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Study on the Prediction Model of Wildfire in Victoria

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Abstract: *Wildfires are one of the most devastating natural disasters in Australia. In this paper, we design a model to predict the likely variability of extreme fires over the next decade. Aiming at the forecasting problem, we downloaded the extreme fire event data from NASA for the last 18 years in Victoria, and established a combined prediction model, combining the* ***unbiased gray GM(1,1) model****,* ***the BP neural network prediction model*** *optimized by genetic algorithm, and finally the resulting prediction data were approximated by Gaussian function on the data point set using MATLAB toolbox to obtain the temporal and spatial prediction results, and the number of drone combinations under different terrains is simulated by simulation.*

Keywords: *unbiased gray GM(1,1) model, Genetic algorithm optimization, BP neural network prediction model*

1. Introduction

Wildfires, or bushfires, are one of the most destructive natural disasters in Australia, which can cause many deaths of stock, native animals, sometimes humans, and huge impacts on infrastructure. Reconstructing past wildfires and exploring the links between wildfires and climate are essential for understanding the dynamics of wildfires and for predicting future risks.

With the progress of science and technology, in the reconstruction, we can use drones to carry high definition & thermal imaging cameras and telemetry sensors that monitor and report data from wearable devices on front-line personnel.

In this paper, we establish a wildfire prediction model for Victoria in the next decade and show how the model can adapt to the possibility of the ever-changing extreme fire events in the next decade. Assuming that the cost of the UAV system remains unchanged, how much more equipment cost is expected to increase.

2. Model Establishment and Solution

To more accurately predict information such as the probability of extreme fires occurring in Victoria, Australia, over the next decade, as a way to test how the model adapts to changing extreme fire events over the next decade, we downloaded observations of fires occurring in Australia from 2002 to 2019 from EARTHDATA of NASA, and filtered the larger fires that occurred during that period based on fire severity fires [1]. In addition, we also combine information on the probability of occurrence of extreme fires with geographic environmental factors such as topography, vegetation, and climate for spatial prediction.

Due to the small sample of extreme fire accident data in Victoria and the high volatility of the data. Therefore, we combine the unbiased grey forecasting model with the BP neural network model optimized by genetic algorithm to establish a combined optimization model, and fit the unbiased gray GM(1,1) model and the BP neural network prediction model optimized by genetic algorithm for each day of fire accidents in Victoria, Australia from 2002 to 2019, respectively, and for each day of the next ten years The resulting predicted data are finally approximated by Gaussian function on the data point set using MATLAB toolbox and the corresponding curves are plotted.

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2.1 Unbiased grey forecasting model after optimization by genetic algorithm

Set the time series to

$$T_0 = \{T_0(1), T_0(2), T_0(3), \cdots T_0(n)\} \tag{1}$$

$$T_0(k) \geq 0, k = 0,1,2\cdots, n$$

A single accumulation of the above time series is performed to generate a new series:

$$T_1 = \{T_1(1), T_1(2), T_1(3), \cdots T_1(n)\} \tag{2}$$

Then determine the data matrix $\boldsymbol{Y}$ and matrix $\boldsymbol{B}$

$$Y_n = \begin{pmatrix} T_0(2) \\ T_0(3) \\ \vdots \\ T_0(n) \end{pmatrix}, B = \begin{pmatrix} -1/2[T_1(1)+T_1(2)] \ , \ 1 \\ -1/2[T_1(2)+T_1(3)] \ , \ 1 \\ -1/2[T_1(n\text{-}1)+T_1(n)] \ , \ 1 \end{pmatrix} \tag{3}$$

The least squares method was used to solve for the gray coefficients and to calculate the unbiased gray coefficients:

$$\begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = \left(B^T B\right)^{-1} B^T Y_n \quad \alpha = \ln\frac{2-\hat{a}}{2+\hat{a}} \quad \beta = \frac{2\bullet\hat{b}}{2+\hat{a}} \tag{4}$$

Finally we get the predicted data sequence:

$$\hat{T}_0(K) = \begin{cases} T_0(1) \ , \ k=1 \\ \beta e^{\alpha(K-1)}, \ k=2,3,4... \end{cases} \tag{5}$$

2.2 Optimized BP Neural Network Time Series Prediction Model

In this model, we choose to use a 3-layer BP neural network, set the number of input layers to p, the number of hidden layers to q, and the number of output layers to 1, as shown in the following block diagram [2]:

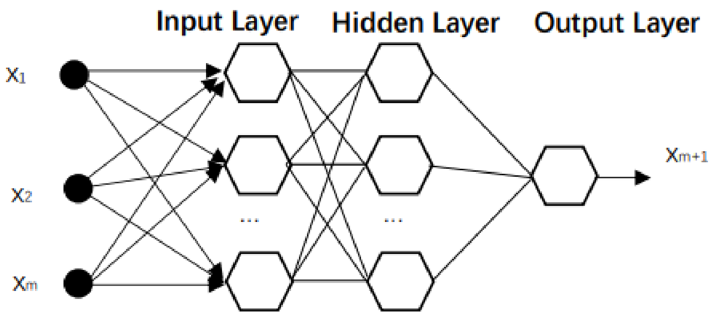

Figure 1: 3-layer BP neural network

The inputs to the hidden layer neurons are:

$$y1_j = \sum_{i=1}^{m} \omega_{ij} x_i - \theta_j \tag{6}$$

Where

- ω_{ij} is the weight of the input layer to the hidden layer;
- θ_j is the threshold value of the hidden layer neuron;

The transfer function of the BP neural network uses the sigmoid function, which is a common S-type function in biology, so the output of the hidden layer is:

$$Out1_j = 1 \Big/ \left[1+e^{\left(-\sum_{i=1}^{m}\omega_{ij}x_i - \theta_j\right)} \right] \quad (j=1,2,3,\ldots,p) \tag{7}$$

The inputs to the output layer neurons are:

$$y2_j = \sum_{j=1}^{p} at_j Out1_j - \phi \tag{8}$$

Where

- at_j is the weight of the connection from the hidden layer to the output layer;
- ϕ is the threshold value of the output layer;

The output value of the output layer is:

$$Out2_j = x(i+1) = 1 \Big/ \left[1+e^{\left(-\sum_{j=1}^{p} at_j Out_j - \phi\right)} \right] \tag{9}$$

2.3 Genetic algorithm optimization parameters

To avoid the initial weights and thresholds that make the BP neural network error, our team uses a genetic algorithm (GA) to optimize the relevant parameters.

First, the structure of the BP neural network is determined based on the input and output vectors of the time series, the population size is set, the initial population is generated, and the chromosomes of the initial population are generated using a linear interpolation function, and the coding length of each chromosome is related to the number of neurons in the input layer, the hidden layer, and the output layer.

Then the fitness function of the genetic algorithm is determined, the corresponding parameters are assigned and the network is trained by inputting samples and setting the selection probability (roulette wheel method).

Finally, the crossover and variation are performed by methods such as the real number crossover method to obtain the optimal parameters of the BP neural network, and the BP algorithm is used to train the prediction model.

Eventually, the prediction data sequence obtained from the unbiased gray GM(1,1) model is input into the optimized BP network for calculation to obtain the final prediction data.

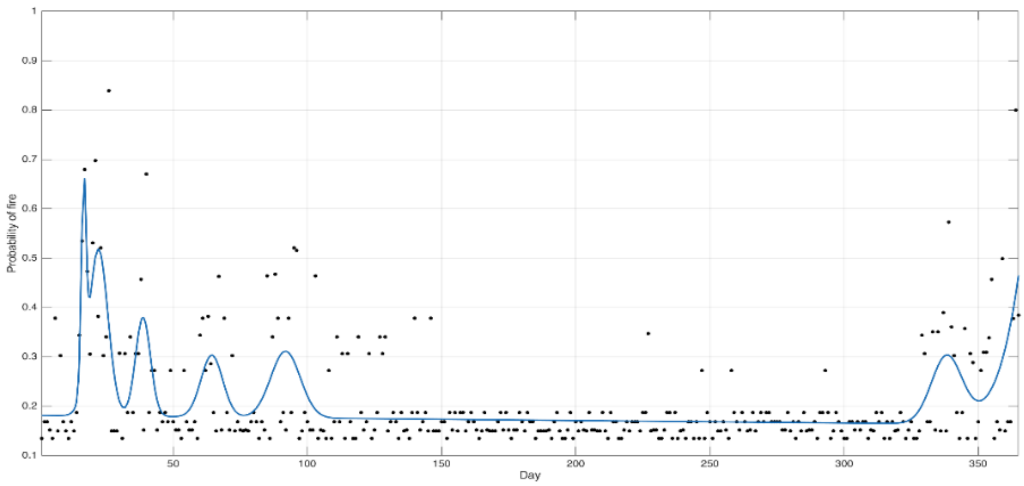

Figure 2: The probability of a fire occurring on each day in the first year ahead

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2.4 Projected results for the next decade

By combining the gray unbiased forecasting model with the BP neural network model optimized by genetic algorithm to obtain the time series of the predicted data, and using Gaussian function to functionally approximate the set of predicted data points to finally plot the predicted information of fire occurrence for each day in the next ten years.

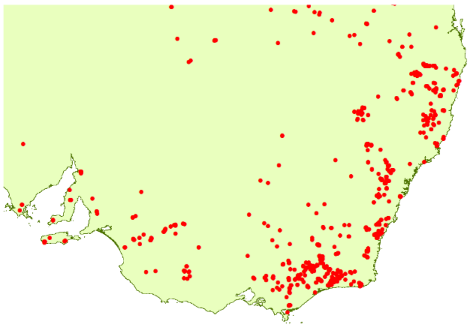

Figure 3: High risk area for wildfires in Victoria in the next decade

Table 1: Forecast results for the next ten years

Year	**Number of wildfires**	**Maximum number of serious fires occurring simultaneously**	**Coverage rate of different number of drones formations**		
			20	30	40
2021	63	21	41.22%	54.16%	55.56%
2022	54	20	46.39%	60.64%	68.46%
2023	56	13	62.57%	69.26%	76.65%
2024	59	29	26.54%	34.89%	36.58%
2025	51	24	26.52%	28.97%	34.89%
2026	47	17	56.81%	65.31%	75.13%
2027	52	25	26.87%	32.16%	45.89%
2028	65	31	15.13%	34.98%	54.12%
2029	61	28	28.49%	39.48%	46.71%
2030	66	37	13.65%	26.13%	39.11%

Table 2: Forecast results for each month

Month	**Number of serious fires in 10 years**	**Maximum number of serious fires occurring simultaneously**	**Coverage rate of different number of drones formations**		
			20	30	40
1	148	31	15.13%	34.98%	54.12%
2	101	29	26.54%	34.89%	36.58%
3	24	2	88.92%	97.81%	97.22%
4	14	2	95.89%	96.48%	99.47%
5	6	1	81.65%	99.62%	99.16%
6	0	0	100.0%	100.0%	100.0%
7	1	1	94.53%	86.48%	97.82%
8	3	2	89.43%	94.61%	98.54%
9	2	1	96.25%	96.89%	97.51%
10	1	1	91.68%	99.10%	98.64%
11	7	4	89.66%	96.15%	97.44%
12	267	37	13.65%	26.13%	39.11%

3. Model Evaluation

In this paper, we use heuristic algorithm to optimize the prediction model, and obtain more favorable results. However, when considering the cost of the model, only the cost of the drone and the cost of electricity are taken into account. And the data used in the mathematical model is still insufficient, and it is unable to select enough data for computer training, resulting in the lack of accuracy and precision of

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the model.

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