Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
B		2111620

Optimization of Australian Fire Fighting Drone System

Frequent fires in Australia have a huge impact on its environment and economy, and the use of drones to help fire monitoring and command will greatly increase the effectiveness of fire prevention and control. This essay mainly explores **the optimization model of drone system** for fire fighting, which has certain practical value.

For problem one, we build three models to solve it. First, we use the **K-means clustering** method to establish an optimized model for region selection, and successfully select a typical region as the model simulation region. Then, we **divide the system of the SSA drones into two parts according to its functions**, and successfully transform the multi-objective planning considering economy, safety and performance into the multi-traveling salesman problem under single-objective planning, and then use the **genetic algorithm** to solve the typical. The optimal drone system in the area, the algorithm's convergence speed is 0.5312 km/gen

For problem two, we use the fire data from 2000 to 2019 in Australia provided by NASA to establish **a time series model of ARIMA(1,1,3)**. Through the forecast of the overall fire development trend in Victoria, we provide the government with the timing and strategy of capital investment; and through the fire points in typical areas Distribution simulation to predict whether government support is needed to increase the purchase of firefighting drones in the short term, and finally to test the sensitivity of the time series model we built, and draw the **QQ diagram** and **the residual distribution histogram**, because residual distribution is close to the normal distribution, thus, we prove the **reliability** of the time series model.

For problem three, we first establish **a radio propagation loss model** based on **the Hata model** and use the clustering method to find the optimal position of the repeater drone. Next, based on the idea of ensuring that the signal is always unblocked, we introduce a **queueing model** to describe one of them. The update of the position of the drones indicates that the model will tend to be chaotic on a longer time scale, and it also presents **a simulation algorithm** for the optimal number of repeater drones that guarantees a long signal transmission under a limited time scale is given.

Keywords: Drone System, Multi-Objective Optimization, ARIMA, Genetic Algorithm

Contents

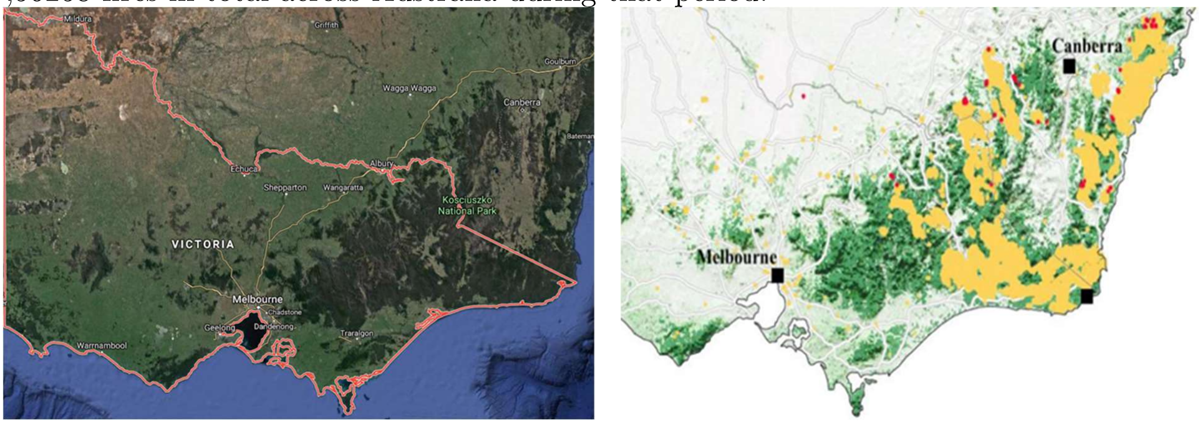
I Introductions

1.1 Problem Background

1.1.1 Australian wildfires

The 2019-2020 Australia wildfires have caused tremendous damage to the environment and economy of Australia.

The following Figure 1 shows the wildfire hot spots in this area from October 1, 2019 to January 7, 2020, with yellow showing fires from October 1st to January 6th, and red showing active fires on January 7, 2020. According to satellite data from 2019-2020, there were 9,56258 fires in total across Australia during that period.



(a)Topographic Map of Victoria, taken by Satellite.

(b) Wildfire Hot Spots in Southeast Australia, Oct 1, 2019 to Jan 7, 2020.

Figure 1 Topographic Map and Wildfire Hot Spots

1.1.2 Fire-fighting with Drones

Researches on fire prevention and control in Australia play an important role in the global climate change problems, This paper mainly studies on the design and optimization of fire-fighting drone system. The fire-fighting drone system mainly consists of three kinds of equipment:

- **Surveillance and Situational Awareness(SSA) drones:**
  SSA drones carry high definition & thermal imaging cameras and telemetry sensors so that they can monitor and report data from wearable devices on front-line personnel.
- **Signal Repeating(SR) drones:**
  SR drones carry 10-watt, weighing 1.3 kg repeaters. It can hovering well above ground level, and its signal can achieve a range of 20 km in ideal topography.
- **Wearable Devices(WD):**
  WD are carried by “boots-on-the-ground” forward teams. They can be used as Personal Locator Beacons or more complex environmental monitors. They can send or receive information to or from **Emergency Operations Center (EOC)**. Signal range of WD is more sensitive to topography than Repeaters, which has a nominal range of 5 km over flat, unobstructed ground, but drops to 2 km in an urban area.

In this problem, we use Akme Corporation's prototype WileE–15.2X hybrid drone, which is projected to cost approximately $10,000 (AUD) when equipped with either a radio repeater or video & telemetry capability.

And the capability of this drone is listed in Table 1.

Table 1 WileE–15.2X Hybrid drone Capabilities

Flight range: 30 km	Maximum speed: 20 m/s	Maximum flight time:2.50 hour
1.75 hour recharge time for the built-in battery		

II Notations

We list notations that are mostly used in this paper in Table 2.

Table 2 Notations

Symbols	Definition
α_i	Latitude of place i.
β_i	Longitude of place i.
$p(\alpha_i, \beta_i)$	The geographic object whose latitude is α_i and longitude is β_i
D_{ij}	Distance between object i and object j.
v_0	Speed when flying in the farthest-flight-distance mode
f_i	Number of fires in area i in 2019-2020

III Assumptions and Justifications

To simplify the problem, we make the following basic assumptions. Some of them are properly justified, and others are made to complement the details in this problem, so we don't give justifications for these assumptions.

- **Assumption 1:** As shown in Figure 2.The use of drone systems for fire fighting is divided into three categories. One is to quickly collect the fire information of each fire point when the satellite monitors the fire that day, and the other is to search for the fire fighting area around the past when the fire fighting starts. We call areas prone to fires as suspected areas. The third is to overcome terrain and climate factors, and to ensure smooth information exchange within the entire drone system.

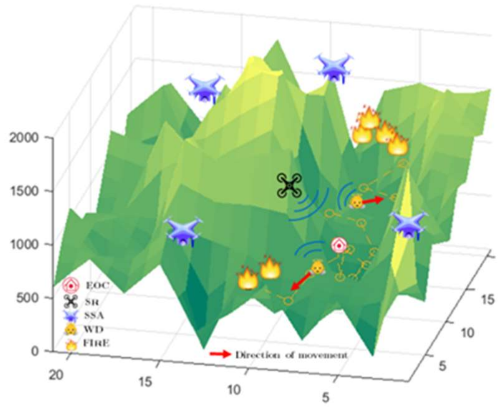


Figure 2

- **Assumption 2:** The movable EOC mentioned in the title is a kind of car that has enough charging devices and spare parts to charge and repair the returning drone. It can only move on the road

- **Assumption 3:** The aircraft can instantly accelerate to 10 m/s from the base, ignoring the power and time consumption of the acceleration process.

($*$)Note: The elements of the collection mentioned in the algorithm description of this article are stored in a cell array in order. When accessing these collections by index, it actually means accessing the corresponding cell array by index.

IV Model Preparation

4.1 Assumptions on Details of the Drones

- All drones fly at a uniform speed, and the power consumption is constant when flying at a uniform speed. Because the maximum flying distance is constant, and the charging time is 1.75 h when the maximum flying distance is reached, the flying distance of the drone is proportional to the flight time. It is proportional to power consumption, so the ratio of charging time to flying distance $\omega = \frac{s_m}{t_m}$ is constant
- The SR drone will only have two state : hovering, or plying between a preset place and the EOC, the latter one will shrink the hovering time of the drone. Actually, the duration that the drone can stay in the sky equals the duration that the drone can hover. Now we assume that SR drones always just exhaust power when they return to the EOC, its moving speed is 10 m/s, and if we let the distance between the drone and the EOC be d, then the hovering time t_H will be

$$2.5 - \frac{2d}{v_0}k \tag{1}$$

In equation (1),it is apparent to find that when we let d be 15 km, then t_H will be 0. In this case, we could find that the number of k is 3.

- Since the flying height is sufficient, it is assumed that the drone's field of view can cover a square area with a side length of 1 km, as shown in the following figure:

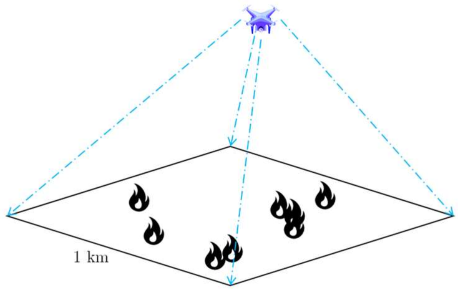


Figure 3 Vision of the Drone

4.2 The Data

4.2.1 Data Collection

The data we used mainly include historical fire hazard data, **Digital Elevation Model (DEM)**. The data sources are summarized in Table 3.

Table 3 Data Sources

Source Websites of the Data	Data Type
https://www.kaggle.com/carlosparadis/fires-from-space-australia-and-new-zeland	Near Real Type Fire Data
https://firms.modaps.eosdis.nasa.gov/country/	Archive Fire Data
https://www.kaggle.com/carlosparadis/fires-from-space-australia-and-new-zeland	Archive Fire Data
https://www.cnblogs.com/lsl1229840757/p/14381482.html	DEM

4.2.2 Data Processing

In order to facilitate analysis and model solution, we process the obtained data files. In the .csv file we obtained, there are 14 columns of data. We first select the latitude and longitude of the fire point, the observed brightness, and the observation date (acq_date) and (acq_time) as the data to be used, and clear the other columns of data; then, because we only consider The distribution of fires in Victoria area, so we choose the longitude range -39--35, the latitude range is 144-151, and clear other data that does not belong to this range; finally, because the second question needs to use time series The frequency of fire occurrence is predicted, and because the date of the data in the file is arranged in positive order, we extract the fire distribution data under the same date according to the date from small to large, and slice the file to facilitate the use of time series to predict. The following figure briefly summarizes the steps we take to process data:

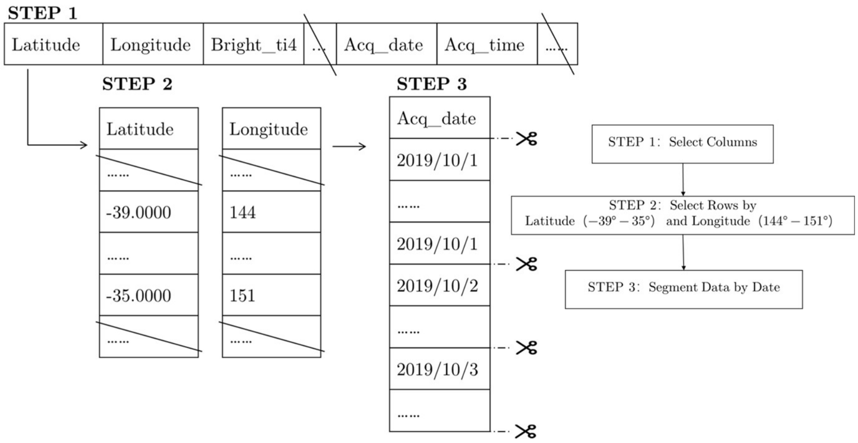


Figure 4 Data Processing

V Models For Problem I

5.1 Region Selecting Model

5.1.1 Visual Analysis

Based on our background assumptions, we know that our rescue is arranged according to the satellite monitoring results of the day, so we first visualize the fire data on January 1, 2020, and use the color depth to represent the brightness of the fire observed by the satellite, and get the following picture:

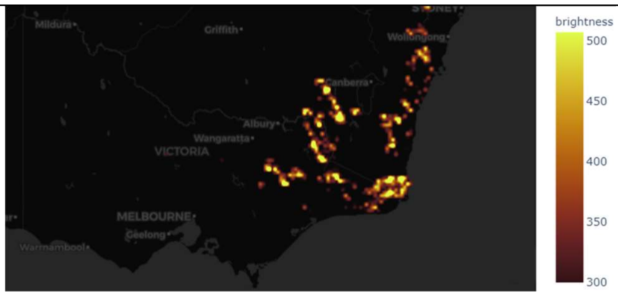


Figure 5 2020/1/1 Fire Heat Map (satellite data)

According to the analysis of the brightness correspondence relationship, it can be concluded that the distribution of fire is always from low brightness to high brightness. The higher the brightness of the fire, the higher the number of fires. Therefore, the distribution of fire is always at the point where the high brightness fire occurs. The surrounding area is denser. If we define these areas as the i-th key fire monitoring area, we can determine the key area to which it belongs according to the distance from the fire place to the hot spot, and iteratively select the key area points with the division effect until each Until the clusters remain unchanged, a relatively scientific classification of key disaster areas is obtained. This is actually the idea of the K-means algorithm.

5.1.2 Model Establishment

We introduce an improved K-means algorithm to search for the best key disaster area classification method. [2]We define the number of groups as K, The resulting set of cluster centers is $M^K = \{m_i\}$And at this time, the point set corresponding to the i$-$th group after clustering is $S_i^K = \{p_{ij}(\alpha_j, \beta_j)\}$, We define the clustering effect when the variable evaluation group number is K as shown in the following formula

$$E(K) = \sum_{i=1}^{K} \sum_{p_{ij} \in S_i^K} \left|\left|p_{ij} - m_i\right|\right|^2 \tag{2}$$

When it is the smallest and M^K no longer changes, we think that we find the optimal clustering scheme when the grouping value is K.

In fact, in order to overcome the sensitivity of the algorithm to the initial value, we set K within a certain range, traverse the value of $e^K = \frac{E(K)}{K}$ of the optimal clustering scheme under all K values in this range, and then use the comparison method to find the minimum value and the corresponding plan.

5.1.3 Model solving

We examine the latitude and longitude information of 47,444 data on January 1, 2020, set the number of groups K to 100-200, find the corresponding optimal group for each K value, and then search for the optimal group corresponding to each K value For the value of E(K), find the group with the smallest error sum of squares, K=113. Because there are too many groupings at this time, it is impossible to express clearly with the color map, so the array with the length of 47444 with elements 1 to 113 is used for storage, and here only the cluster map when K is small (K=3) to explain the fitting effect

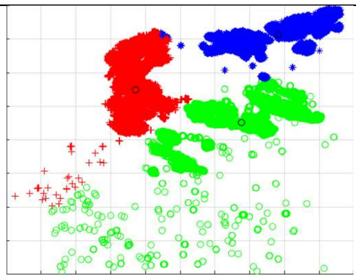


Figure 6 Sample of K-means Clustering Algorithm

From the classification data obtained above, we further select the area for Model I. From the previous assumptions, EOC often chooses the edge of the road, so we searched on the map and integrated the clustering results. We selected the center of the area as (37.6S, 149.0E) and the selected area had a side length of 15km (see the third question for details) ,and show as below:

Figure 7 (37.6S,149.0E) And its Enlarged Topographic Map

Read its road data and historical fire information according to its latitude and longitude information, and draw its topography, immediate disaster distribution, and historical disaster distribution as follows, and these data constitute the important parameters of the following model. So let's start to model and solve the number and flight path of the two types of SSA systems.

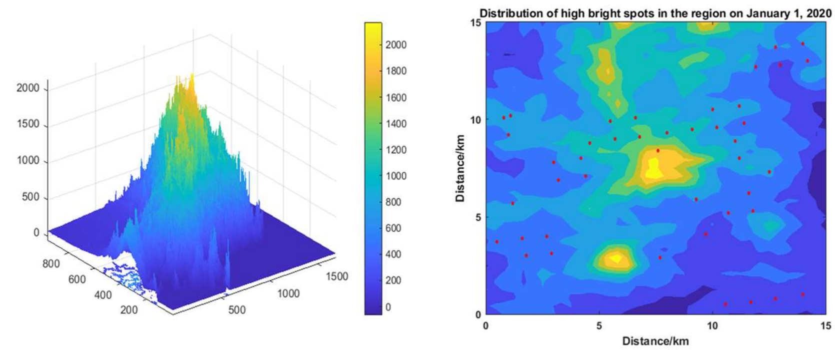


Figure 8 Topography Map(left) and
Hot Fire Spot Map with Altitude Distribution(right)

5.2 SSADS I Model

5.2.1 Model Establishment

We comprehensively consider factors such as economy, safety, efficiency, etc., and set the optimization goal of this model to complete the detection of all fire points, with the shortest total time spent and the least number of drones. The objective function is:

$$\text{Min } t, \text{Min } x_1 \tag{3}$$

In this formula, t is the time spent by the drone when all points are traversed, and x_1 is the number of SSA I, Since we assume that the drone flight rate is v_0, this time is proportional to the total path length traveled by all drones, Let the set of paths traveled by the i-th SSA I be $SD_i^1 = \{p_j\}$, the total set of fire areas is S_0, so the objective function is transformed to be:

$$\text{Min } \sum_{i=1}^{x_1} \sum_{p_j \in SD_i^1} D(p_{j1}, p_{j2}) \tag{4}$$

At this time, part of the problem is transformed into the solution of the multi-traveling salesman problem. According to graph theory, it can be known that for such problems, when the number of points and the starting point in the graph are fixed, the optimal path value will increase in the traveling quotient When it reaches a certain number, it tends to be locally stable. When the number of traveling salesmen is equal to the number of cities, the optimal path value will be equal to the sum of the distance between each city and the starting point. If the starting point is p_b, According to the assumption that the flying distance of the drone is limited to 30 km, we can conclude that the solvable conditions of the problem are:

$$30x_1 \leq \sum_{p_j \in S} D(p_j, p_b) \tag{5}$$

From the above content, it is not difficult to speculate that if we find the path of the drone and the number of drones when the difference between the actual flying distance of each drone and the upper limit of the flying distance is minimized, because of this When the Drone is the most efficient and can complete the traversal of all fire points, it will meet the economic, safety, and performance goals at the same time, and the optimal solution will be obtained.

The constraints of this model are:

- The flying speed of the drone is determined to be 10 m/s.
- Each fire point must be traversed, that is, the union of the set of points traveled by each drone is equal to the union of the fire point and the starting point in the area.
- The total flying distance of each drone is less than 30 km.
- The starting point must be located on the highway.

In summary, we can express the planning model of the problem as:

$$\text{Min } Z(\gamma) = \textstyle\sum_{i=1}^{x_1} (30 - sd_i)^2 \tag{6}$$

$$s.t.\begin{cases}\bigcup_{i=1}^{x_1} SD_i^1 = \bigcup(S_0,\{p_b\}) \\ v=10 \\ sd_i<30,(i=1,\dots,x_1) \\ p_b \in SH\end{cases}$$

In the formula, sd_i is the total flight distance of the i-th drone, SH is a collection of points on the highway, $\gamma=(x_1,P,p_b)^{\mathrm{T}}$ is the solution vector of the formula.

5.2.2 Model Solving

This model is similar to the mTSP problem at this time. Genetic algorithm is often used to solve the mTSP problem.[1] Therefore, we design the genetic algorithm as follows to solve the planning model described by equation (6):

(1) Set the initial parameters of the algorithm

For the initial parameters we set population size is n, crossover probability is p_c, mutation probability is p_m, generation is t, Their value settings are as follows:

Table 4

n	p_c	p_m	t
50000	0.6	0.005	2000

(2) Chromosome coding strategy

The actual decision variable of the model are x_1 (the number of drones), location of EOC $(\alpha_{EOC},\beta_{EOC})$.

In this algorithm we use decimal encoding , use random integer arrays $\{n_i,k_{i,0},k_{i,1},k_{i,2},\dots,k_{i,n_i+1}\}$ as the chromosome of the *i*-th drone, and n_i represents the number of the i-th drone passing the fire point, $k_{i,0}=0=k_{i,n_i+1}$, it means that any drone starts from the starting point and returns to the starting point. k_{i2} means that the i-th drone reaches the second fire point as the k_{i2} fire point in the set of fire points. Combine the chromosome of the machine and the random integers *f* and m to get the individual code. *f* represents selecting the *f*-th point in the SH set as the EOC position, which is the starting point. m represents the number of drones selected at this time. Because the objective function is transformed into a dependent variable of the number of drones, it avoids the iterative collapse problem caused by the model independent variable being called the objective function.

(3)Fitness Function

Firstly, we obtain the conservative estimate of the objective function in equation (6). We take the worst case of the planning model, $x_1=card(S)$, and in this case the objective function is the wost one:

$$Z_{max}=\sum_{j=1}^{x_1}(30-D(p_j,p_b))^2 \tag{7}$$

Then, take the conservative estimate value 20% of the maximum value to construct the available fitness function

$$F(\gamma) = \frac{1}{1 + Z_{max} + Z(\gamma)} \tag{8}$$

(4)Search space limitation algorithm

We set up a search space $N = \{\gamma_1, \dots, \gamma^*, \dots\}$, the current population is G, it is obvious that G is the true subset of N, We design a program to eliminate individuals in the population that do not belong to the search space. The algorithm is as follows:

Algorithm 1: Search Space Limit

Input: G, the constraint in equation (6)

Output: The index of the eliminated individual

declare an integer variable i=1

for $\boldsymbol{i < card(G)}$ **do**

Bring the individual chromosomes into the constraint equation

if the individual does not meet constraints, **then** store its index in an array.

end

end

In this genetic algorithm, the design of individual selection, chromosome crossover and mutation follows the classic scheme, so it will not be explained.We import the previously selected center (37.6S, 149.0E) and the 15km side of the fire data on January 1, 2020, solve it, and draw the optimal plan as follows, the EOC coordinate in the figure is (6.3 km, 6.5km), the flying distances of the three aircraft are 29.3810 25.3624 25.8946.

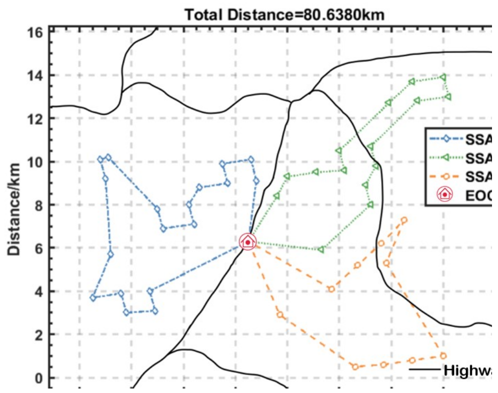


Figure 9 Optimal Plan for SSADS I

5.2.3 Analysis of Iterative Process

The genetic algorithm written according to the steps of 5.3.3 has the characteristics of stable convergence. We record the relationship between the algebra t of the genetic algorithm and the optimal path length of each generation, and make a figure. In Figure 9, the optimal path length starts from 240 km , It converges to the optimal path after about 300 generations, and the approximate speed of convergence (curve slope) is $\frac{240-80.63}{300} =$

0.5312 km/gen, which proves the superiority of our solution algorithm.

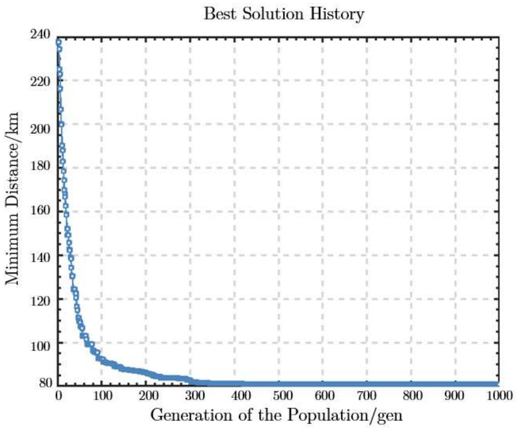


Figure 10

5.3 SSADS II Model

5.3.1 Model Establishment

Resemble to SSADS I Model, this model is used to provide the optimal combination of the number and path of SSA UAVs, but this model is for safety reasons, in order to prevent the existence of fire points that are missed by satellites near the fire area, thereby protecting the safety of the fire brigade Causes threats, so we need to use historical fire data to evaluate the size and frequency of fires in a certain area, and determine its weight accordingly. Because the historical data is integrated at this time, the amount of data is too large. If you still have to traverse each historical fire location, it is too cumbersome and unnecessary, so we consider processing from the perspective of clustering first, first according to the area division model described above Solve the optimal cluster number K and the optimal classification set $\{SD_1^K, \ldots, SD_K^K\}$, At this time, the data scale is relatively small, and the classification result is shown in Figure 9. However, there are still many points in this way, and the simplification effect is not obvious.

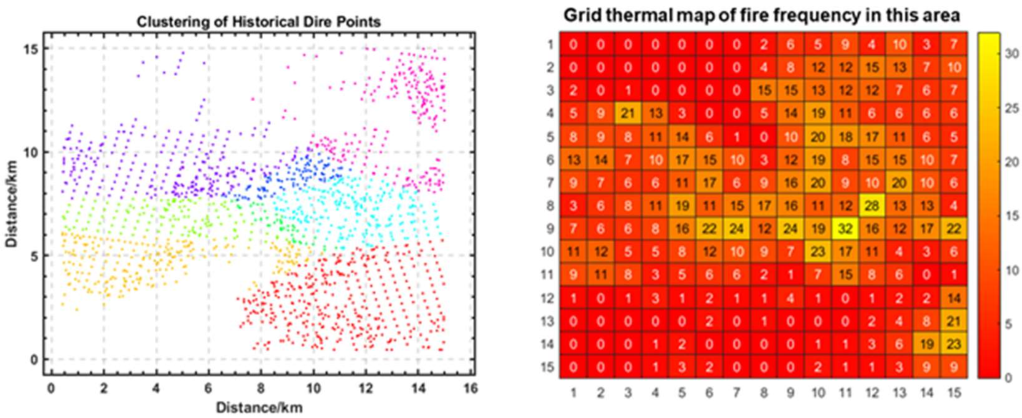


Figure 11 Result of K-means (left) and Grid Thermal Map

So we considered starting from the area where the fire occurred, gridding the map by 1km*1km, and defining the number of historical fires that occurred in the grid as the historical fire frequency of the grid, as the selection of the location when the drone was flying. The weights, the processing results are plotted as Figure 11. At this time, we define as $P_i = \{p_{i1}, p_{i2} \dots .\}$ the set of points traversed by the i-th SSA II UAV, where p_{ij} represents the i-th UAV experienced j grid locations, the historical fire frequency in the grid is reflected by the historical fire occurrence times, and corresponds to the geographic location of the grid one-to-one. If the corresponding relationship is Q, the frequency $f = Q(p)$, then the optimization function will be:

$$\text{Max } \mathrm{Z}_2(\delta) = \sum_{i=1}^{x_2} \sum_{p_{ij} \in P_i} Q(p) \tag{9}$$

At this time, because the drones does not consider the distribution of points, the optimization function of SSADS I is integrated. If the drones flight path is 30 km, it can traverse 30 grids including the starting point. The coordinates of the starting point are in accordance with SSADS I The Model is determined to be (3 km, 6.5 km). At this time, the decision variables of the problem are the number of drones and their respective traversal paths. The constraint is that the total number of traversal points for each drone is 30. In this condition solve the optimal number of drones and their corresponding paths to maximize the objective function, so the overall mathematical model is:

$$\text{Max } \mathrm{F}_2(\delta) = \sum_{i=1}^{x_2} \sum_{p_{ij} \in P_i} Q(p)\,, s.t.\, card(P_i) = 30, (\ i = 1 \dots x_2) \tag{10}$$

5.3.2 Model solving

Because the planning model variables of the problem at this time are still the number of drones and the flight path of each drone, some changes can be made to the solution of the SSADS I Model.

(1)Fitness Function

We use the equation (9) to build the new fitness function:

$$F(\gamma) = \frac{1}{1 + Z_{max} - Z_2(\gamma)} \tag{11}$$

(2) Search Space Limit

The search space will be the 255 grids of this area.

Except for the two, the rest of the algorithm remain unchanged.

5.3.3 Results

The planning model based on regional grid division, and the final solution of the planning scheme is shown in the figure below:

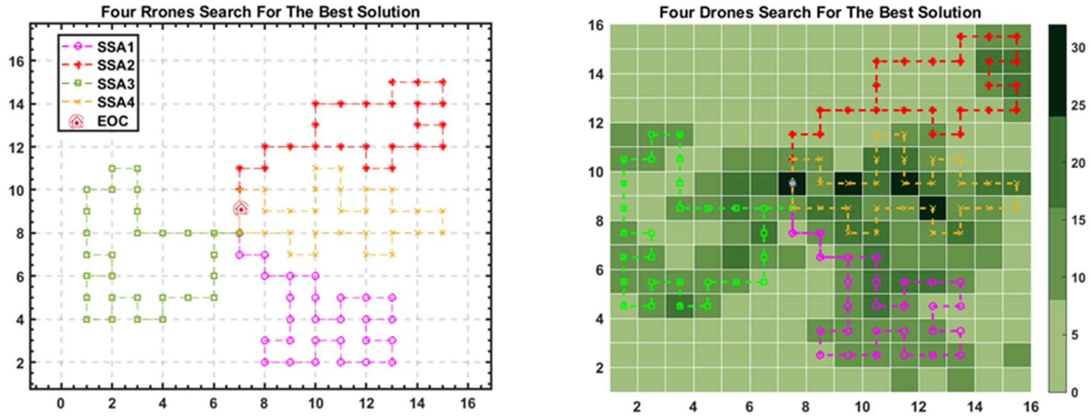


Figure 12 Results of SSADS II Model

VI Model for Problem II

6.1 Fire Forecasts in Eastern Victoria and Analysis of Response Methods for Government Material Reserves

6.1.1 Model Establishment

We processed and observed the fire data in Australia from 2001 to 2019, and found that the time series were non-stationary. For non-stationary time series, we can transform it into a stationary time series by difference processing, and then use a variety of existing stationary time series forecasting methods for analysis.

In terms of model selection, we use the ARIMA model (Autoregressive Integrated Moving Average model).

Define ∇ as the difference operator, and namely

$$\nabla = y_t - y_{t-1} \tag{12}$$

For delay operator B， $y_{t-p} - B^p y_t, \forall p \geq 1$ So we can get $\nabla^k = (1-B)^k$ For the first-order and second-order non-stationary series y_t, if ∇y_t is a stationary time series, the ARMA(p,q) model can be used. It satisfies $\lambda(B)(\nabla y_t) = \theta(B)\varepsilon_t$. Among them $\lambda(B) = 1 - \lambda_1 B - \lambda_2 B^2 - \cdots - \lambda_p B^p$ $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p$ They are respectively defined as autoregressive coefficient polynomial and moving average coefficient polynomial.[3]

The resulting model is called ARIMA model with a set of parament (p, d, q).

6.1.2 Model Solving

We substitute the number of data points that may occur in Australia during 2001-2019 that may occur wildfires into the ARIMA model.

According to the prediction, the order of the model is determined to be d=1, p=1, q=3, that is, the model is established as ARIMA(1, 1, 3).

The solution result of our model is shown in Figure 12.

The picture on the left in Figure 12 shows the comparison between the predicted data in the original data set and the real data. The picture on the right shows our prediction of the number of possible data points in Australia in the next ten years based on the model.

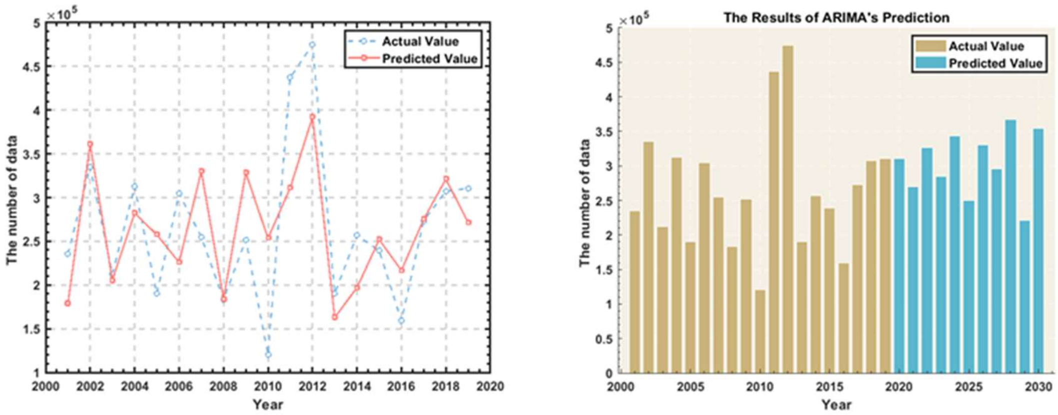


Figure 13

Specifically, we show the forecast value in Table 5.

Table 5

Year	Predicted Value	Year	Predicted Value
2021	326141.2629	2026	295783.7649
2022	284982.7403	2027	367369.2073
2023	343059.7172	2028	221309.4871
2024	250341.0032	2029	354767.3897
2025	330134.5209	2030	271309.4871

It can be seen that the wildfire situation is erratic and has a certain upward trend.

The wildfire data in 2011 and 2012 are unusual. According to the information obtained, a huge wildfire occurred in Australia in 2011, in order to avoid such huge wildfires as 2011 and 2019.

The government should select the data for further analysis based on the historical experience of the extreme wildfires in 2011, so as to be adequately prepared to deal with the possible future extreme fires.

Regarding the increase in the equipment budget, we will give the answer in question 4.

6.1.3 Sensitivity Analysis

Draw the residual distribution diagram and QQ diagram as shown in Figure 13. The residuals can better meet the normal distribution. The residual points on the QQ diagram are densely distributed along the line y=x. It can be considered that the model fits well.

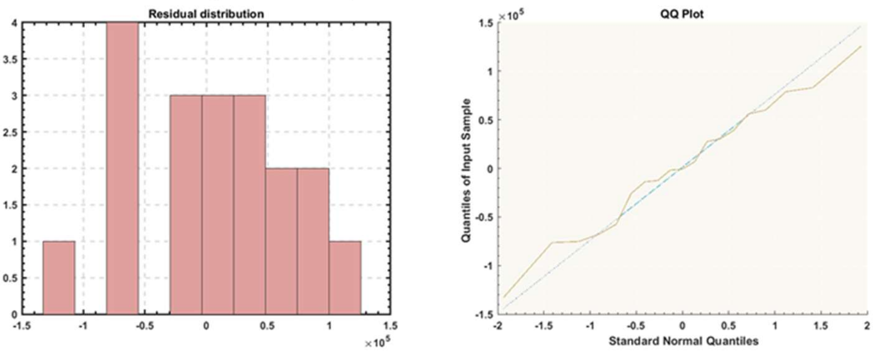


Figure 14

6.2Regional Fire Short-term Prediction and Dynamic Control Model

For a suspected area with fire history, we adopt the method of time series forecasting in blocks. A 1km×1km grid is used to partition the area, and the time series prediction model of 6.2 is used to predict the probability of fire in each area at the next moment.

We still use the 15km*15km data in question 1. Predict and plot the distribution of fires 30 days later (January 31, 2020). The image is shown in Figure 15.

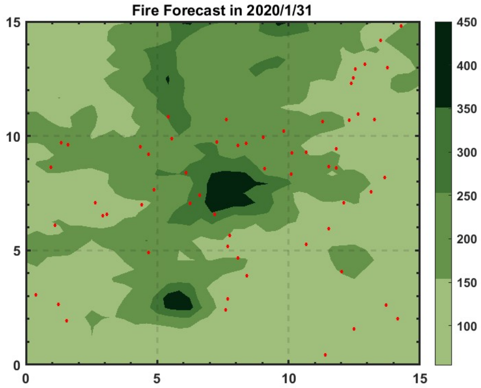


Figure 15

Verification of the corresponding relationship between quantitative estimation points and drones input: We predict the fire data and fire distribution for 30 days after 2020/1/1, and from this, we solve the optimal drone distribution corresponding to the number of fire points, and extract the number of SSA drones and repeater drones. Calculate the correlation coefficient, and use the method of question one to fit, and get the distribution relationship diagram between the number of fire points and the number of drones.

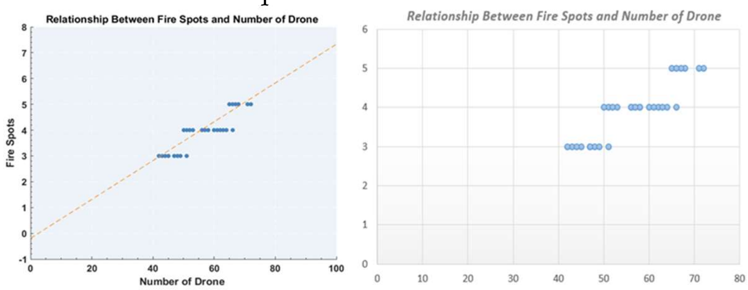


Figure 16

The fitting results are as follows:

$y \ = \ p1 * x \ + \ p2$

Coefficients (with 95% confidence bounds):

$$\begin{aligned} p1 &= \quad 0.07252 \ \ (0.05874, 0.08629) \\ p2 &= \quad -0.1881 \ \ (-0.9740, 0.59780) \end{aligned}$$

Goodness of fit:

SSE: 2.943 R-square: 0.7999 Adjusted R-square: 0.793 RMSE: 0.3186

It can be seen that the number of fire points is approximately proportional to the number of optimal drones. Therefore, when we are making short-term predictions and dynamic adjustments on regional fires, we can quickly arrange the number of SSAs based on the predicted fire point data. Then plan the trajectory of SSA according to the actual fire situation.

VII Models for Problem III

We need to consider the signal loss caused by terrain factors and further optimize the location of the SR. Therefore, we should clarify the communication relationship between various devices in the system.

First of all, a generally recognized truth is that the power of a device only affects the energy of the radio it emits, and the nominal distance of the radio it emits refers to the farthest distance that the signal it emits can reach. Only when the receiver is within the range of the signal transmitted by the transmitter can the signal be received.

Secondly, our hypothetical communication process is as follows: EOC can communicate with WD and SSA in both directions, and SR should only rely on WD to extend the signal transmission distance to achieve communication with EOC. This hypothesis can also reflect its rationality in the analysis of the previous two questions.

Finally, we can make the following reasonable assumptions about the situation where the communication between the four devices is affected by the terrain:

(1) EOC has strong communication capabilities and a wide range of transmitted signals. The signals sent in the designated area can be received by any SR and SSA.

(2) The SR is hovering in the air, and the EOC is built on a flat road with strong signal receiving ability. The transmitted signal allows the EOC to receive a distance within the nominal 20km.

(3) The communication between SR and WD is affected by complex terrain and will be weakened within the nominal range.

(4) SR and WD two-way communication, because SR's nominal coverage (20km) is much larger than WD's nominal coverage (5km), we can think that as long as the signal transmitted by WD can be received by SR, then the signal transmitted by SR must also be WD received.

(5) For the purpose of saving SR power and improving transmission efficiency, it can be considered that the SR flight altitude is slightly higher than the mountain altitude and lower than the SSA altitude. In this way, where the terrain is not undulating, we can approximate the communication distance between SR and WD as the Euclidean distance on a two-dimensional plane.

The above communication process can be shown in Figure 17, and the effective communication area S_c is defined as the coverage area of the signal transmitted by WD on the map.

Due to the complexity of communication between mountains, only using the two nominal ranges of 5km and 2km in the title cannot describe the attenuation changes of the signal in the mountains. Therefore, we use the empirical model of short-distance signal transmission: Okumura-Hata model to estimate the loss.

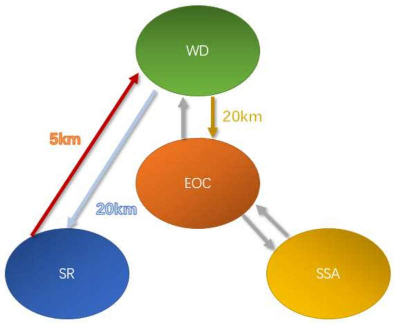


Figure 17

7.1 Signal transmission loss model of WD in mountains based on Okumura-Hata

7.1.1 Model Establishment

In order to explore the specific situation of WD signal weakening in the mountains, we use the Okumura-Hata model in communication engineering to build a model of the signal transmission of WD in the mountains.

The Okumura-Hata formula for the median basic loss is as follows:

$L_b = 69.55 + 26.16\lg f - 13.82\lg h_b + (44.9 - 6.55\lg h_b)(\lg d) - a(h_m)$

L_b- Median base propagation loss in urban area. Unit: dB

d-Transmission distance. Unit: km

f- Frequency of signal. Unit: MHz

h_b、h_m-Effective height of antenna of base station and mobile station. Unit: m

For mountains, the Hata model introduces mountain correction factor K_h.

$$K_h = \begin{cases} 0 & \Delta h < 15 \\ -(-5.7 + 0.024\Delta h + 6.96\lg\Delta h) - (9.5\lg h_1 - 7.2) & \Delta h \geq 15, h_1 > 1 \\ -(-5.7 + 0.024\Delta h + 6.96\lg\Delta h) + 7.2 & \Delta h \geq 15, h_1 \leq 1 \end{cases}$$

Δh is defined as topographic relief height, as shown in the figure. Starting from the mobile station, it extends 10km to the base station, and the difference between 10% and 90% of topographic relief height is calculated within this range as the Figure 18 shows.

$$h_1 = h_{mg} - \Delta h/8 - h_{min}$$

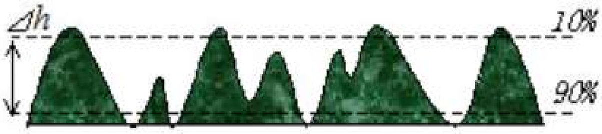
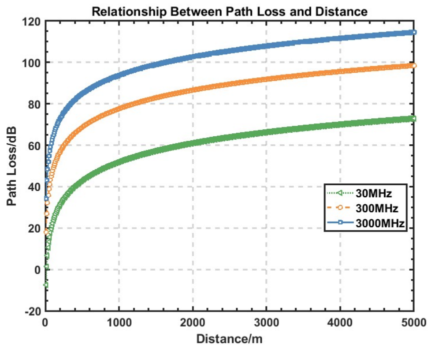


Figure 18

We take the typical values $h_b = 100m$、$h_m = 1.5m$，and the corresponding $a(h_m) = 0$.

We draw the reference path loss vs. propagation distance map in rural areas. It can be seen that the attenuation rate of low-frequency signals is slow and the transmission distance is long. The high-frequency signal has a fast attenuation rate and a short transmission distance.



For the mountainous complex terrain, we consider selecting a 300MHz signal as the transmission signal reference. As can be seen from the figure, for a signal with a frequency of 300 Hz, as stated in the title "the maximum distance of signal transmission in a flat and open rural area is 5km", we can define the maximum transmission loss for the signal L_{bmax}, and

$$L_{bmax} = 69.55 + 26.16\lg 300 - 13.82\lg100 + (44.9 - 6.55\lg100)(\lg5000) \approx 98.49\text{dB}$$

Therefore, we define the distance d_{max} that the signal can transmit in the mountains as the transmission distance when the signal transmission loss L_b reaches L_{bmax}.

Below we will explain how to quantitatively solve the problem of SSA communication signal loss in a specific area.

We still select the small area of 15km*15km mentioned above.

Step1: Grid the regions and solve the altitude h_i of each region。

Step2: The regional altitude distribution is analyzed and maximum value h_{max}、 minimum value h_{min} and variance $D_{altitude}$ of altitude distribution is obtained.。

Step3: According to variance analysis, if the variance is not large, this part of the region can be considered as a relatively stable region, and the mean $E_{altitude}$ is taken as the average altitude of the whole region.

Step4: Calculate the value of 80% of the difference between the lowest and highest elevation of the whole region as Δh, and calculate K_h of this region.

Step5: For L_b joining K_h， solving $L_b = L_{bmax}$. Obtain the corresponding transmission distance d. So we can take d as the effective distance of this region.

7.1.2 Model Solving

We found the highest and lowest altitude in the area

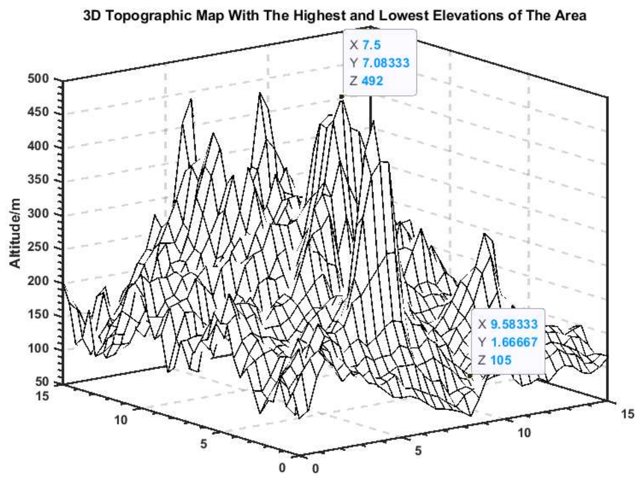
$$h_{max} = 492m、h_{min} = 105m。$$

$$\Delta h = 0.8 * (h_{max} - h_{min}) = 310m。$$

Substitute into the model to solve

$$K_h = 5.63\text{dB}, d \approx 3.24km.$$

Therefore, we can think that in this area, the effective distance of SR and WD communication is 3.24km.



7.2 Optimization Model of SR Drones Based on Clustering and Queue Simulation

7.2.1 Model Establishment

With the conclusions drawn from the above Hata model, we can establish a communication model between SR and WD, which is an optimized model for the target area and drones.

Optimization goal 1: The system should be able to meet the communication between SR and WD as much as possible. Considering the problem of battery life in SR, S_c is a function related to time t. Our goal is to maximize the effective communication area:

$max\ \ S_c(t)$

Optimization goal 2: For economic cost considerations, it is required to meet the smallest possible number of SRs. That is:

$min\ \ N_{SR}$

There are two states $C_i(i = 1,2 \dots, N_{SR})$ for each drone, it can be defined as

$$C_i(t) = \begin{cases} 1 \text{ , } working\ time \\ 0 \text{ , } charging\ or\ flying\ time \end{cases}$$

The total effective area is defined as

$$S_c(t) = \sum_{i=1}^{N_{SR}} C_i S_0$$

And S_0 is the maximum detection range of an SR

$$S_0 = \pi d^2$$

The change of the drone state C_i with time is shown in Figure 19, which satisfies the constraint condition as

$$t_{charge} \geq 1.75\text{h}$$

$$t_{fly} = \frac{3d_i}{2v_0}$$

$$t_{work} = 2.5\text{h} \ - 2 \times t_{fly}$$

Where $d_i(i = 1,2 \dots, N_{SR})$ is the distance from EOC to the target point.

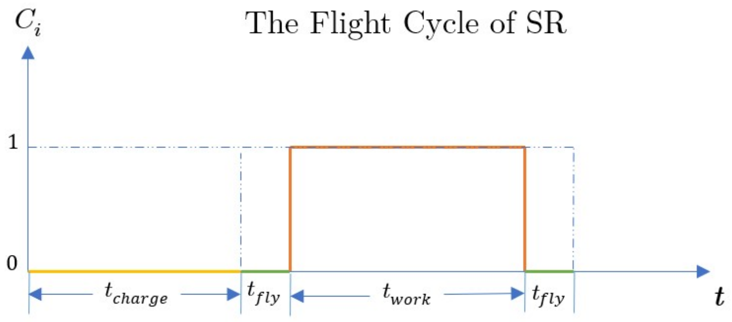


Figure 19

7.2.2 Model Solving

Due to the clustering nature of fires, we can get inspiration from SSADS I Model in question one. As shown in the figure, we have found the points with higher confidence among the suspicious fire points in this area on January 1, 2020. We can consider these fire points to be real fire points, and the data of the present points are aggregated. Cluster analysis results in Figure 20:

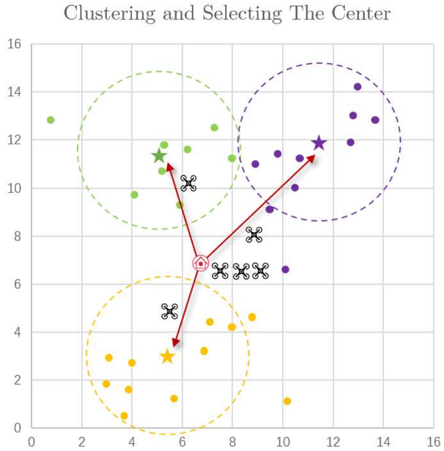


Figure 20

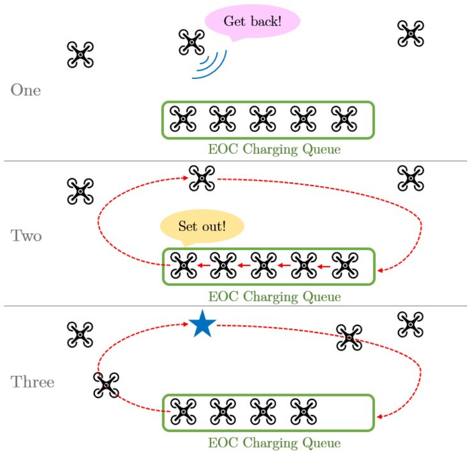


Figure 21

It can be seen that the data has obvious clustering and the clustering effect is very good. Therefore, we can think that the result of cluster analysis makes the condition of $max\ S_c(t)$ satisfied.

As can be seen from the figure, our goal is to make each cluster center point (hereinafter referred to as the target point) always have a drone staying. Therefore, our SR scheduling strategy follows the following queue rules:

There is a queue in the EOC charging station. [4]The queue follows the principle of "first in, first out". In the initial state, there are N_{SR} drones in the queue. The drones in the queue are in the charging process by default, and only drones Fully charged (that is, the time to enter the queue reaches the charging time of 1.75h before being able to leave the queue.)

The simulation process of the queuing algorithm is shown in Figure 21. We describe the process as follows:

(1) When the mission starts, three drones fly out from the queue to each target point.

(2) When a drone completes the work process, there is only t_{fly} time left in the entire cycle, and immediately sends a message to EOC to notify EOC to arrange for a drone in the existing queue to leave the queue to replace the drone that finished the work. (Note: Not every drone has the same life cycle. For drones flying to different places, the flight time t_{fly} and the working time t_{work} are different. Only the life cycle of the battery is the same. The life cycle depends on the distance flown.)

(3) The completed drone starts to return and will be charged in the EOC after returning. The EOC will determine whether the drone at the head of the queue is fully charged. If it is fully charged, it will be allowed to take off and take over from the previous drone. the work.

(4) In this way, the mission of drone flight allocation is carried out until when the EOC finds that the power of the drone that is about to take off in a certain queue is not full and does not meet the take-off conditions. If the flight mission is terminated at this time, the mission is deemed to have failed. We will increase N_{SR} in the initial queue and execute the task from the beginning.

(5) When the task has been carried out for a long time, there is still no phenomenon in

(4). At this point, we can consider that N_{SR} is sufficient to allow the system to operate normally, and this N_{SR} is the minimum required.

The distance from the EOC to each cluster center is different, and the flight time of each drone is different, which leads to different charging times. Mathematically, this kind of system is like a chaotic system, the difference is that it has a unique solution at every moment. It is difficult for us to solve such problems with precise mathematical relationships. However, according to the basic rules of the system, we can simulate the whole process by writing a computer program, the pseudo code is as follows:

Algorithm 2: SR Queue Simulation

```
Input: d_1, d_2, d_3, S_0
Output: N_SR
for N_SR = 4: N_max do
  N_SR drones in the queue. Three drones set out to complete the mission.
  while True do
    Calculate the flight time t_i of each drone.
    if The remaining time of a drone is t_fly.
      if The first drone in the queue stays not longer than t_charge(1.75hours).
      break
      else
      The next drone in the queue leaves the queue.
      Recalculate the t_i of the drone.
    end
  end
  N_SR = N_SR + 1.
  if Program running time is long enough
  break
end
```

Through the above procedure, we have solved the optimal number of drones

$$\boldsymbol{N_{SR}=5.}$$

Therefore, we can get the total budget for deploying drone system in this area, as shown in the Conclusion.

VIII Conclusion

8.1 Strengthes and Weaknesses

8.1.1 Strengthes

(1) For the large amount of wildfire data, we adopted the method of cluster analysis to avoid a large amount of data processing and simplify the solution process. At the same time, we adopted regional gridding to estimate the totality with the quantification of gridded regional analysis.

(2) The two SSA search methods are of practical significance. The genetic algorithm is used to solve two complex target planning problems, which has fast convergence and stability and high accuracy.

(3) The operation process of the complex wildfire monitoring system is reasonably abstracted, and the functions, positions and communication methods of the four main equipments in the system are determined, making the complex model solvable and simple.

(4) Adopting the idea of "queue out and put into the queue" to propose a simulation algorithm for the flight process of WD, and avoid complicated mathematical planning by means of computer simulation.

8.1.2 Weaknesses

(1) Time series forecasting is difficult to consider the impact of emergencies, and the sequence forecast results are not ideal when there are emergencies (such as 2011).

(2) The model is based on the analysis of small regional samples, and the overall prediction and quantification are too rough. For the forecast of wildfires in eastern Victoria and the estimation of the cost of emergency measures, only a rough value range can be given.

8.1.3 Promotion of Model

In terms of data forecasting, neural networks can be used to make more accurate forecasts of time series. When cluster analysis has no obvious rules for sample distribution, the density-based DBSCAN algorithm can be used instead of K-means. For the division of the entire Eastern Victoria area, it is more reasonable to adopt a jurisdiction system based on towns.

8.1.4 Budget of selected area

According to the typical data selected from the previous three questions

SSAI:3 SSAII:4 SR:5 Total:12

According to the predicted extreme conditions, we can add 3 drones as backup drones. So a total of 15 drones are needed.

In addition, EOC construction and labor costs also require certain expenses. For this area, it can be considered that it needs \$ 50,000.

Total cost:15×10,000+50,000= \$ 200,000

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[1] Honglei Zhang,Serkan Kiranyaz, Moncef Gabbouj.Finding Better Topologies for Deep Convolutional Neural Networks by Evolution,2018

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[3] Liangli Zuo,Li Yan.A Weighted DTW Approach for Similarity Matching over Uncertain Time Series[J].Journal of Computing & Information Technology,2018,26(3).179-190.

[4] HOU Feng-zhen,BI Lu, SU Jing. Improvement of Subset Partition Algorithm Based on Queue in Data Structure Course [J]. Computer Education, 2015, 000(013):72-75.

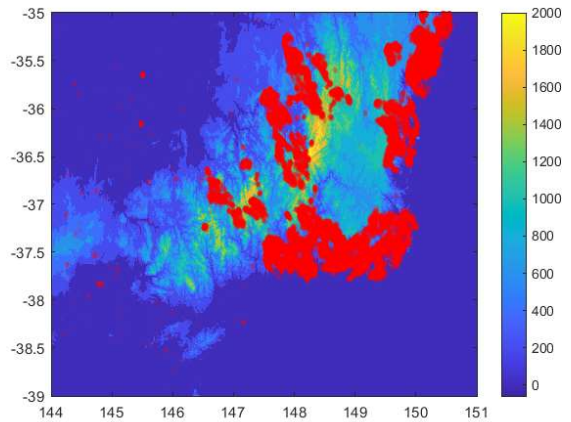
Budget Request

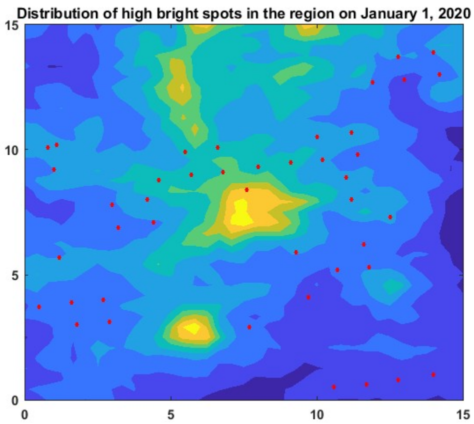
Dear Victoria's Country Fire Authority,

Fire season in 2019-2020 brings serious economic loss and destruction of natural ecology. There is no doubt that the fires caused a devastating impact to Victoria State. And it's urgent to find out a solution for the disasters.

Nowadays, firefighters can use drones for surveillance and situational awareness. Fires need to be discovered and extinguished in time, which is very demanding for the shortest path of drones. At the same time, attention should be paid to economic and time factors, and the number of drones should be controlled to achieve the best economic benefits. We focus on the research of design and optimization strategy of fire-fighting drone system in order to reduce fire damage and save budget.

Tests has been carried out to study and we found that Fires in Australia occur in mountains and vegetation-covered areas. According to topographical factors, there are historical similarities between important disaster areas. So, we used historical data to predict future fires. Statistical analysis demonstrates that it will have long-term effects for future fire prevention and control.



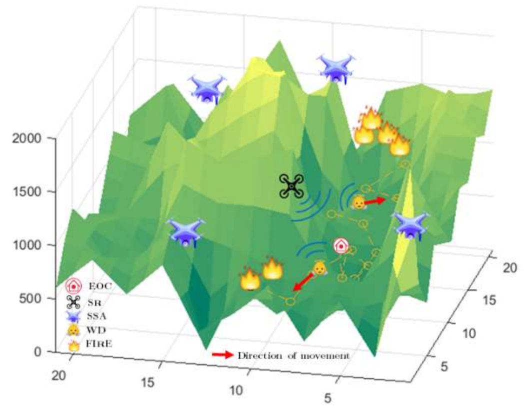


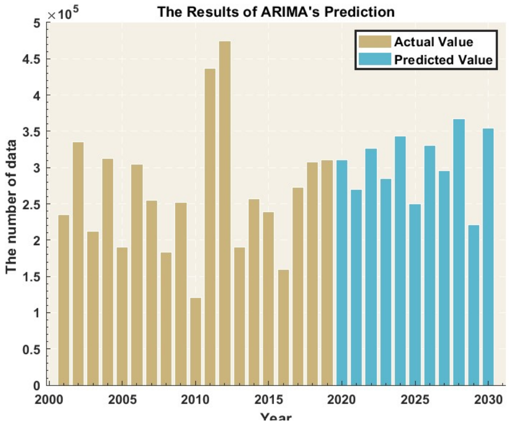
What's more, facts show that it's hard to use Victoria's huge fire data directly, so we've processed the data according to vegetation and terrain factors in Victoria. To make the fire-fighting drone system more efficient, We use satellite-monitored fire brightness data to classify key fire monitoring areas in Victoria. The Fire Heat Map(left) and Hot Fire Spot Map with Altitude Distribution(right) can help us observe the pattern more directly. The result of this study can be generalized for the solution commonly used throughout Victoria State.

Finally, we classified drones and calculated their optimal flight path to calculate the number of drones. In order to minimize the flight time, we calculated the position of

Emergency Operations Center based on the model we made. Results show that we will use about **15** WileE-15.2X Hybrid Drones while spending the least money and reaching the goal.

Based on our research, the result of this system can be also generalized for the Future fire prevention and control in Victoria State. With high efficiency and accuracy, the drone system has a good economic effect considering the low cost and the loss it saved. The results of the research can indicate the number of fire data in 10 years. Also, the study of fire prevention and control in Australia plays an important role in controlling global climate change. The following picture is an abbreviation of our model, and it can be easily found how the system works.





As per our last discussion, we have formulated a budget for the Fighting Wildfires in part of the Victoria State. ***We want to experiment in some areas first to ensure correctness and then carry out the entire State of promotion.*** We are writing to request that you review and approve the budget.

If you approve this request, kindly allocate the funds to the following accounts:

15 WileE-15.2X Hybrid Drones–$150,000

Other expenses such as EOC arrangement and labor costs- $50,000

Total- **$200,000**

We look forward to hearing from you at your earliest convenience. Thank you for your time and consideration.

Sincerely,

MCM