

# Research and Analysis of UAV Fire Monitoring Index Optimization Strategy based on PSO Algorithm

Yuan Chen\*, Shiyu Wei

Wuhan University of Science and Technology, HuBei, 430065, China

\*Corresponding Author.

## Abstract:

With the rapid development of artificial intelligence, drones are gradually developing in the direction of miniaturization and intelligence, and they are commonly used in emergency rescue operations due to their low cost, strong concealment as well as high flexibility. The Emergency Operations Center uses drones to monitor emergency situations to adjust personnel plans to ensure efficient and safe emergency procedures. In order to more effectively deal with an emergency, and consider the needs of the uav communication task, related to the terrain, fire frequency and size, safety, economy and so on many aspects, the influence of the optimum combination model and particle swarm optimization algorithm, the combination of Q learning algorithm supporting scheme was put forward, helping determine the unmanned aerial vehicle (uav) in the process of monitoring the most comprehensive and efficient state. This study takes fire of Australian as an example to explore the effectiveness, feasibility and optimization of UAV monitoring in many aspects. The occurrence of fire is actually affected by many aspects, such as meteorological conditions, building environment, firefighting ability, etc. Based on the randomness, suddenness and fuzziness of fire, the time series model is used to predict and analyze the possible fire situation in the next 10 years, and the influence of day and night, season, climate and human factors on fire spread is effectively analyzed, which confirms the feasibility of the research idea to some extent.

**Keywords:** UAV, PSO algorithm, Time series model, Q-learning algorithm.

---

## I. INTRODUCTION

### 1.1 Background

By using the Australian Fire Archive, we developed a map of the fire-prone areas. In terms of time, our data includes the period from 2019 to 2020, effectively targeting the four months of bushfires in Australia; In terms of space, as shown in figure 1, we can clearly see the geographical location of fire-prone areas relative to the world, whose longitude and latitude are respectively: 147.2 E to 147.7 E and -37.5 S to -37.2 S.

But this is far from enough, figure 1 can't reflect the different heights of the fire, the fire area environment situation on different heights, such as size, and it cannot reflect the specific and concrete conditions of the

fire, either. So we according to its specific geographical areas by the software called matlab through frequent random matrix in the fire area randomly selected from 10 different altitude to random field structure diagram. The randomly generated data is shown in figure 2, and the mountain field structure diagram is shown in figure 3.

With the development of science and technology, Radio Repeater drones arises at the historic moment, and it can expand the scope of communications so that the communication work in the scene of the fire can accomplish more outstanding. We created the scene of the fire general communication situation of drones, as shown in figure 4. We have tried to improve the efficiency of fire fighting with Radio Repeater drones and SSA drones, the area, scale and size of the fire is not what we can predict in advance. And fires of different sizes are handled differently, as are the number and distribution of drones needed. So it is not clear what is the optimal number of SSA drones and Radio Repeater drones to deploy in the event of a fire.

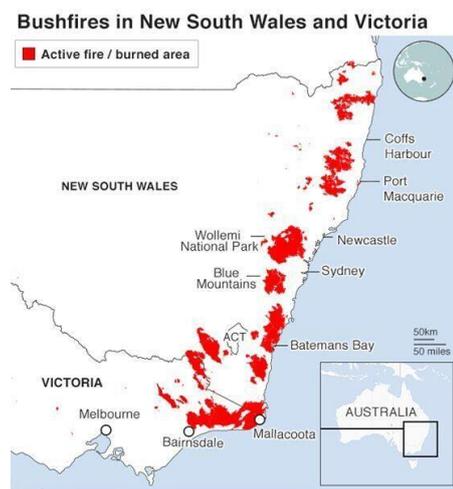


Figure 1: Fire prone areas in Australia 2019-2020 Source from DAFF and fire services, 6 Jan

latitude	longitude	altitude
-37.4891	147.2083	369.00
-37.4891	147.2250	529.00
-37.4891	147.2417	461.00
-37.4891	147.2583	329.00
-37.4891	147.2750	295.00
-37.4891	147.2917	443.00
-37.4891	147.3083	337.00
-37.4891	147.3250	545.00
-37.4891	147.3417	471.00
-37.4891	147.3583	543.00

Figure 2: Randomly generated data

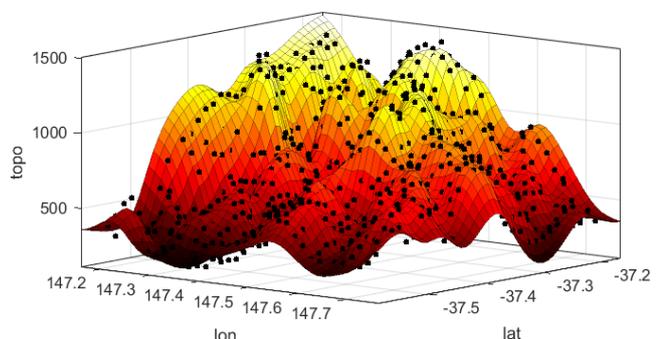
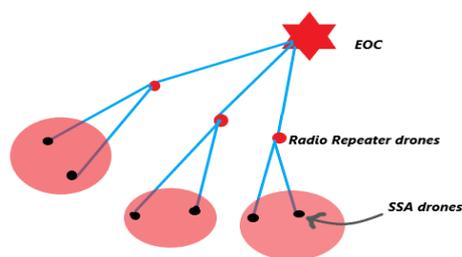


Figure 3: Fire scene construction

In order to find the optimal number of SSA drones and Radio Repeater drones to be able to fight fires most efficiently, we need to find a way to determine the number of drones in terms of safety, economic terrain and so on. This paper introduces our proposed method: PSO algorithm. And the PSO algorithm is a

kind of global optimization algorithm, which can effectively solve the global optimal solution.



Radio Repeater drones and SSA drones collaboration schematic

Figure 4: Collaborative schematic of the fire scene

Considering the background information and restricted conditions identified in the problem statement, we need to solve the following problems:

- Determine the specific number allocation of SSA drones and Radio Repeater drones to deal with the fire, in terms of terrain, economy and so on.
- According to different terrains and sizes to optimize the locations of hovering VHF/UHF radio-repeater drones so as to achieve the best effect.
- Adapt to changes in extreme fire events over the next decade, that is, predict the likelihood and cost variability of wildfires over the next decade.

### 1.2 Research process

- ◆ We first adopted the optimized PSO algorithm for the total number of SSA UAV and repeater UAV and selected the optimal solution.
- ◆ Due to the limitation of gray scale prediction model in this problem, we used the Time series model to predict the fire disaster.
- ◆ In order to adapt to the situation of different altitudes, the dynamic planning model of repeater UAV flight movement is adopted for planning.
- ◆ The research results are summarized by comparison and consideration in all aspects

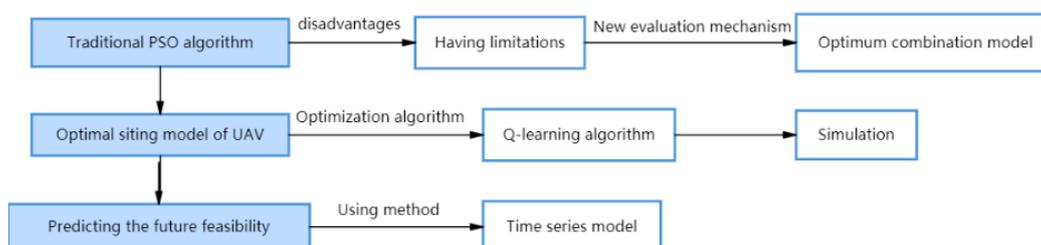


Figure 5:Flowchart of thesis overview

### 1.3 Symbols

Attention:

- The regional position determines the terrain factors in the region.
- The area is proportional to the severity of the fire and the number of fire fighting points, which means that the larger the area, the higher the severity of the fire, and the more the number of fire fighting points.
- We defined  $n_1=T*S/P$
- The location of the fire fighting point is  $(p_1, p_2, p_3, \dots, p_{n_1})$ , from this we can determine the distance between the fire fighting point and the EOC,  $d = (d_1, d_2, d_3, \dots, d_{n_1})$
- The locations of SSA drones are  $(m_1, m_2, m_3, \dots, m_N)$ , and the locations of Radio Repeater drones are  $(n_1, n_2, n_3, \dots, n_M)$

Table 1 shows symbols and notations used in this paper. Note that symbols used only once are not included and will be defined later.

**TABLE 1.** Variables and their meanings

Number	Sign	Significance
1	$B$	The area of the fire
2	$S$	The area of the fire area
3	$k$	The complexity of the terrain in the fire area
4	$T$	The severity of the fire
5	$n_1$	The number of fire fighting points
6	$P$	Coefficient of determination (have specified in advance)
7	$Q$	The location of the EOC
8	$N$	The number of SSA drones
9	$M$	The number of Radio Repeater drones
10	$F$	The range of radio transmission

## II.BEST METHOD OF UAV BASED ON PSO ALGORITHM

### 2.1 Optimum combination model

By setting the above related variables, we need to minimize the sum of the number of SSA drones and the number of Radio Repeater drones, which means to we need to get the minimum of  $M+N$ . And the constraint condition should be able to achieve safety conditions, such as the SSA drone can cover all the fire fighting personnel, so we get

$\min_{1 \leq i \leq M, 1 \leq j \leq N_i} \|P_j - m_i\| \leq 2$ . And the rescue point can be connected to a nearby repeater,

which means we can get  $\min_{1 \leq i \leq M, 1 \leq j \leq N_i} \|P_j - n_j\| \leq F$ . The distance between adjacent repeaters should be less

than 20km, so we can get  $\min_{1 \leq i \leq M, 1 \leq j \leq M, i \neq j} \|n_j - n_i\| \leq 20$ . And there must be a repeater next to a drone, which we can get  $\min_{1 \leq i \leq M} \|n_i - Q\| \leq 20$ .

Based on what I have mentioned above, we establish the optimal decision model:

$$\min N + M \tag{1}$$

$$\min_{1 \leq i \leq M, 1 \leq j \leq N_i} \|P_j - m_i\| \leq 2 \tag{2}$$

$$\min_{1 \leq i \leq M, 1 \leq j \leq N_i} \|P_j - n_j\| \leq F \tag{3}$$

$$\min_{1 \leq i \leq M, 1 \leq j \leq M, i \neq j} \|n_j - n_i\| \leq 20 \tag{4}$$

$$\min_{1 \leq i \leq M} \|n_i - Q\| \leq 20 \tag{5}$$

## 2.2 Particle swarm optimization algorithm

Particle swarm optimization (PSO)[3] algorithm, proposed by Eberhart and Kennedy in 1995, is studied by simulating the predatory behavior of birds. Imagining a scenario where there is only one piece of food in a certain area, and a flock of birds randomly search the area for food. None of the birds know the exact location of the food, but they know the distance between their current location and the food. The easiest and most effective way to find food is to look for it in the area around the birds that are currently closest to the food.

PSO algorithm is inspired by this behavior and uses it to solve optimization problems. The following table shows the variables involved in the PSO algorithm:

**TABLE 2:** Variables in the PSO algorithm and their meanings

Number	Sign	Significance
1	$W$	Inertia weight coefficient
2	$c_1$	The learning factor of particles
3	$c_2$	The acceleration factor of the particle
4	$r_1, r_2$	Random numbers from (0,1) and uniformly distributed

5	$M$	Population size
6	$t_{\max}$	The maximum number of iterations of a particle

Attention: Speed and position have maximum speed and maximum position limits respectively.

### 2.2.1 Solving process of particle swarm optimization algorithm

The particle swarm optimization algorithm initializes a group of particles which are distributed in the search space at first, and each particle representing a solution. In the three-dimensional search space, let's say the position vector of the  $i$  th particle is:

$$X_i = (X_{i1}, X_{i2}, X_{i3}) \quad (6)$$

$$\text{Let's say the velocity vector of the } i \text{ th particle is } : V_i = (V_{i1}, V_{i2}, V_{i3}) \quad (7)$$

After  $t+1$  iteration, we can get

Historical best position for particles is  $P_{ij}^{t,best}$

The global best position of the population is  $g_j^{t,best}$

So we can get new formulae for the position and velocity of the particle :

$$\begin{cases} V_{ij}^{t+1} = W V_{ij}^t + c_1 r_1 (P_{ij}^{t,best} - X_{ij}^t) + c_2 r_2 (g_j^{t,best} - X_{ij}^t) \\ X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1} \end{cases} \quad (8)$$

The above optimal decision model can be transformed into a nonlinear programming problem:

$$\begin{aligned} & \min f(x) \\ & s.t. g_i(x) \leq 0, i = 1, 2, 3, 4 \end{aligned}$$

Where  $g(x)$  is the inequality constraint.

To deal with this constraint, we introduce the constraint violation function:

$$f_v(x) = \sum_{i=1}^3 \max(0, g_i(x)) \quad (9)$$

The traditional methods of evaluating particles are not well considered and do not consider the particles which violate the constraints[5]. This paper improves it to avoid missing the feasible solution due to excessive rejection. The new particle evaluation mechanism based on the comparison criteria is as follows:

1. When both particle  $x_i$  and particle  $x_j$  satisfy constraints, if  $f(x_i) < f(x_j)$ , then the individual of  $x_j$  is optimal.
2. When both particle  $x_i$  and particle  $x_j$  do not satisfy the constraint, if  $f_v(x_i) < f_v(x_j)$ , then the individual  $X_i$  is optimal.
3. When particle  $x_i$  satisfies the constraint, particle  $x_j$  does not satisfy the constraint. if  $f_v(x_i) < \varepsilon_v$  and  $f(x_j) < f(x_i)$ , then  $x_j$  individual is better, or  $x_i$  individual is better ; Wherein  $\varepsilon_v$  is the required precision index.

We learn that the larger the inertia weight coefficient[4] of PSO algorithm is, the stronger its global search ability is. The smaller the inertia weight coefficient of PSO algorithm is, the stronger the local search ability is. The inertial weight coefficient in this paper is not a fixed value, and its value is determined according to the disaster situation of the fire.

$$\text{The descent formula is: } W = W_{\max} - \frac{t^*(W_{\max} - W_{\min})}{t_{\max}} \quad (10)$$

Where  $W_{\max}=0.95$ ,  $W_{\min}=0.4$ .

In the search process of PSO algorithm, the particle speed may exceed the maximum speed limit, at this time the velocity update formula is:

$$\begin{cases} V = X_l - X_u & V > X_l - X_u \\ U = X_u - X_l & V > X_l - X_u \end{cases} \quad (11)$$

The position of the particle may exceed the boundary of the solution, at this time the position update formula is:

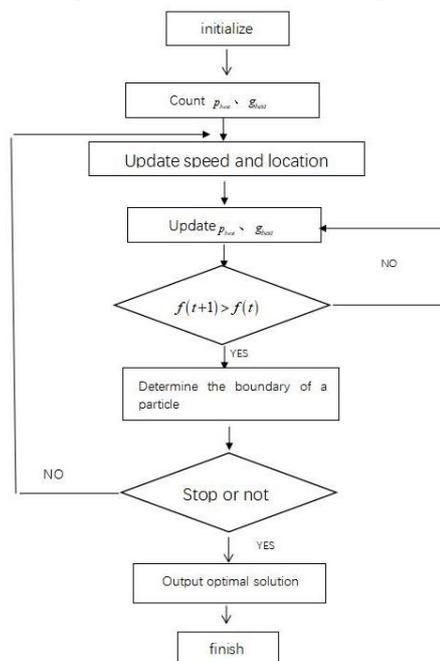
$$\begin{cases} X = X_u & X > X_u \\ X = X_l & X < X_l \end{cases} \quad (12)$$

Where

- $V$  is the current velocity of the particle.
- $X_u$  is the upper bound value of the position of the particle.

- $X_i$  is the lower bound value of the position of the particle.

The steps of the improved PSO algorithm are shown in figure 6 below:



**Figure 6: The flow chart of PSO algorithm**

### 2.2.2 Result of particle swarm optimization algorithm

From the perspective of safety, the larger the size of fire, the greater threat to the life of personnel. So it is necessary to ensure that there are sufficient number of SSA drones to test the equipment of each firefighter. In addition, when fire occurs, the environment around it is variable, so we need to detect the objective factors that may affect the drones such as wind direction and environmental values, so as to design the most appropriate cooperation mode of SSA drones and Radio Repeater drones. From the perspective of economy, life is above everything else. Seek the lowest cost while ensuring reliability. From the perspective of terrain and the frequency of fire events, the inertial weight value in the solution process can be obtained as 0.8 according to the formula (5).

We simulated the fire conditions in 10 areas with different elevations by randomly selected method and obtained the results with the PSO algorithm as shown in the figure 7 and 8:

According to figure 7, in the case of random selection, the optimal number of SSA drones and Radio Repeater calculated by us is 6 and 2 respectively. In order to view the final result more clearly and comfortably, we drew a more beautiful result diagram (figure 8).

To get the total number of drones needed in Victoria, we compared the longitude and latitude data here with GIS longitude and latitude data in Victoria to screen out wildfire hotspots in Victoria. After that, the longitude and latitude of Victoria are divided equally, and an appropriate space is selected to turn Victoria

into ground blocks and number them, as shown in the figure below (figure 9). Through comparison, the optimal combination of the number of drones required by Victoria State is 9000 SSA drones and 3000 Radio Repeater drones.

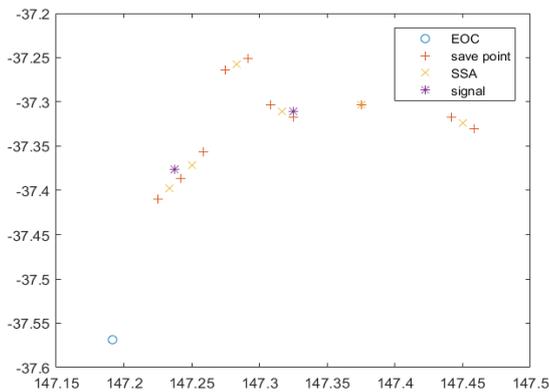


Figure 7: Program diagram

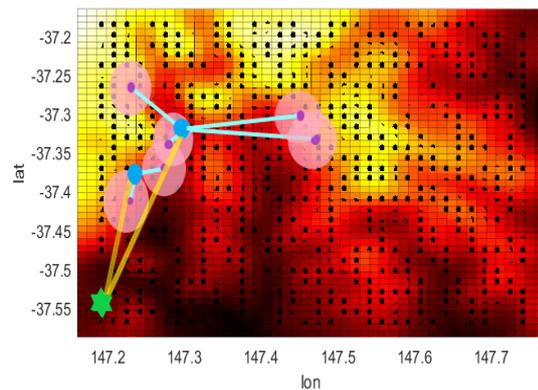


Figure 8: Intuitive collaboration of UAV



Figure 9: Victoria is equidistant in latitude and longitude

### III. MONITORING OPTIMIZATION SCHEME BASED ON Q-LEARNING ALGORITHM

#### 3.1 Particle swarm optimization algorithm

The location of the UAV is also critical to the fire, and the optimization of the UAV scheme requires that it is adjusted according to the changing terrain and fire conditions. Based on this, we need to consider the following factors:

- terrain influence on handheld radio range
- terrain influence on relay communication range
- fire size affect coverage repeater

We are now trying to establish a dynamic programming model for the flight movement of the Radio

Repeater drones, so as to achieve the purpose of transmitting information as much as possible. The fire area  $B = (d_{ij})$ , and the terrain complexity of each position in the fire area can be expressed as matrix  $A = (a_{ij})$ . Since the terrain complexity is bound to be related to the landform nearby, we use the 5\*5 region near the target point for terrain analysis (figure 10):

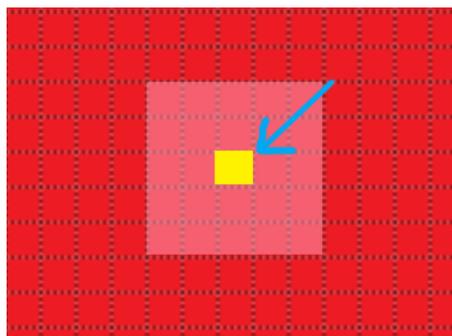


Figure 10: Area model diagram

So the element  $a_{ij}$  is given the formula:

$$a_{ij} = \begin{cases} a_{i\pm 1, j\pm 1}, & \text{if } d_{ij} \text{ is boundary} \\ \frac{\sum_{-2 \leq m \leq 2, m \neq 0, -2 \leq n \leq 2, n \neq 0} |d_{ij} - d_{i+m, j+n}|}{\rho}, & \text{if } d_{ij} \text{ is not boundary} \end{cases}$$

Where  $\rho$  represents the terrain complexity parameter, and converts the sum of the difference square into a number greater than 0 and less than 1, which is convenient for our subsequent calculation. Because of the terrain, we specify the terrain complexity and range of the handheld radio, repeater (table 3):

TABLE 3: Performance description diagram

Topographic complexity (a)	Radio range F(km)	Repeater range H(km)
$0 < a < 0.2$	5	20
$0.2 < a < 0.7$	$5 - 6 * (a - 0.2)$	$20 - 6 * (a - 0.2)$
$0.7 < a < 1$	2	17

In order to maximize the information transmitted by the repeater in the time period of fire rescue, we define the matrix of information transmitted by the rescue point in the time period as  $News = [l_{ij}]_{N \times t}$ , and  $l_{ij} \in \{0, 1\}$ . If a repeater exists near the rescue point to transmit information, then  $l_{ij} = 1$ , or  $l_{ij} = 0$ , this is to maximize the sum of the elements in the transmission information matrix, which means  $Max \sum(News)$

Constraining conditions: In order to ensure that the EOC can communicate with the front line, there must be a repeater adjacent to the EOC, so we can get  $\min_{1 \leq i \leq M} \|n_j - Q_1\| \leq H_i$ . The distance between adjacent Repeaters

must be less than the maximum transmission distance, so we can get  $\min_{1 \leq i \leq M, 1 \leq j \leq M, i \neq j} \|n_j - n_i\| \leq \min\{H_i, H_j\}$ , and the flight speed of the aircraft is  $v_i \in [0, 20]$ . The objective function and constraint conditions based on the problem of maximizing transmission information can be expressed as:

$$\begin{aligned} & \text{Max } \text{sum}(\text{News}) \\ & \text{s.t. } \min_{1 \leq i \leq M} \|n_i - Q\| \leq H_i \\ & \min_{1 \leq i \leq M, 1 \leq j \leq M, i \neq j} \|n_j - n_i\| \leq \min\{H_i, H_j\} \\ & n_1 = T^*S/P \\ & v_i \in [0, 20] \end{aligned}$$

The specific process is as follows:

1. The member  $p_i$  with communication needs sends the communication request information to the relay point, and sends the smallest member in  $d_{p,n}$  to transmit the information. Determine whether the restriction conditions are satisfied after the drone is moved. If not, enter Step 2; otherwise, enter Step 3;
2. Calculate the time of information loss when the constraint condition is not satisfied, and move the adjacent UAV to shorten the interruption time. In this period, the data point of the information matrix of the rescue point that cannot transmit information is denoted as 0.
3. Reach the required transmission point, transmit for a period of time, calculate the rescue point in the process of information transmission, and reserve it in the information matrix.
4. Determine whether the time point  $t_i$  is less than the total rescue time. If yes, return to Step 1; otherwise, jump out of the loop, calculate the total amount of information transmission at all points, and get the result.

These steps provide a solution to the model. However, considering that this algorithm may not be the best in selecting the nearest point, which may lead to a long time of information loss, we try to introduce Q-learning algorithm[9] to optimize the algorithm for solving the model.

Q-learning algorithm is an enhancement learning algorithm for solving the optimization problem of MDP[10], in which the long-term optimization problem is solved by selecting the actions with the minimum Q value. The iterative equation of the optimal Q value is expressed by the optimal Behrman equation:

$$Q^*(s, a) = u + \gamma \sum P(s' | s, a) \min_a Q^*(s', a) \quad (13)$$

In the process of algorithm iteration, after an action is selected, the corresponding Q value of the action will be used to train the Q table so as to gradually reach the optimal action selection strategy  $\pi^*(s)$ . The Q value of the corresponding position in the Q table will be updated as :

$$Q_{t+1}(s, a) = [1 - \alpha(t)]Q_t(s, a) + \alpha(t) \left[ u(t) + \gamma \min_{a' \in A} Q_t(s', a') \right] \quad (14)$$

Where  $s = s(t), s = s(t+1), a = a(t), a = a(t+1), \alpha(t)$  are the learning rate they can be calculated as  $\alpha(t) = 1/(t + c_\alpha)^{\varphi_\alpha}$

where  $C_\alpha > 0, \varphi_\alpha \in (1/2, 1]$ , this parameter represents the degree of influence of the iteration learning result on Q.

Due to the limitation of the initial optimization problem, only part of the action space can be selected in each state. Actions that can be selected in state  $s(t)$  are defined as legal actions.

The soft  $\epsilon$  greed mechanism is applied to guide the action selection of the agent, in which the decreasing probability is defined by the random selection of the action, which is expressed as:  $\epsilon_\alpha = \begin{cases} 1 & t \leq \epsilon \\ \epsilon/t & t > \epsilon \end{cases}$  where  $\epsilon$  is an integer.

According to the definition of  $\epsilon_\alpha$ , the value of  $\epsilon$  in Q-learning will affect the tradeoff between the exploration of the movement space and the exploration result. A large  $\epsilon$  can realize sufficient exploration, but the proportion of randomly selected actions is high, which will affect the stability of long-term calculation of Q value.  $\epsilon$  affects the exploration of action space and the utilization of learning results, which together determine the convergence rate and convergence value of content transmission delay. Here, we take

$$\epsilon = \frac{\sqrt{5} - 1}{2}.$$

### 3.2 Simulation

We used the fire data of the Victoria region provided by NASA to simulate one of the regions, and its topographic map is shown in figure 12:



Figure 11: Satellite image of Victoria fires

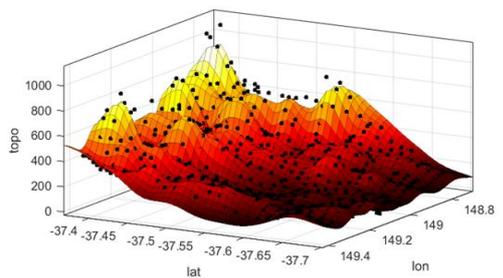


Figure 12: Victoria Mountain Map made by matlab

We also set up mobile EOC and 10 firefighting points to test the effectiveness of our algorithm. We used every 2 minutes as a time unit to obtain the change of information amount received by EOC at any time indirectly at each firefighting point and the change of the total amount of information received over time. As can be seen from the figure 13, each firefighting point sent a message to the EOC, and the final value was nearly the same. And the total amount of information received by EOC increases with time, so our algorithm is reasonable and effective, which can better solve the problem that the repeater cannot completely cover the firefighting point caused by the large fire scale. This model can obtain the local optimal solution under given conditions, basically meeting the actual demand.

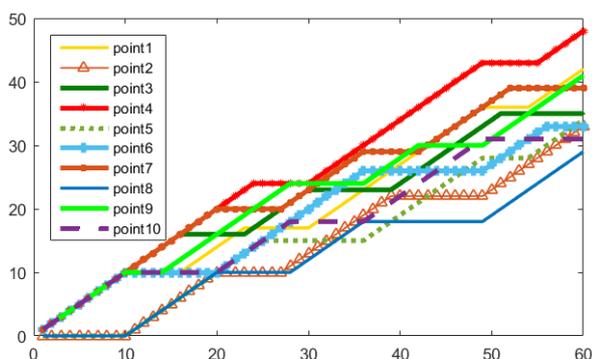


Figure 13: Changes of information content at fire fighting points

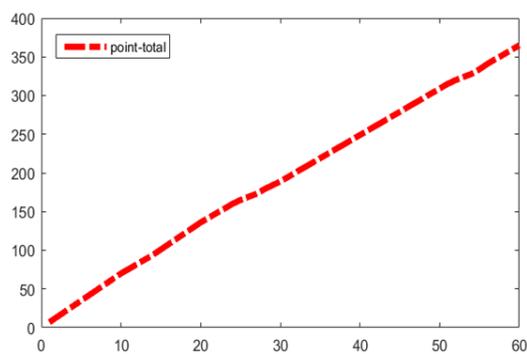


Figure 14: Total information received

#### IV. ADAPTABILITY ANALYSIS

In order to determine the feasibility of this study, we will use statistical methods which is based on recent fire data in Australia to predict the likely fire situation in the next 10 years, so as to determine the number of drones to effectively adapt to the extreme fire situation in the next 10 years. Based on the randomness, suddenness and fuzziness of fire, which is a complex gray system behavior with incomplete information, we consider to use time series model to solve the problem.

##### 4.1 Time series model

Time series analysis focuses on the study of the interdependence of data series. In fact, it is a statistical

analysis of the random process of discrete indicators, so it also can be regarded as a component of the statistics of the random process. There are many time series models and it is necessary to decide which model to choose according to the graphic shape of actual data. Here we mainly introduce ARMA model of time series[8], namely autoregressive moving average model.

The sequence of  $\{X_t, t = 0, \pm 1, \pm 2, \dots\}$  is general stationary sequence, let the mean value  $E(X_t) = \mu$ , then the ARMA model is:

$$(X_t - \mu) - \varphi_1(X_{t-1} - \mu) - \dots - \varphi_p(X_{t-p} - \mu) = \varepsilon_t - \theta_1\varepsilon_{t-1} - \dots - \theta_q\varepsilon_{t-q}$$

Where  $\varepsilon$  is zero-mean, the variance is the stationary white noise of  $\sigma$ ,

By backward shift operator  $\varphi(B)$ ,  $\theta(B)$ , the above model can be expressed as:

$$\varphi(B)(X_t - \mu) = \theta(B)\varepsilon_t \quad (15)$$

The least square estimation method is used to estimate the parameters in the model

$$\text{Let } X_t \text{ have the inverse form: } X_t - \sum_{j=1}^{\infty} I_j X_{t-j} = \varepsilon_t \quad (16)$$

The above formula can be written as:

$$(1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p) X_t = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) \varepsilon_t$$

$$\text{Where } \varepsilon_t = (1 - I_1 B - I_2 B^2 - \dots) X_t$$

We can get the operator identity :

$$1 - \varphi_1 B - \dots - \varphi_p B^p = (1 - \theta_1 B - \dots - \theta_q B^q) (1 - I_1 B - I_2 B^2 - \dots)$$

Compare both sides of this equation to the same power of  $B$ , and you get:

$$\begin{cases} \varphi_1 = \theta_1 + I_1 \\ \varphi_2 = \theta_2 - \theta_1 I_1 + I_2 \\ \varphi_3 = \theta_3 - \theta_1 I_2 - \theta_2 I_1 + I_3 \\ \dots\dots\dots \\ \varphi_j = \theta_j - \theta_1 I_{j-1} - \theta_2 I_{j-2} - \dots - \theta_{j-1} I_1 + I_j \end{cases} \quad (17)$$

Where when  $j > q$ ,  $\theta_j = 0$ ; when  $i > p$ ,  $\varphi_i = 0$ .

$$\begin{cases} I_1 = \varphi_1 - \theta_1 \\ I_2 = \varphi_2 - \theta_2 + \theta_1 I_1 \\ I_3 = \varphi_3 - \theta_3 + \theta_1 I_2 + \theta_2 I_1 \\ \dots\dots\dots \\ I_j = \varphi_j - \theta_1 I_{j-1} + \dots + \theta_{j-1} I_1 \end{cases} \quad (18)$$

Let  $\varphi = (\varphi_1, \varphi_2, \dots, \varphi_p)^T$ ,  $\theta = (\theta_1, \theta_2, \dots, \theta_q)^T$ , extrapolating from the above equation, we can get the reverse form:

$$I(B)X_t = X_t - \sum_{j=1}^{\infty} I_j X_{t-j} = \varepsilon_t \quad (19)$$

Conditional least squares estimator gives the following sum of squares of residuals:

$$\sum_{j=1}^n \hat{\varepsilon}_t^2 = \sum_{j=1}^n \left( X_t - \sum_{j=1}^{\infty} I_j X_{t-j} \right)^2 = \min$$

$I_j$  is a function of  $\varphi$  and  $\theta$ , so the residual sum of squares is also a function of  $\varphi, \theta$ :

$$S(\varphi, \theta) = \sum_{j=1}^n \left( X_t - \sum_{j=1}^{\infty} I_j X_{t-j} \right)^2$$

Note that the sum of squares above is a nonlinear function of  $\varphi$  and  $\theta$ , and the minimization requires the nonlinear least square method to find  $\varphi_L^*$  and  $\theta_L^*$  in the stationary invertible domain of  $X$ , such that

$$S(\hat{\varphi}_L^*, \hat{\theta}_L^*) = \min$$

$\hat{\varphi}_L^*, \hat{\theta}_L^*$  is called the conditional minimum scalar estimation of  $\varphi$  and  $\theta$ .

In this way we can get the conditional least squares estimate of the parameter. For the stationarity of  $X_t$ , we use Daniel test to check the stationarity of our sequence. Daniel test method is based on Spearman correlation coefficient. Spearman correlation coefficient is a rank correlation coefficient.

Let  $x_1, x_2, \dots, x_n$  is a sample of size  $n$  from a unitary population, and the order statistic is  $x_{(1)}, x_{(2)}, \dots, x_{(n)}$ . If  $x_i = x_{(k)}$ , then  $k$  is the rank of  $x_i$  in the sample, denoted  $R_i$ .

Spearman correlation coefficient was defined as the correlation coefficient of rank statistics of the two groups, that is, Spearman correlation coefficient is

$$q_{xy} = \frac{\sum_{i=1}^n (R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^n (S_i - \bar{S})^2}} \quad (20)$$

$$\text{Where } \bar{R} = \frac{1}{n} \sum_{i=1}^n R_i, \bar{S} = \frac{1}{n} \sum_{i=1}^n S_i, \text{ it can prove: } q_{xy} = 1 - \frac{6}{n(n^2 - 1)} \sum_{i=1}^n d_i^2 \quad (21)$$

Where  $d_i = R_i - S_i$

Consider the Spearman correlation coefficient  $q_s$  of the variable with respect to  $(t, R_t)$

$$q_s = 1 - \frac{6}{n(n^2 - 1)} \sum_{i=1}^n (t - R_i)^2 \quad (22)$$

Construction statistics:  $T = \frac{q_s \sqrt{n-2}}{\sqrt{1-q_s^2}}$

We do the following hypothetical experiment:

$H_0$  : sequence  $X_t$  is smooth       $H_1$  : sequence  $X_t$  is non-stationarity

Daniel test method: for significance level  $\alpha$ , Spearman correlation coefficient  $q_s$  of  $(t, R_t)$  is calculated from time series  $X_t$ . If  $|T| > t_{\alpha/2}(n-2)$ , then refuse to consider the  $H_0$  sequence nonstationary. And when  $q_s > 0$ , it is believed that the sequence has an upward trend; when  $q_s < 0$ , it is believed that the sequence has a downward trend. Then when  $|T| \leq t_{\alpha/2}(n-2)$ , accept  $H_0$  and consider the sequence to be stable.

## V. CONCLUSIONS

We have collected the fire data of Australia in recent five years, and selected the high incidence of fire 60 months each year to the fire intensity data statistics. Based on the time series model, we first estimated the parameters in the first 30 months, and then predicted the fire intensity in the next 30 month. The predicted results are shown in the figure 15. From figure 15, we can see that there are still errors between the predicted results and the actual data, but the development trend of fire intensity is generally similar. According to figure 16, we can observe that our model has a high accuracy rate and has certain credibility and validity.

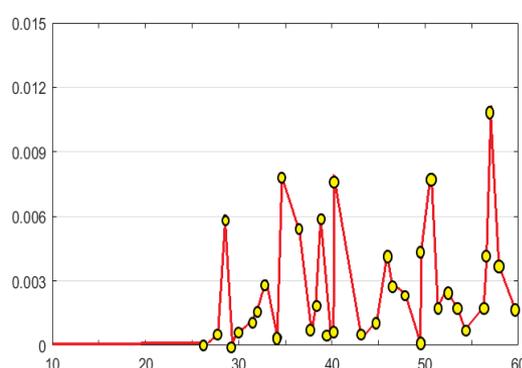
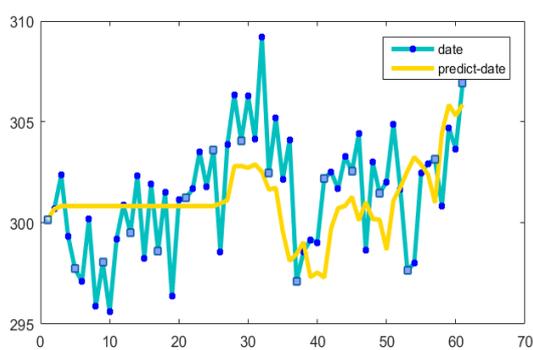


Figure 15: Fire intensity prediction diagram

Figure 16 : Error analysis diagram

## REFERENCES

- [1]. Zhang Ziqian. Research on UAV Communication System[J]. Shanxi: Southern agricultural machinery. 2019.
- [2]. MIAO Qing-yu. Research on Technology and Performance of Repeater in Cellular Communication System [D]. Beijing University of Posts and Telecommunications. 2010.
- [3]. Yuan Han, Xu Chunmei, Yang Ping. Identification of Unstable Process and Stable Process Based on PSO [J]. Bulletin of Science and Technology. 2017.
- [4]. Guo Siyuan, Li Zhenwen, Hong Quan, Wu Jinbo, Li Li. Research on Parameter Optimization of PSS4B-W Based on Adaptive Weighted Particle Swarm Optimization [J]. Hunan Electric Power. 2017.
- [5]. Fu Qiufeng, Xiao Jun, Li Shuchen, Zhang Yongqiang, Liu Wei. Constrained generalized predictive control algorithm based on particle swarm optimization and simulated annealing[J]. Journal of Petrochemical University. 2010.
- [6]. CHEN Jun. Application of Quantum Genetic Algorithm in Grayscale Image[J]. Computer programming skills and maintenance. 2013.
- [7]. Lin Feng, Yang Jicang, Diao Qinghua. Time series analysis of fire information. Fire science and technology [J]. 2006.
- [8]. Yun Ling, Wang Fucai, Zhang Qiufen. Application of differential autoregressive moving average model to the prediction of mosquito density distribution characteristics [J]. Chinese Journal of Vector Biology and Control. 2020.
- [9]. JING Chen, FU Xiao-Tong, DONG Wei, ZHAO Yun-Fei. Research on Fuzzy Test Method of Stateful Network Protocol Based on Q-Learning Algorithm [J]. Application of Electronic Technique, 2020.

- [10]. Giao Ji,Rong Tian Yonghong,Dang Yunfeng.Research on a New MDP Algorithm [J].Microcomputers and Applications.2012.
- [11]. Wu Zhiqing and Cai Weijia.An algorithm for Simulation of Flight Track Simulation [J].Computer and Modernization.2018.
- [12]. Li Xiaomeng,Wang Daobo,Guo Jikai, Yang Hua,Wang Bohang.Unmanned Aerial Vechicle Path Planning Based on a Biological Heuristic Algorithm [J].Machinery & Electronics.2018.Wu Zhongbo,Yi Jianqiang.Cooperative Communication Relay Strategy of UAV Formation Support Network [J].Journal of Aviation.2020.