Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
B		2112657

Wildfire Response Plan Based on Drones

Summary

Because of the severe drought and persistent heat caused by the trend of global warming, wildfire has become one of the most severe problem in Australia. Victoria, as the one of the worst impacted state, proposed to establish a new division, "Rapid Bushfire Response", to fight the wildfire. With the help of two kinds of drones, efficiency and safety of the front team can be significantly improved: The Radio Repeater drone equipped with radio repeater is able to extend the communication range; the surveillance and situational awareness (SSA) drone equipped with video & telemetry capability can help to monitor the evolving situation on the front line. We devoted to find the optimal deployment plan of two kinds of drones and the optimal numbers and mix of them.

First, considering that the distribution of fire line and front teams is affected by the size and terrain of the fire, we explore a fire field model to simulate the spread of fire in different environment referring to the Wang Zhengfei Fire Spread Model. The model takes the effect of topography into consideration by Perlin Noise Terrain Generation Algorithm. Our fire field model also considers the effect of terrain on the signal range when calculating the front teams' location. Through this model, we are able to obtain the distribution of the fire line and the location of front teams with respect to different size and terrain of wildfires.

Second, since the signal range of the handhold radio is small and the flight range of the drone is limited, the Radio Repeater drones have to move between the front teams and the Emergency Operations Center (EOC). To address the deployment problem, we explore an optimization model based on Multiple Traveling Salesman Problem (MTSP) and take the topography of each front team into consideration. For given locations of the front teams, we need to find the optimal path and hover time of the Radio Repeater drones. To solve this problem with complex constrains and nonlinear cost function, we use Genetic Algorithm to find the optimal solution.

Third, assuming that the SSA drone needs to fly along the line of fire to monitor the evolving situation, we need to balance safety (interval time between every inspection) and economics (number of drones assigned). Since the number of drones is an integer, we explore an integer programming model with nonlinear cost function to take both the cost of drone purchase and the cost of interval time into consideration. Exhaustive method is used to solve this problem efficiently.

Fourth, we find the data set of Australia wildfire during 2019-2020 fire season to obtain the size and location information of wildfires. We also obtain the topography information through assigning the longitude and latitude of each fire onto the precise topography map of Victoria. With these data, we calculate the maximum number of two kinds of drones needed in the fire season through our model. Referring to the result, we obtain the optimal numbers and mix of two drones.

Assuming that the cost of drone stays constant, we also study the equipment cost increasement due to accessories replacement and maintenance cost through our model.

Finally, considering the extreme fire event might occur in the future, we test our model through a super wildfire with extremely large size and examine the output of each sub-model as well as the final result.

Keywords: Fire field model, genetic algorithm, MTSP problem, nonlinear integer programming.

Contents

1 Introduction

1.1 Problem Background

Wildfire in Australia has become a pressing problem. Because of the severe drought and persistent heat wave caused by climate-change, almost every state in Australia was suffered from devastating wildfires, especially Victoria. In order to keep wildfires under control, a new division, “Rapid Bushfire Response”, was proposed by Victoria’s Country Fire Authority. With the help of drones equipped with radio repeater or video & telemetry capability, not only the communication range of the “Boots-on-the-ground” forward teams can be extend, the evolving situation on the front line can also be better monitored. However, considering the limited budget of the government, the purchase plan of drones should balance economics with capability and safety. Besides, the deployment plan of drones should take the flight range and the topography into consideration, which complicate the problem further. Therefore, it is necessary to study how to organize the drones reasonably and determine the optimal plan of drones’ purchase.

1.2 Literature Review

- **Wildfire Spread Speed**

  Miguel G. Cruz, Martin E. Alexander, Paulo M. Fernandes, Musa Kilinc and Ângelo Sil evaluated the accuracy of the "10% wind speed rule of thumb", and found that the mean absolute error of this method varied between 1.7 and 1.75 km/h.[1]

  A.M.G. Lopes, L.M. Ribeiro, D.X. Viegas, and J.R. Raposo simulated the forest fire spread with a two-way coupling algorithm and found that static simulation tend to overestimate fire area by a large amount.[2]

- **GA model to solve MTSP problem**

  John holland raises the Genetic Algorithm, imitate the mechanism of biological evolution to conduct global search, so as to solve the optimize problem.[3]

  Mohammad Sedighpour, Majid Yousefikhoshbakht, Narges Mahmoodi Darani used the GA model to solve the MTSP problem. Encode the pathway and breakpoint information into the genes.[4]

1.3 Our work

1. Referring to the **Wang Zhengfei Fire Spread Model**, we simulate the fire field in different environment. The model takes topography into consideration by using **Perlin Noise Terrain Generation Algorithm**. Through this model, we are able to obtain the distribution of the fire line and the location of the front teams. Calculation of front teams’ location also considers the effect of terrain on the signal range.

2. For given locations of front teams, we need to find the optimal path and hover time of the Radio Repeater drones. To address the deployment problem of drones, we explore an optimization model based on **Multiple Traveling Salesman Problem (MTSP)** and take the topography of each front team into consideration. To solve this problem with complex constrains and nonlinear cost function, we use **Genetic Algorithm** to find the optimal solution.

3. The deployment of SSA drones need to balance safety (interval time between every inspection) with economics (number of drones assigned). We explore an **integer programming** model with **nonlinear cost function** to take both the cost of drone purchase and the cost of interval time into consideration. We solve the nonlinear integer programming problem by **exhaustive method**.

4. We use the **data set** of Australia wildfire and the precise **topography map** of Victoria to obtain the frequency, size, and terrain of each bushfire happened in Victoria during the 2019-2020 fire season. We used these data as the input of our model and obtained the maximum number of two drones needed in the fire season. The result of our model can be seen as the **optimal number and mix** of drones Rapid Bushfire Response would need.

5. We study the **equipment cost increasement** (such as accessories replacement and maintenance cost) assuming that the cost of drone systems stays constant while the frequency of wildfire increases.

6. Considering the extreme fire event might occur in the future, we test our model by input a fire with an extremely large size and examine the output of each sub-model.

2 Preparation of the Models

2.1 Assumptions

Assumptions we made to simplify the model are listed below:

1. According to the history data of wildfire in Victoria, size of the fire is much smaller than the flight range of drones, so we assume that drones' activity range can always cover the wild fire.

2. The front teams are densely distributed along the line of fire.

3. There is only one Emergency Operations Center for a fire and all drones are charged in it.

4. Only after the Radio Repeater drone reach the signal range of the handheld radio, the drone can receive and transmit the signal from the front team.

5. The SSA drone should fly along the line of fire to monitor the evolving situation.

6. The interior of the fire field is burned out, and the drone can fly through the interior of the fire field.

7. The drones can keep moving at full speed.So the drone can travel maximal 180km per trip.

2.2 Notations

The primary notations used in this paper are listed in Table 1.

Table 1: Notations

Symbol	Definition
$\vec{R}$	original velocity of fire entity
$\vec{R}_0$	original velocity of fire entity
K_w	Wind correction parameter
K_φ	Terrain correction parameter
K_s	Material correction parameter
T_0	the max mission time(2.5h)
ΔT	hovering duration for each gathering point
T_c	the charging time(1.25h)
s	the path length of the route
v	max speed (20m/s or 72km/h)
N_p	the number of target points
N_d	the number of the drones

3 Drone Deployment Model

3.1 Fire Model Considering Size and Topography

3.1.1 Fire Field Model Preparation

In this section, we introduced perlin noise terrain generation algorithm and Wang Zhengfei forest fire spread model to simulate the fire field in different enviroument s. Then, we deployed the boots-on-ground team on the line of fire.

3.1.2 Sub-Model Assumption

1. Only the outmost burning trees in the fire field will spread out fire.
2. The boots-on-ground teams are uniformly distributed along the line of fire.
3. Distance between adjacent boots-on-ground teams shouldn't be longer than the range of radio.

3.1.3 Terrain Generation

Fire spread at different speed under different terrain circumstances. To better simulate the expansion of fire field, we will generate different types of terrain.

We implemented perlin noise to generate random height maps[5]. Then, we modify the noise with several low-pass filters to reduce the bumpiness. Such technique is often used in open-world game map generation.

We use three sets of filters to generate the terrain of plain, hill and mountain.

3.1.4 Fire Field Model Construction

We charaterize the fire field model in the following aspects:

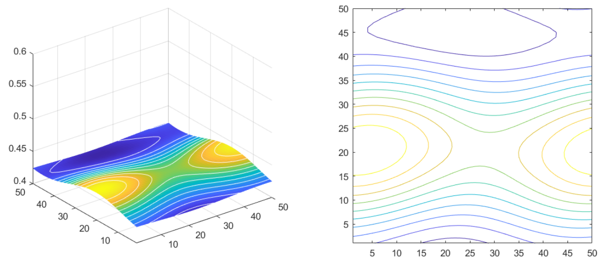


Figure 1: PlainTerrain

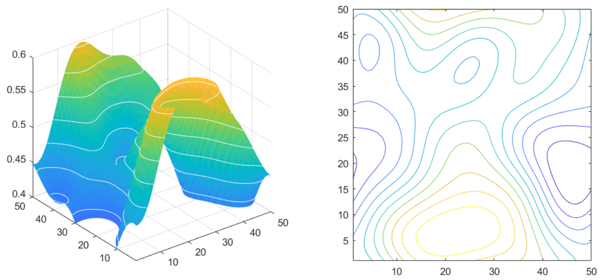


Figure 2: mountainousTerrain

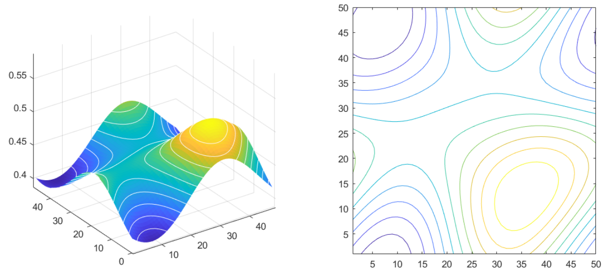


Figure 3: HillTerrain

1. The outermost ring of the fire field is called 'the line of fire'. **Fire entity is the most basic unit of the line of fire.**
2. **Every fire entity stands for the fire spreading towards a direction.** By calculating the position of each entity we can get the shape and size of the fire field.
3. The speed of fire entity is only determined by the speed of wind and the terrain at any moment. The impact of wind and terrain is calculated based on **Wang Zhengfei forest fire spread model**.
4. At the very beginning, the fire entities moving towards all directions concentrate at the same spot.

3.1.5 The Steps Of The Fire Field Generation Algorithm

The schematic of the algorithm is shown in Figure 4.

step1 **Initialization**

During initialization, the program will genenrate a random terrain and random wind.

step2 **Main Loop**

The main part of the program runs in loop. In each loop, all fire entities will be traversed, periodically updating the speed and position status. The speed calculation is based on Wang Zhengfei Forest Fire Spread Model, which requires wind and terrain correction parameter.

step3 **Calculating Wind Correction Parameter**

$$K_w = e^{0.1783\ \mathrm{V}} = e^{0.1783\left(|R_0|\cdot\frac{\vec{R}_0\cdot\vec{V}_{wind}}{|\vec{R}_0|\cdot|\vec{V}_{wind}|}\right)}$$

step4 **Calculating Terrain Correction Parameter**

$$K_\varphi = e^{3.533(\tan\varphi)^{1.2}} = e^{3.533\left(\nabla f(x,y)\cdot\frac{\vec{R}}{|\vec{R}|}\right)^{1.2}}$$

Where φ is relative slope between fire entity and ground.

step5 **Calculating Overall Speed**

The overall formula is:

$$\mathrm{R} = R_0 K_s K_w K_\varphi$$

The position of fire entity will be updated based on the speed at this instant.

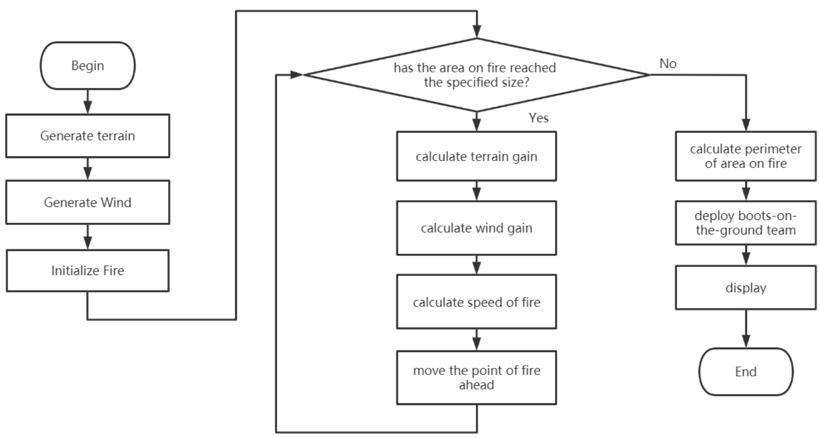


Figure 4: The schematic of the fire field generation algorithm

3.1.6 Result

The result of simulation is shown in Figure 5-7.

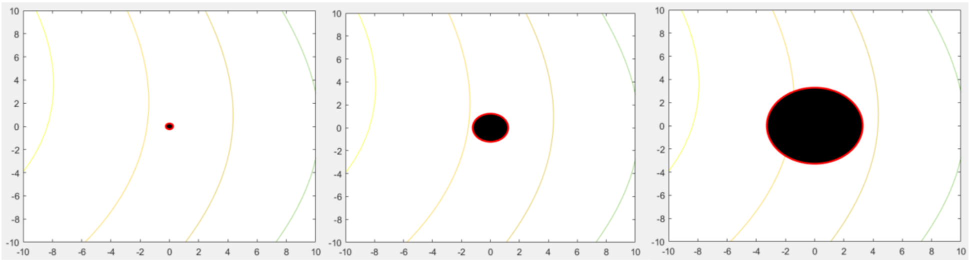


Figure 5: Fire variation without wind in plain

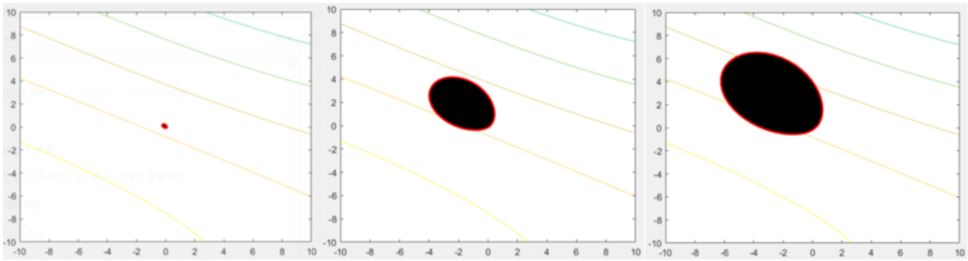


Figure 6: Fire variation with wind in plain

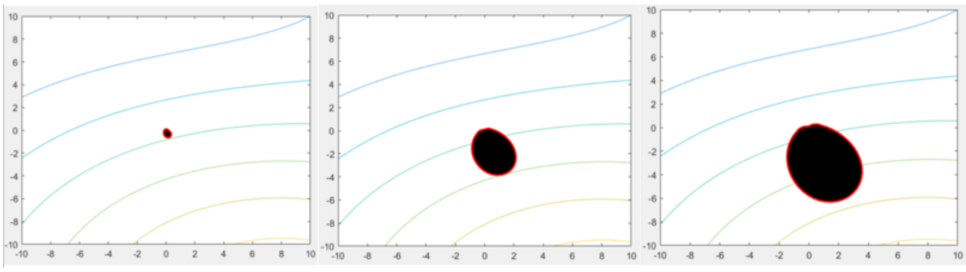


Figure 7: Fire variation without wind in mountain

3.1.7 Deployment Of Boots-On-Ground Team

To ensure that the adjacent Boots-On-Ground teams can keep contact with each other, the distance between them shouldn't be longer than the range of their radios.

According to Walfisch-Ikegami Model, forest have signal sheilding effect on radios. The shielding effect is extremely strong in mountounaus area. When in mountainous forest, the effective range of the equipped radio is approximately 3km.

Based on this phenomenon, we modified our Boots-On-Ground Team deployment strategy for different terrain.

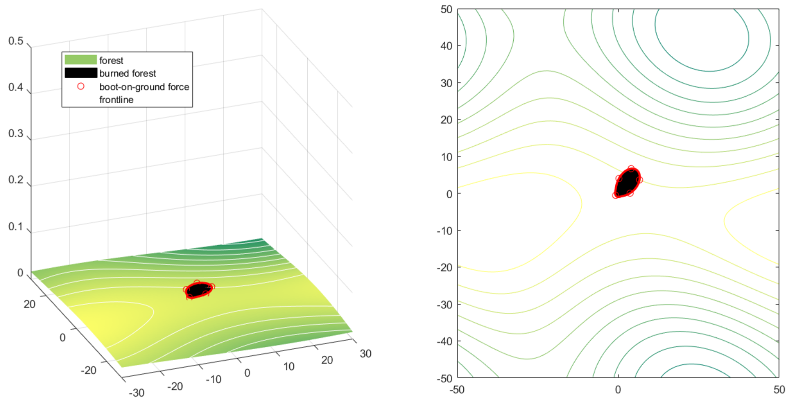


Figure 8: squads position deployment on plain area

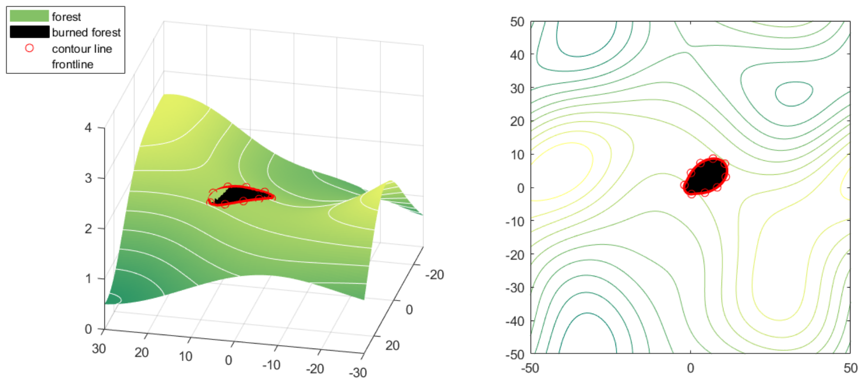


Figure 9: squads position deployment on mountains area

3.2 Deployment Model of Radio Repeater Drone

3.2.1 Sub-Model Assumption

1. The wireless communication need to keep connecting, for security reasons.
2. The radio-repeater drones need to hovering over the target points to work effectively.
3. The firefighter are continuously and uniformly distributed in the line of fire.

3.2.2 MTSP Model Construction

The maximum operation time of each UAV is only 2.5 hours. However, we can find that the duration of each fire-fighting mission is often longer than 2.5 hours from past statistics. Therefore, when arranging the routes, we should consider the situation of returning EOC and charging before continuing to perform the mission. So we have to take into account of shifts between drones.

As we assumed before, the firefighter are continuously and uniformly distributed in the line of fire. Then we discretize the distribution into several firefighter gathering points based on the range of the handhold radio. Therefore, these gathering points are the mission target points of radio repeater drones. We also assume that the radio repeater drones need to hover over the gathering point to provide a stable, uninterrupted communication network.

In this case, the work-flow of radio repeater drones is as follow: start from the EOC and move to the gathering point, hover at the gathering point, move to the next gathering point or back to EOC to get charge, then repeat the previous work.

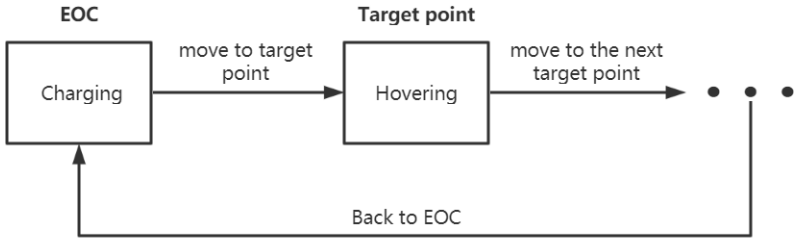


Figure 10: Radio Repeater Drones Workflow

Because the effective working time of the UAV is the hover time on the gathering point, while the time in the road is the ineffective time.Therefore, in order to maximize the efficiency of the UAV, we want to maximize the effective working time of the UAV in one mission cycle.

Because the effective working time of radio repeater drones is the hovering time over the gathering point, while the time moving in the road is the ineffective time. Thus, in order to maximize the efficiency of the radio repeater drone, we need to maximize the proportion of effective working time in a working cycle.

$$Max(\frac{T_e}{T_e+T_u})$$

$where\ T_e\ denotes\ the\ effective\ working\ time\ and\ T_u\ denotes\ the\ uneffective\ time.$

This allows radio repeater drones to hover at gathering points all the mission time, except when they're on the road. Therefore, we can get the hovering duration for each gathering point.

$$\Delta T = \frac{T_0 - \frac{s}{v}}{N_p}$$

Because we need an uninterrupted communication network, we have to make the total hovering time of each radio repeater drone equal to the working cycle time.

$$\frac{T_0+T_c}{\Delta T} = N_d$$

We can get the amount of the radio repeater drones we need from this relationship.

So far, we have turned the routing of radio repeater drones into a MTSP problem. That is, given the positions of the gathering points, we need to optimize the routing to obtain an uninterrupted radio network and minimize the amount of the radio repeater drones at the sam time. Nevertheless, there are some difference from the traditional MTSP problem[4]. That is the hovering time need to be taken into account after the radio repeater drones arriving at the gathering point.

3.2.3 GA Model Construction

Searches reveal that there are many precedents of using intelligent algorithms to solve MTSP problems.Here, we use genetic algorithm(GA) to solve it. That is, imitate the mechanism of biological evolution to conduct global search, so as to solve the optimize problem.

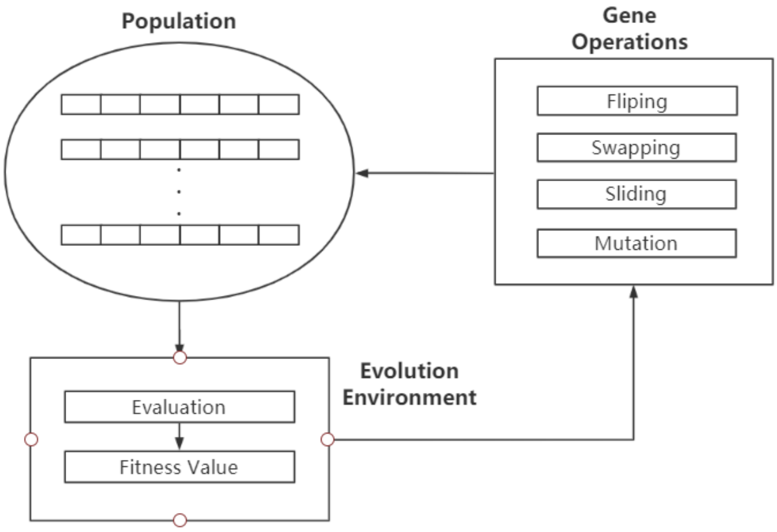


Figure 11: GA Workflow

Based on the study of relative paper[3], to use GA, we need to complete the gene coding. That is, encode the information used to filtrate into the gene fragments. Here, we divide genes into pathway genes and break-point genes.The break-point genes are used to divide the path genes. Multiple drone sub-paths are divided according to the number of break-point.

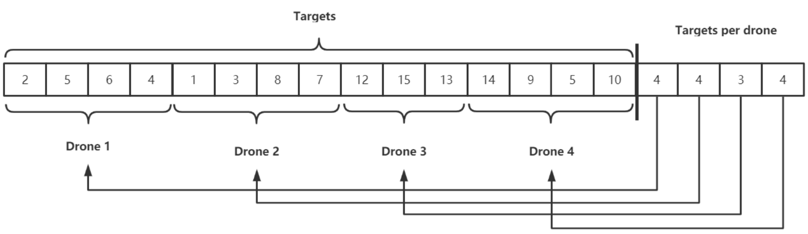


Figure 12: The gene sequence

What we are optimizing here is to minimize the total amount of radio repeater drones required, so the fitness function is naturally the amount of drones.

$$Min(\sum N_d)$$

In the process of evolutionary iteration, the population is divided into groups of 8. And the individual that need the minimal drones is selected from each group. After that, the selected individuals are performed gene flipping, swapping, sliding and mutation on their genes of the pathway and the break-point respectively to obtain the offspring. Iterative evolution is carried out by doing the same filtering on the children generation. To avoid being trapped in local optima, we set the population amount to 64 to ensure the randomness.

Using the GA model requires input of the number of sub-paths, that is, how many sub-paths we need to divide into. Since we can't know the optimal arrangement, the approach that going through all the scenarios from 1 to the number of gathering points. Then, we can find the arrangement that requires the least number of radio repeater drones.

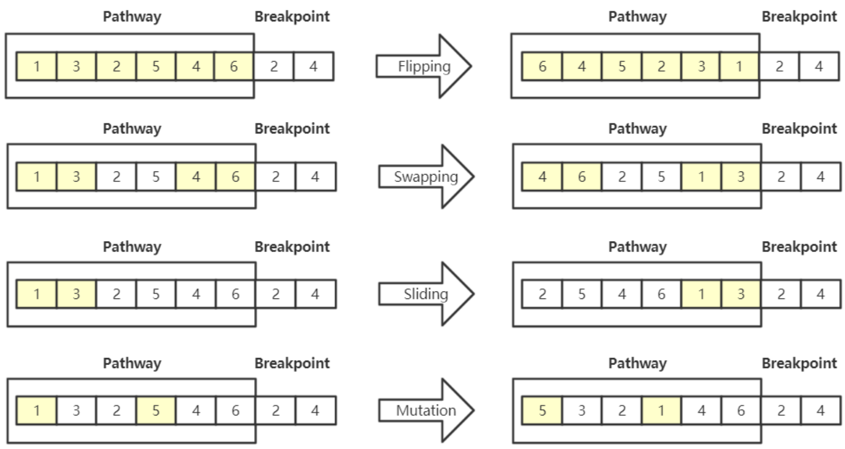


Figure 13: Gene Operation

3.2.4 Result

To show the effect of our model, we use this model to sovle the fire field whose size is $70km^2$. And the result is shown below. We can find that we need 6 radio-repeater drones at least.

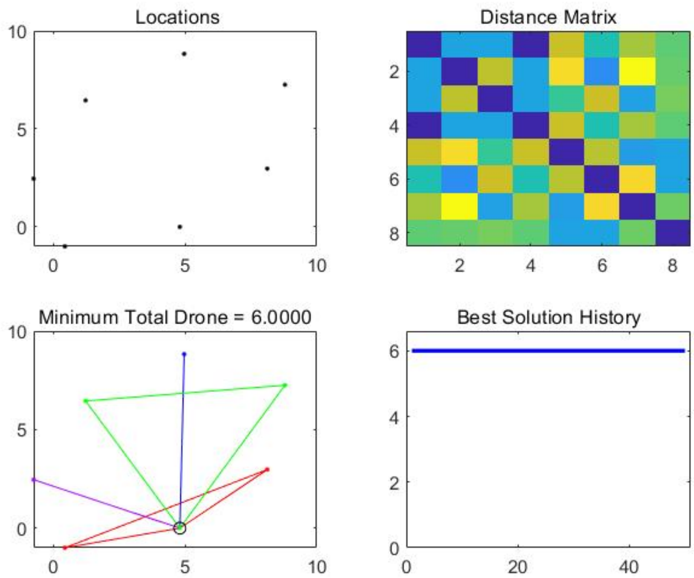


Figure 14: The radio-repeater drone deployment for $70km^2$ fire field in hill area

So far, given the size of the fire and the terrain, using the GA model, we can get the optimal the locations and amount of radio-repeater drones.

3.3 Deployment Model of SSA Drone

3.3.1 Sub-Model Assumption

1. The job of the SSA drone is to cruise along the line of fire all the time, probing the surrounding environment while collecting data from the wearable of front-line firefighters and reporting to the EOC.

2. The faster information of the fire site can be updated, the more EOC's command can be timely, the safer front-line personnel can be and the more effective fire fighting can be.

3.3.2 Optimal Model Construction

We assumed that the job of the SSA drone is to cruise along the line of fire all the time. Therefore, it can be assumed that the SSA drones' cruising path is the contour line of the fire site, and thus the time required for the SSA to cruise one circle can be obtained.

$$T_p = \frac{s}{v}$$

According to the statistics, the area of many fire is about $40km^2$, the length of the fire line is about 22.5km. As a result, the SSA can fly multiple cycles per trip. In this case, we assume the charging time is linear for the sake of simplicity. Thus we can get the period of the SSA drones:

$$T = \frac{s}{v} + \frac{s}{v} * \frac{T_c}{T_0} = \frac{s}{v} * (1 + \frac{T_c}{T_0})$$

Then, the relationship between the number of SSA drone and the update period of information is as follows:

$$\Delta T = \frac{T}{N_d}$$

It is natural to find that the more drones there are, the faster information of the fire site can be updated. However, on the other hand, the higher the cost. Therefore, we need to make a trade-off between cost and safety to find a optimal solution.

Here we construct a function to measure the cost of the arrangement:

$$CostFunc = g(N_d) + h(\Delta T)$$

The former is the cost term of SSA drones, which is a linear function:

$$g(N_d) = 10000 * N_d$$

The latter is the lost term due to the delay of information updating, which is hard to quantify the exact function because of the lack of data. So we just assume that this term is an exponential function here:

$$H(\Delta T) = K * e^{\Delta T} + M$$

It is easy to know that under ideal circumstances, when there is no delay of information updating, the loss term is zero:

$$H(0) = 0$$

So we can obtain the lost function:

$$H(\Delta T) = K * (e^{\Delta T} - 1) = K * (e^{\frac{T}{N_d}} - 1)$$

where K is the lost coefficient.

The value of parameter k is related to a series of factors such as firefighter mortality caused by information lag and loss of trees due to loss of firefighting efficiency:

$$K = C * \lambda_1 * \lambda_2 * \cdots$$

where λ_1, λ_2 *are the factor related to safty and efficiency*

However, due to the lack of data, it is hard for us to get an exact value.

3.3.3 Exhaustive Method

Since the value of Nd is a discrete integer, this is a nonlinear integer programming problem. For the sake of convenience, we use the exhaustive method to find the optimal solution.

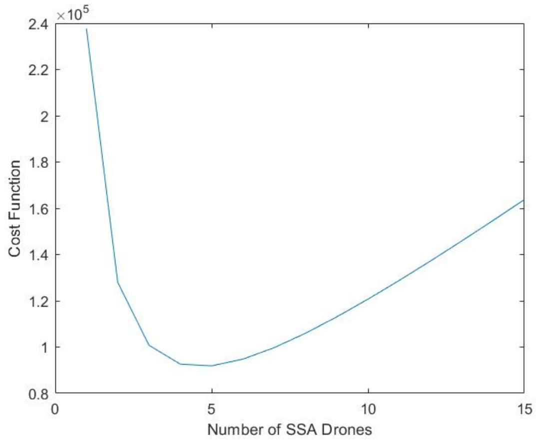


Figure 15: The effect of exhaustive method

So far, we've obtained the model that can get the amount of SSA and radio-repeater drones required.

4 Optimize the Number and Mix of Drones with Size and Frequency as Parameters

4.1 History Data Processing

We find the data set of Australia bushfire from 2019-10-01 to 2020-01-11 (2019-2020 fire season) provided by NASA FIRMS MODIS and VIIRS Fire/Hotspot. The data set only provides the hotspot information (the fire size in a 1km pixel), which cannot reflect the size of fires larger than $1km^2$.

To address this problem, we first use the longitude and latitude of two hotspots A and B to compute the surface distance in kilometers between them:

$$surface\ distance\ C = \sin(LatA) * \sin(LatB) * \cos(LonA - LonB) + \cos(LatA) * \cos(LatB)$$

$$where\ LatA,\ LatB\ denote\ latitude\ of\ A\ and\ B,\ LonA,\ LonB\ denote\ longitude\ A\ and\ B.$$

Then, we use the distance in kilometers to check if two or more hotspots belong to one fire. If yes, we sum up the size of those hotspot together to get the size of one fire.

Since we focus on the fire in Victoria state, we use the longitude and latitude to screen out the fire happened in Victoria. By this method, we obtain the size-frequency function of the fire happened in Victoria during the 2019-2020 fire season.

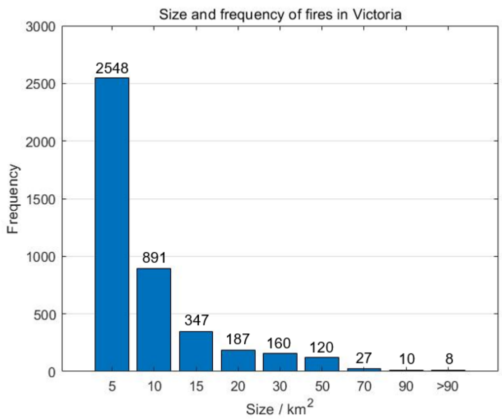
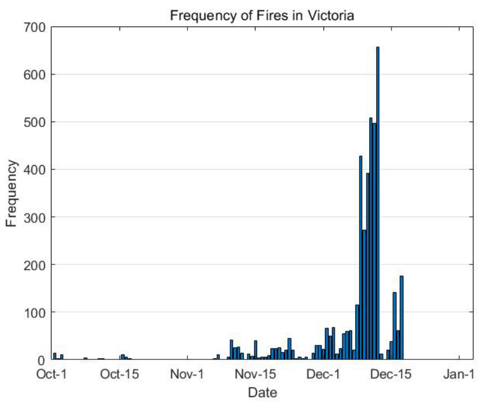
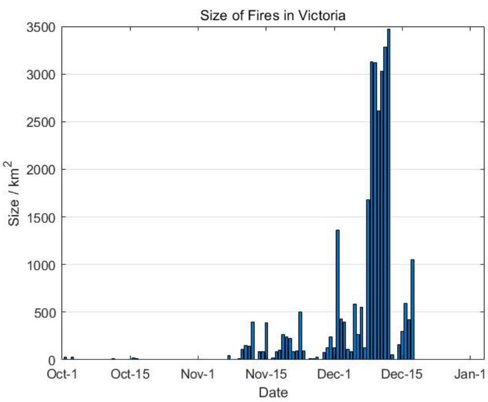


Figure 16: Size and frequency of fires in Victoria



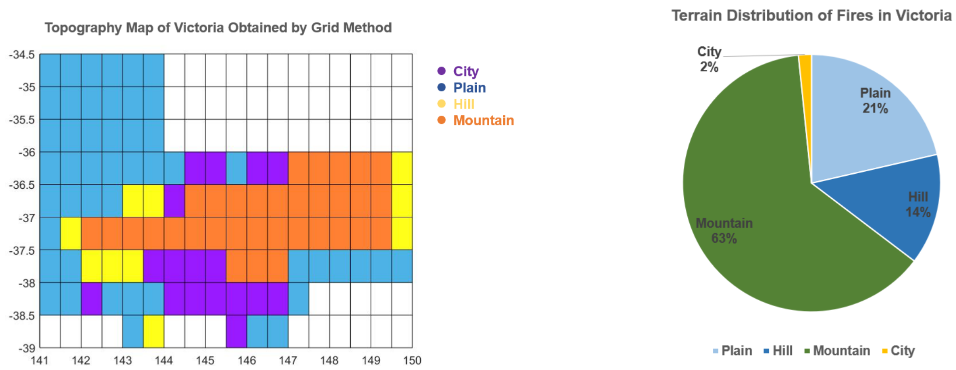
(a) Frequency of fires in Victoria



(b) Size of fires in Victoria

Figure 17: The frequency and size of fires in Victoria

Besides, we also need the terrain of fires happened in Victoria. We find the precise topography map of Victoria. By assigning each fire onto the topography map according to the longitude and latitude through grid method, we obtain the terrain of each fire happened in Victoria.

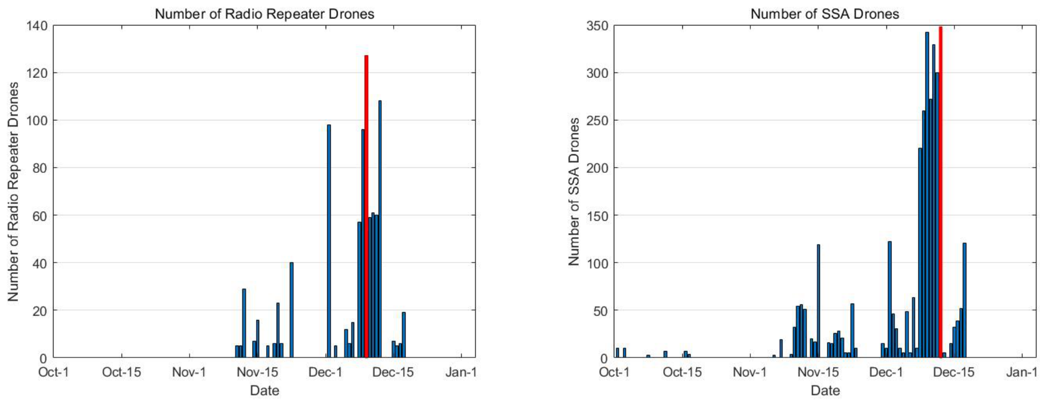


(a) Topography map of Victoria obtained by grid method (b) Terrian distribution of fires in Victoria

Figure 18: The topograpghy mesh map and distribution in Victoria

4.2 Result of the Model

Now we obtain all the information we need. For each fire in Victoria, we take its size and terrain as input and get the output number of two drones through our model. For every day during the fire season, we sum up the number of two drones the Rapid Bushfire Response need in one day.



(a) Number of radio-repeater drones (b) Number of SSA drones

Figure 19: The number of two kind of drones

Referring to the result of our model, in order to cover the daily requirement during the fire season, the optimal number and mix of two drones the Rapid Bushfire Response should purchased is: **127 Radio Repeater drones and 348 SSA drones.**

5 Research of Equipment Cost Increasement

Assuming that the cost of drone systems stays constant, we study the equipment cost increasement may occur.

According to the failure rate table of drone system, we can obtain the failure rate of the accessories R(failure). Referring to the duration-frequency of wildfire in Victoria during the

System Description	λp System FIT (F/10^6 hrs)	MTBF (hours)	Incidence (%)
Ground Control System	2.00	500,000.0	6.62%
Mainframe	2.77	360,984.8	9.16%
Power plant	9.94	100,603.6	32.88%
Navigation system	9.41	106,269.9	31.13%
Electronic system	5.01	199,600.8	16.57%
Payload	1.10	909,090.9	3.64%
λ TOTAL =	**30.23**	**FIT**	
MTBF (R_{Total}) =	**33,079.50**	**Hours**	
	1378.31	**Days**	
	49.23	**Months**	

Figure 20: Failure table of drone system

2019-2020 fire season and the required number of two kind of drones, we are able to calculate the cost of accessories replacement approximately:

$$Number\ of\ replacement = R(failure) * \int Duration(f)df$$

$$Maintenance\ cost = Replace\ number * Unit\ price$$

With the increasing trend of fires' duration and frequency, it is obvious that both the number of replacement and maintenance cost will increase.

6 Test of the Model

Due to the trend of global warming and climate change, the likelihood of having extreme fire event is increasing. We test our model by input a fire with an extremely large size which may happened in the next decade and examine the output of each sub-model.

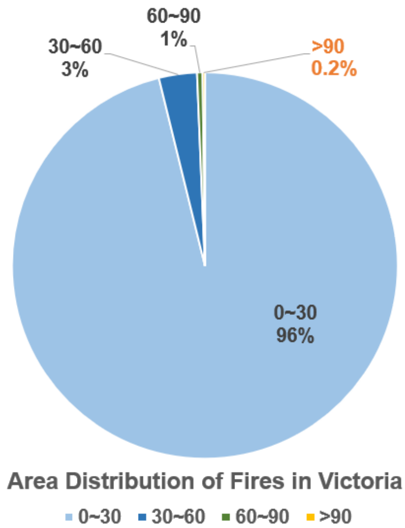
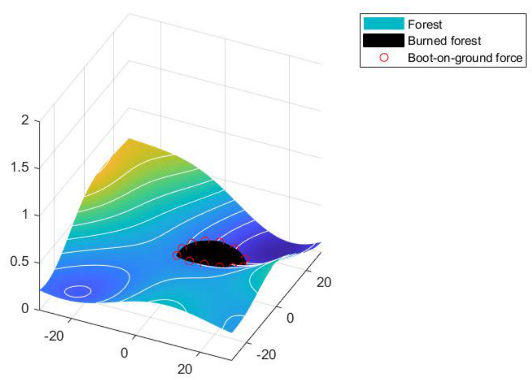


Figure 21: Area distribution of fires in Victoria

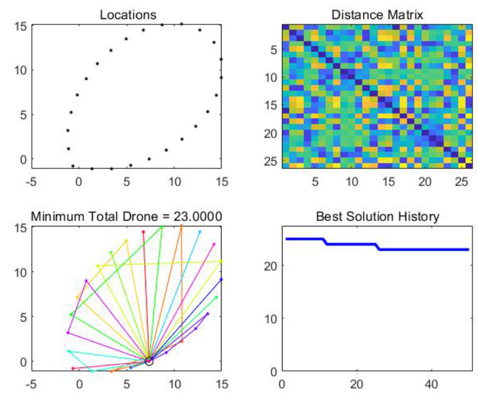
According to the history wildfire area data of Victoria state, only 0.2% are around $1000km^2$. However, with the increasing trend of wildfire area, the likelihood of having a super wildfire is noneligible. Besides, property damage due to a super wildfire is much larger than a normal one.Therefore, it is necessary to make sure that our model can adapt to extremely large fires may happen in next decade.

Take a super wildfire with area of $1000km^2$ as the input of our model. Although the fire line is much longer and the target points generated is much more, the result of our fire field model can still be considered reasonable.

Although with larger numbers of target points, the iteration time of the Genetic Algorithm becomes longer, the total time of finding the optimal deployment method is acceptable.



(a) Super wildfire with $1000km^2$ area



(b) Radio repeater drone deployment in super fire field

Figure 22: The super fire and the radio-repeater drones deployment

Final result obtain by our model is reasonable (23 Radio Repeater drones and 15 SSA drones). Therefore, our model can be considered as having certain ability to adapt the extremely large fire might occurred in the future.

7 Sensitivity Analysis

When addressing the deployment problem of SSA drones, we use an exponential model to map the interval time between each inspection of the drone to the economics cost. To justify the equation, we further analyze the effect of the interval time under the situation that the number of SSA drones stays unchanged.

We let the number of drones be a constant and change the interval time. The result of the nonlinear cost function is shown below.

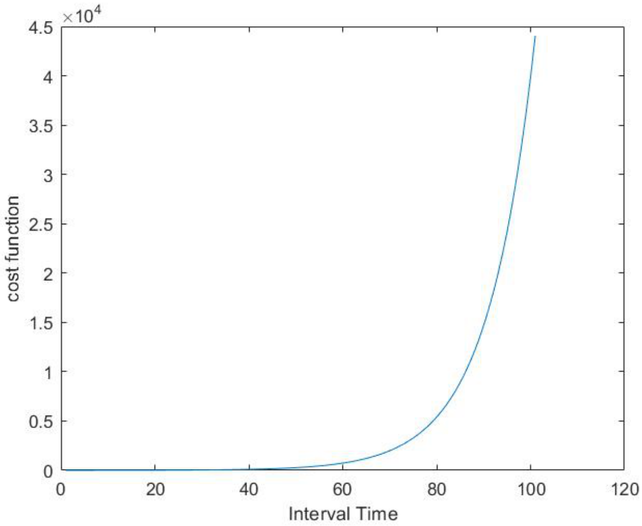


Figure 23: Sensitivity analysis

According to the result, the increasing speed of the cost function fiercely rise with the increase of the interval time, which is consistent with the actual situation that the longer the interval time of each inspection is, much more economics lost it will cause.

8 Strengths and Weaknesses

8.1 Strengths

- Fully consider the effect of different type of terrain. We also introduce a random terrain generate system to make the test sample more universal.
- Take the previous fire data into consideration, make the result of the model more valuable for reference.
- Use the genetic algorithm, which can make the model converge quickly.
- The specific route arrangement of the drones can be obtained, which make the model easy to use.

8.2 Weaknesses

- Fail to introduce the actual terrain of Vectoria. The generation result may not perfectly represent the actual fire field there.
- Since the model focus on the response to the fire within the range of single EOC, super fire that requires multiple EOCs to work together cannot be handled.

9 Budget Request

Budget Request Justifications

Because of the severe drought and persistent heat caused by the trend of global warming, the 2019-2020 fire season in Australia has seen devastating wildfires in almost every state. As one of the worst impacted state, Victoria is expected to make some change.

In order to keep wildfires under control, a new division, “Rapid Bushfire Response”, was proposed by Victoria’s Country Fire Authority. In order to extend the communication range of the “Boots-on-the-ground” forward teams and improve the monitor of the evolving situation, a certain number of drones which equipped with radio repeater or video & telemetry capability are expected to purchase.

In a typical super wildfire (with an area larger than $1000km^2$), about 20 Repeater drones and 15 SSA drones are needed. (See Part 6.) But due to the growing frequency of wildfires(See Part 4.1), more drones are needed in case multiple great wildfire occur together. To cope with the most difficult situation, we will have to put 127 repeater drones and 348 SSA drones into use.(See Part 4.2).

To determine the optimal numbers and mix of the radio-repeater drone and the drone used for surveillance and situational awareness (SSA), we first build the fire field model with respect to different size and topography of the wildfire. Then, we optimized the deployment of the drones and take capability, safety and economics into consideration. Finally, by processing the data set provided by NASA, we obtain the data of wildfires happened in Victoria during 2019-2020 fire season. With the location, size, and terrain data of wildfires, we calculated the numbers of two kinds of drones required to cover the need of fire season. Besides, we also determined the cost of other accessories through our model referring to the repair rate of each accessories.

The exact amount of our budget and other detail is listed below. We sincerely hope the request could be accepted.

Budget Request

Victoria Country Fire Authority

Victoria CFA is planning to set up a new division 'Rapid Bushfire Response'(RBR) to combat wild fire. The division will be equipped with prototype drone swarm developed by Akem Corp. This budget request is written to introduce all of the necessary costs involved in the drone network program.

Budget Request	
Equipment	5,013,625
Service	70,000
Total	5,083,625

The budget request includes equipment purchasing request and service purchase request. Detail information of the required equipment/service is shown below.

Equipment

No.	Item	Specification	Brand	Qty	Unit Price	Total Price
1	Drone	WileE–15.2X (with SSA module)	Akme	348	10,000	3,480,000
2	Drone	WileE–15.2X (with repeater module)	Akme	127	10,000	1,270,000
3	Lipo Battery	22000mah 22.2v 6s 25c	JiuHang	1,425	185	263,625
5	**Total Expenses**					5,013,625

Service

No.	Item	Total Price
2	Flight Control Software	10,000
3	Drone Operators Training	60,000
4	Total Expenses	70,000

References

[1] Miguel G. Cruz, Martin E. Alexander, Paulo M. Fernandes, Musa Kilinc, Ângelo Sil,Evaluating the 10% wind speed rule of thumb for estimating a wildfire's forward rate of spread against an extensive independent set of observations,Environmental Modelling & Software,Volume 133,2020.

[2] A.M.G. Lopes, L.M. Ribeiro, D.X. Viegas, J.R. Raposo,Simulation of forest fire spread using a two-way coupling algorithm and its application to a real wildfire,Journal of Wind Engineering and Industrial Aerodynamics,Volume 193, 2019.

[3] John H. Holland,Computer programs that "evolve" in ways that resemble natural selection can solve complex problems even their creators do not fully understand, Natural and Artificial Systems,1975.

[4] Mohammad Sedighpour, Majid Yousefikhoshbakht, Narges Mahmoodi Darani, An Effective Genetic Algorithm for Solving the Multiple Traveling Salesman Problem, Journal of Optimization in Industrial Engineering, 2011.

[5] HyeongYeop Kang, Yeram Sim, JungHyun Han, Terrain rendering with unlimited detail and resolution, Graphical Models, Volume 97, 2018, Pages 64-79.

Appendix A: Further on LaTeX

MTSP GA code(part):

```
for iter = 1:num_iter
    % Evaluate Members of the Population
    for p = 1:pop_size
        %d = 0;
        p_rte = pop_rte(p,:);
        p_brk = pop_brk(p,:);
        rng = [[1 p_brk+1];[p_brk n]]';
        everyDis = zeros(1,salesmen);
        % the number of drone for each route
        everyDrone = zeros(1,salesmen);
        everyInfo = zeros(3,salesmen);
        for s = 1:salesmen
            everyDis(s) = everyDis(s) + dmat(1,p_rte(rng(s,1)));
            for k = rng(s,1):rng(s,2)-1
                everyDis(s) = everyDis(s) + dmat(p_rte(k),p_rte(k+1));
            end
            everyDis(s) = everyDis(s) + dmat(p_rte(rng(s,2)),1);
            SS = everyDis(s);
            Np = rng(s,2) - rng(s,1) + 1;

            everyDrone(s) = ceil((SS+90)*Np/(180-SS));

        end
        total_drone(p) = sum(everyDrone);
        total_every_drone{p} = everyDrone;
    end
     % Find the Best Route in the Population
    [min_drone,index] = min(total_drone);
```

Fire Field Generation code:

```
function SquadPosition3D = ...
   getSquadPositionWithArea(originalRadius,terrain,windSpeed,showAnimation,targetArea
    windDir = windSpeed/norm(windSpeed);
    A = 0.5;width = 50;
    x = -width:A:width;y = x';
    [gradX,gradY] = gradient(terrain);
    gradX = gradX/A; gradY = gradY/A;
    a = originalRadius;b = originalRadius;
    x0 = 0;y0 = 0;theta = 0;
    ecc = axes2ecc(a,b);
    [xDot,yDot] = ellipse1(x0,y0,[a ecc],theta,[]); %edge of fire
    defaultSPD = 15; %scalar
    dt = 0.001;
    for t = 1 : 302
        xDot = real(xDot);
        yDot = real(yDot);
        xDotOnGrid = roundn(xDot/A,0) + 2 * width + 1;
        yDotOnGrid = roundn(yDot/A,0) + 2 * width + 1;
        for i = 1 : length(xDot)
            dir = [xDot(i),yDot(i)]/norm([xDot(i),yDot(i)]); % the ...
               direction of fire
            windAmp = dot(dir,windSpeed);
```

```
            windSupplement = exp(0.1783*windAmp);
            grad = ...
                [gradX(xDotOnGrid(i),yDotOnGrid(i)),gradY(xDotOnGrid(i),yDotOnGrid(i))
            slope = atan(dot(grad,dir));
            terrainSupplement = exp(3.533*tan(slope)^1.2);
            actualSPD = (windSupplement * terrainSupplement * ...
                defaultSPD) .* dir;
            xDot(i) = xDot(i) + actualSPD(1)*dt;
            yDot(i) = yDot(i) + actualSPD(2)*dt;
        end
        xDot = real(xDot);yDot = real(yDot);
        xDotOnGrid = real(roundn(xDot/A,0) + 2 * width + 1);
        yDotOnGrid = real(roundn(yDot/A,0) + 2 * width + 1);
        zDot = zeros(1,length(xDot));
        for i = 1 : length(xDotOnGrid)
             zDot(i) = terrain(xDotOnGrid(i),yDotOnGrid(i)) + 0.025;
        end
        curveLength = sum(sqrt((xDot(2:end)-xDot(1:end-1)).^2 + ...
            (yDot(2:end)-yDot(1:end-1)).^2));
        squadCount = ceil(curveLength/3);
        SquadPosition = interparc(squadCount,xDot,yDot,'linear');
        SquadPositionX = real(SquadPosition(:,1));
        SquadPositionY = real(SquadPosition(:,2));
        SquadPositionXOnGrid = roundn(SquadPositionX/A,0) + 2 * width ...
            + 1;
        SquadPositionYOnGrid = roundn(SquadPositionY/A,0) + 2 * width ...
            + 1;
        SquadPositionZ = zeros(1,length(SquadPositionX));
        for i = 1:length(SquadPositionX)
            SquadPositionZ(i) = ...
                terrain(SquadPositionXOnGrid(i),SquadPositionYOnGrid(i)) ...
                + 0.025 ;
        end
        SquadPositionZ = SquadPositionZ';
        clf
        if(showAnimation)
            contour(x,y,terrain,10);hold on
            fill(xDot,yDot,'k'); hold on
            plot(xDot,yDot,'r','LineWidth',2)axis([-10,10,-10,10]) ...
                          pause(0.001);
        end
        area = polyarea(xDot,yDot);
        if area > targetArea
            sprintf("current area is: %f",area);
            break
        end
    end
    if(¬showAnimation)
        figure;subplot(121);
        s = surf(x,y,terrain);hold on;
        fill3(xDot,yDot,zDot,'k');
        s.EdgeColor = 'none';
        colormap summer;hold on
        scatter3(SquadPositionX,SquadPositionY,SquadPositionZ,'r');hold ...
            on;
        contour3(x,y,terrain,10,'w');hold on;
        plot3(xDot,yDot,zDot,'color','r','LineWidth',2);hold on;
        legend('forest','burned forest','contour line','frontline'); ...
            axis([-30,30,-30,30,0,4]);
        subplot(122);contour(x,y,terrain,10);hold on
```

```
        fill(xDot,yDot,'k');hold on;
        scatter(SquadPositionX,SquadPositionY,'r');hold on;
        plot(xDot,yDot,'r','LineWidth',2)
    end
    SquadPosition3D = [SquadPositionX,SquadPositionY,SquadPositionZ];
end
```