, using our Repeater Drone Lasso Distribution Algorithm, we were able to randomize and generate a topography using the topographic data from [5] to determine the total positions occupied by the drone in this event and thereby, determine the number of drones needed to supply an event of the highest degree based on previous history of events in Australia [7]. We used equation ref 11 to find this total number of Repeater Drones. As for the total price, we used the price of Akme Corporation's prototype WileE–15.2X hybrid drone which was $\$10,000$ (AUD).

- **Costs for Maintaining an EOC Team:** The final expense was the EOC expenses which are simply accommodation expenses. (Note: our budget does not take into account the cost of electricity or other utility services as it varies by region and consumption) The Budget Request cab=n be seen below:

[Date]

Budget

Operating Expenses

SSA Drones Type 1	Estimated	Actual
Rho >0.7		
Drone per Unit	$39,000.00	
# of Drones:3	$78,000.00	
Maintenance/Year		
Total	$117,000.00	$0.00

SSA Drones Type 2	Estimated	Actual
0.4< Rho <0.7		
Drone per Unit	$18,826.22	
# of Drones:2	$18,826.22	
Maintenance/Year		
Total	$37,652.44	$0.00

SSA Drones Type 3	Estimated	Actual
Rho <0.4		
Drone per Unit	$11,036.06	
# of Drones:2	11036.06	
Maintenance/Year		
Total	$22,072.12	$0.00

Repeater Drone	Estimated	Actual
Drone per Unit	$10,000.00	$10,000.00
# of Drones ()		
Maintenance/Year		
Total	$10,000.00	$10,000.00

EOC	Estimated	Actual
Per	$45,442.60	
Total	$45,442.60	$0.00

SSA Drones	Estimated	Actual
X7		
Type 1 (x 3)		
Type 2 (x 2)		
Type 3 (x 2)		
Total: 7	$0.00	$0.00

Total Expenses	Estimated	Actual
	$194,514.72	$10,000.00

11 Conclusion

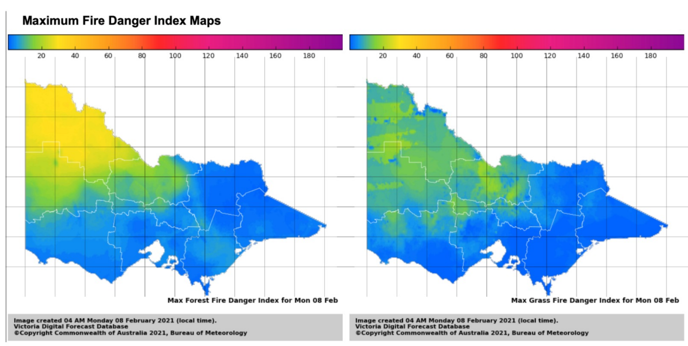
Our approach to modeling this problem was to break it down into two main categories:

1. Constructing Optimal Pathway For Maximum Area and Surface Area Coverage
2. Constructing Optimal Distribution For Continuous Sharing

With economical factors in mind, constructing the optimal drone path reduces operational expenses while in surveying fire-prone regions. We are looking to maximize the survey area within the area of interest and at the same time minimize the number of drones. Increasing the likelihood of early detection in an unexpected wildfire would improve the chances of containing the spread. Utilizing the modified Decentralized Coverage Path Planning Method which applies cellular decomposition to subdivide drone coverage regions such that flight paths could be planned in relation to the shape of the cells for optimal coverage over the area of interest. Furthermore, the OTO Decentralization algorithm based on the proximity measures interlinks the drone paths as information is being exchanged, broadening coverage from a single drone to the entire network of drones. In the case where a fire is detected, the Lasso distribution of Repeater drones are deployed to the fire. We devised this position arrangement in our algorithm considering the optimal location for the drones to be positioned around the perimeter of the fire, in consideration of uncontrolled variables such as the growth rate of fire and time dependencies. Ensuring the stream communication of the front-liners is vital in fighting natural disasters and the collaboration between humans and drones should collaborate in a state of commercialism. This process can be effective in real life situations if all underlying factors are considered. This model is adaptive to any region as long as the metrics can be collected and the resources can be applied.

12 Appendix

12.1 Fire Danger Index



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