Establishment of Wildfire Monitor-Repeater-EOC System Based on TOPSIS and Genetic Algorithm

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ABSTRACT
To get the frequency and magnitude of forest fires in Victoria, the Forest Fire Danger Index (FFDI) is used to characterize some parameters of fires. First, an FFDI calculation model is established based on meteorological data. For the necessary parameter drought factor DF, we used the TOPSIS method to estimate and finally calculated the FFDI value of weather stations in Victoria. Based on the FFDI, we established a single-stream hierarchical facility location model based on genetic algorithm distance constraints. Finally, we got the distribution of fire-prone points and the distribution of monitor-repeater-EOC.

Keywords: *Fire prediction, TOPSIS, Genetic Algorithm.*

1.INTRODUCTION

The 2019-2020 fire season in Australia saw devastating wildfires in every state, with the worst impact in eastern Victoria. Firefighters have used drones for surveillance and situational awareness (SSA) to cope with the situation for several years. SSA drones help monitor the evolving situation, letting the Emergency Operations Center (EOC) best direct active crews for optimal effect and maximal safety. Due to the constraints of distance and topography, the layout of the monitors-repeaters-EOCs system in Victoria is needed to be solved with the consideration of capability, safety, and economics.

To better characterize the frequency of forest fires in Victoria, we used the McArthur Forest Fire Danger Index (FFDI) magnitude to represent the frequency and size of forest fires. We designed a model to calculate the FFDI, and the magnitude of FFDI was estimated for each weather station area in Victoria.

The genetic algorithm based on the calculated FFDI data is used to plan the layout of the monitor-repeater-EOC system. To optimize the algorithmic efficiency of the location problem, we establish a distance-constrained single-stream hierarchical facility location model based on a genetic algorithm and improve it to meet the practical needs to solve this problem.

2.MODEL ESTABLISHMENT AND SOLUTION

2.1.The Victoria Fire Frequency Forecast Model the Victoria Fire Frequency Forecast Model

The calculation of FFDI is as follows:

$$\text{FFDI} = e^{0.0338T-0.0345RH+0.0234v+0.243147} \times DF^{0.987} \quad (1)$$

Among them, T stands for temperature (°C), v stands for wind speed (km/h), RH stands for mean relative humidity (%), and DF stands for drought factor, the first three data have been collected, and the value of parameter DF needs to be obtained.[1]

2.1.1.Obtain the Drought Factors

As the drought factor data cannot be directly obtained, we design another method to estimate the drought factor. According to the regulations of the Bureau of Meteorology of the Australian Government, the drought factor is based on a temporally accumulated soil moisture deficit and can be calculated here using the Keetch-Byram drought index (KBDI).[2] The KBDI is based on temperature and rainfall data. It estimates the soil moisture below saturation to a maximum field capacity of 203.2 mm (corresponding to KBDI=203.2, representing the driest conditions).

The Technique for Order Preference by Similarity is used to an Ideal Solution (TOPSIS) to score the degree of drought at different weather station locations to determine the value of KBDI at different locations. We choose five indicators: longitude (x), latitude (y), elevation (h), monthly mean rainfall (b), monthly mean maximum temperature ($\hat{T}$). For the type of each indicator, we know: Victoria is located in the southeast corner of Australia, so the bigger the latitude, the smaller the longitude, and the further from the ocean, the drier the climate will be; the higher the elevation, the smaller the frequency of forest fire will be; the higher the monthly mean maximum temperature, the drier the climate will be; the lower the monthly mean rainfall, the drier the climate will be. Therefore, except that the monthly mean maximum temperature is a maximum index, the other four are minimum indexes. The minimum index needs to be positively converted into a maximum index.

For the 89 groups of Longitude, Latitude, Elevation, Mean Maximum Temperature, Mean Rainfall we collected, we use them to form a positive matrix:

$$X = \begin{bmatrix} x_{lon,1} & y_{lat,1} & h_1 & \overline{T_1} & \overline{b_1} \\ x_{lon,2} & y_{lat,2} & h_2 & \overline{T_2} & \overline{b_2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{lon,89} & y_{lat,89} & h_{89} & \overline{T_{89}} & \overline{b_{89}} \end{bmatrix} \quad (2)$$

After normalization, the score of each position is calculated separately in matrix $Z = (z_{ij})_{89\times5}$. Define the distance between the i-th evaluation object and the maximum value (Z^+) and minimum value (Z^-) as follows: $D_i^{\pm} = \sqrt{\sum_{j=1}^{89} \omega_j \left(Z_j^{\pm} - z_{ij}\right)^2}$. The score of the i-th evaluation object (S_i) and normalized to get the final score $\tilde{S}_i = \left(\frac{D_i^-}{D_i^+ + D_i^-}\right) / \sum_{i=1}^{89} S_i$. The KBDI formula can calculate the score of each position calculated by the TOPSIS method:

$$KBDI_i = \frac{\tilde{S}_i - \tilde{S}_{min}}{\tilde{S}_{max} - \tilde{S}_{min}} \times 203.2 \quad (3)$$

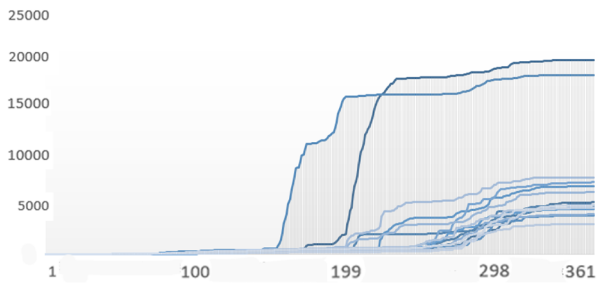

Figure 1 KBDI of each weather station

2.1.2.Results

Based on the data, we can use the FFDI formula to get the FFDI value of each weather.

Figure 2 Density graph of FFDI in January

From the density graph (Figure 2), we can see that the FFDI value was the highest in January, which is consistent with our observation of fire count in Victoria in Figure 2. The first day starts on Jun 1st. It can be seen that the rapid rise of the curve is nearly half a year later. In January, it is said that a fire event is easier to occur. Meanwhile, two weather stations located in Merbein CSIRO Research Station and Mildura Airport have the highest FFDI value in Victoria. Australia is in summer around January and is in the tropics. The average daily maximum temperature is relatively high. Furthermore, Merbein CSIRO Research Station and Mildura Airport are located at the northwestern corner of Victoria, which is far from the ocean with high altitude and low rainfall. It is prone to forest fires.

2.2.The EOC-repeater-UAV system based on the genetic algorithm

By analyzing Victoria's map and the forest fire situation in the past few years, it is demonstrated that the probability of forest fires in some areas is significantly higher than that in other areas, and higher priority should be provided when planning the fire protection system. We extract these areas as points to form a map and make the range and signal of the drone in the drone system to be planned cover all such points, and at the same time, the cost is minimal. It means that all points can be monitored, and the monitoring data can be sent back to EOC through the repeater.

After a deeper analysis of this problem, we believe this is an NP-hard multi-layer facility location problem (HFLP). This problem is characterized by a large amount of data to be processed; it is difficult to obtain an analytical solution. Thus, we decide to use heuristic algorithms to solve it. [3]

To optimize the algorithm efficiency of the location problem, we established a distance-constrained single-stream layered facility location model. This model has been proven effective in previous studies. According to the actual situation, the model is simplified and improved, and the final result can meet the safety and economic needs.

When constructing the graph, we analyze the points with FFDI higher than 62. We extract some of these

points to make up the point set needs to be covered up according to the sparsity of the point distribution and the probability determined by density relative distribution. Finally, 89 points are extracted. Their distribution and relative FFDI size are represented by circles in the map (Figure 3).

Figure 3 89 points extracted in Victoria

2.2.1.Model building

To build the model, the point set is divided into three parts: ordinary nodes, point set of EOCs, and point set of monitors, which are denoted by uppercase letters *N*, *E*, *M*, respectively. The lowercase letters denote the points belonging to the corresponding uppercase point sets, respectively.[4]

We set the cost of building EOC (c_{ne}) as 20,000 AUD and the monitor's price (c_{nm}). It is considered the price of the drone (c_d), which is 10,000 AUD.

We determine the maximum speed of the drone (v_m) as 20 m/s and the maximum flight time (t_m) as 2.5 hours, then the maximum flight distance (l) in a single flight is 18 km. We set the average price of using the drone in a single flight (c_{ud}) as 100 AUD.

The maximum distance between the monitor and the EOC (l_E) that can be signaled is 20km, and the maximum distance between the UAV and the monitor (l_d) that can be signaled is 5 km, and the minimum is 2 km. We use the average distance (3.5km) as the drone signal transmission distance.

To minimize the expense of building the EOC-repeater-monitor system, we use the total cost as the fitness function in the genetic algorithm. A fitness function with a smaller value represents a lower cost, which means it is much economical.

$$F = \sum E_n c_{ne} + \sum M_n c_{nm} + n_d c_d + \sum \left(\frac{d_{nm}}{v_m l} c_{ud}\right), n \in N (4)$$

The first three terms in Equation (4) denote the EOC, monitor, and the construction or purchase cost of the drone, respectively, and the fourth term denotes the cost of the drone to reach the point from the closest monitor for each point covered, which means the cost of using the drone.

The constraints are mainly considered from three aspects: First, the constraints brought by the variables' nature. Second, the constraint in terms of quantity is brought by the fact that the point set is a closed system, and the points outside the set are not processed. Third, the constraints brought by the requirement of the shortest possible distance between the monitor and the possible fire point and the monitor to the EOC, and the shortest distance, for the safety of the drone monitoring the fire.

The constraints for the variables are shown below:① If there is equipment in node n, v_n equals to 1; otherwise, 0.②If there is an EOC in node n, E_n equals to 1; otherwise, 0.③If there is a monitor in node n, M_n equals to 1; otherwise, 0.④n_d>0.⑤d_{nm}>0.

The constraint-based on the point set is a closed system, which is reflected in two main aspects. First, each point has at most one of the EOC or monitor devices. Second, the total number of devices is not greater than the total number of points. ⑥ $M_n + E_n = v_n$⑦$\sum(M_n + E_n) \leq v_n$

The consideration of safety is concentrated in the shortest distance constraint. To make the fire emergency system respond to fires at each point with the fastest speed, the definition of the shortest distance formula is first introduced. The shortest distance from a point to a nearby point is the length of the shortest edge among all connected edges. ⑧ $\forall m' \in M, d_{mn} \leq d_{nm'}$ ⑨ $\forall e' \in E, d_{me} \leq d_{me'}$

We expect that the distance from each possible fire to the nearest monitor will not exceed the drone signal transmission distance and that the distance from each monitor to the nearest EOC not exceed the monitor signal transmission distance. ⑩ $\forall n \in N, d_{nm} \leq l_d$ ⑪ $\forall m \in M, d_{me} \leq l_E$

2.2.2.The genetic algorithm

All possible fire-starting points are considered as possible device construction points. Thus, the genetic algorithm generates a chromosome with 89 genes, representing 89 possible fire-starting points. We label each point with *E*, *M*, *N*, indicating that the point builds EOC (*E*) or monitor (*M*) or is a normal node (*N*). A sample chromosome is illustrated in Figure 4.[5]

The crossover operator randomly selects a pair of chromosomes and it is used the Partial-Mapped Crossover method to swap a gene from a segment of the parental chromosome to generate a new filial generation. The mutation operator randomly changes the property of a gene in the chromosome with very low probability (taken as 0.01 in this model). The two operators are illustrated as in Figure 5.

With the genetic algorithm model and the three operators above, the layout of the monitor-repeater-EOC system can be obtained.

Figure 4 A sample chromosome

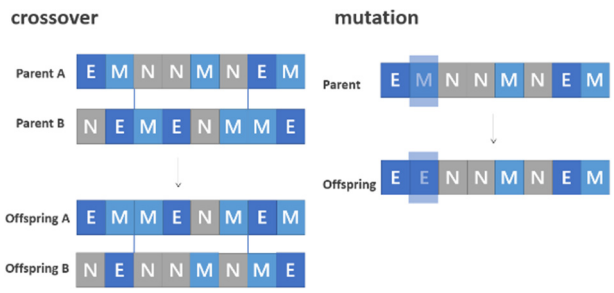

Figure 5 The two operators

2.2.3.The optimization of model

Based on the genetic algorithm, we got the construction method that makes the minimum number of established monitors and EOCs, and at the same time, the signal can cover all the fire-prone points for safety consideration. The distribution of fire-prone points is obtained, as shown in Figure 6.

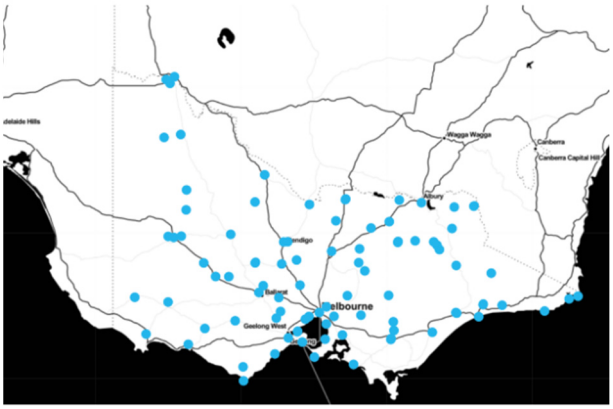

Figure 6 The distribution of fire-prone points

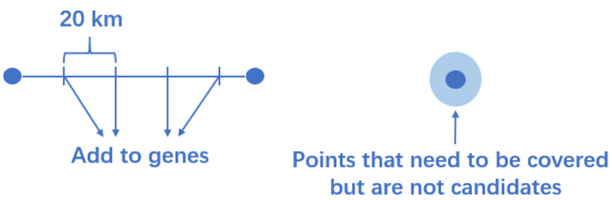

Figure 7 The changes of candidate point set

Considering that the distance between two fire-prone points is usually long, the actual calculation is performed by dividing two points by every 20 km from one of them and adding the dividing point between the two nodes into the candidate point set. It is considered as the gene of the chromosome. It allows the model to be applied in practice with more than the original number of 89 genes.

In addition, we expand the area of a part of the points with high FFDI values, requiring the model to cover a circle of points near the point, but these expanded areas are not among the candidate points (Figure 7).

The above two points are the improvements we made to the model based on the actual situation.

2.2.4.Results

Using the model, we can calculate the latitude and longitude of the EOC and the repeater. The results are visualized, and the final results of the EOC-repeater distribution are shown in Figure 8. Where repeaters are represented using their signal coverage (blue circles), EOC is represented using orange dots, and blue dots indicate possible fire points.

Based on analyzing the results, it can be seen that the system is made up of 47 repeaters and 39 EOCs. The minimum number of drones that the algorithm finds is 256 to respond to possible forest fires timely, without taking into account drone shift change, and the total construction cost of the system is 3,810,000 AUD.

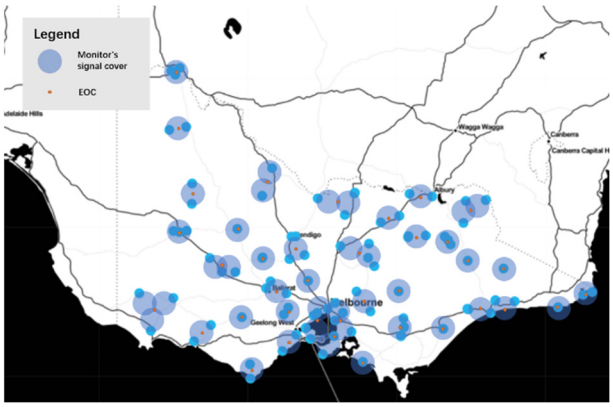

Figure 8 The result of EOC-repeater distribution

3.CONCLUSION

As can be seen from Figure 8, the location selected by the EOC often coincides with the monitor signal cover centroid, which is often on the possible fire point or at the center of several centroids. It is in line with geometry so that the shortest distance between the equipment ensures safety.

In the prediction model, due to the large sample size, there should be better prediction models available for different data, such as the exponential smoothing model and the ARIMA model.

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