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Fire Alarm System and Management Level Evaluation Model Design

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Abstract

This paper examines the issue of fire alarm systems. With the rapid development of fire detector industry, fire detection and alarm technology is becoming more and more perfect, and the number of newly installed fire detectors in buildings is huge every year. Therefore, improving the reliability of fire detectors and reducing the failure of fire alarm systems has a major role in timely detection of fire, control of fire and protection of life and property. In response to question 1: First, data cleaning was performed on Annex 1 to remove some missing values, compare the remaining data for the same address, machine number and loop code, and check the number of the same alarm message, and finally determine the real number of fires as 440. The top three fires in the brigade area were 51 in G Brigade, 49 in M Brigade and 41 in C Brigade. The frequency of use, the number of alarms per square kilometer, the false alarm rate and the failure rate were used as evaluation indicators to build the evaluation model, and the CRITIC weighting method, the entropy weighting method and the coefficient of variation method were used to analyze the degree of correlation between the two factors, followed by the game theory comprehensive weighting method to obtain the weights of frequency of use, number of alarms per square kilometer, false alarm rate and failure rate as 0.243, 0.227, 0.229 and 0.301 respectively. Finally, the evaluation model of TOPSIS was established to score the various detectors, in which the signal valve detector has the highest score of 0.98854, followed by the intelligent photoelectric detector with a score of 0.97571. Therefore, the optimal detector is the signal valve detector. For problem two: data cleaning based on the data findings given in problem one, reselection of indicators, elimination of irrelevant data. Secondly, RUSBoost prediction model, Random Forest prediction model and Adaboost prediction model were picked to train the sample data respectively, compare and use the RUSBoost algorithm with the highest accuracy rate. Then this model was used to predict the target and evaluate the authenticity of the data in Annex 3. Some of the real fire probability prediction results: The probability of real fire in G brigade, J brigade and N brigade are 0.4167, 0.2746 and 0.3242. For question 3: Based on the above questions and Table 1, the data were first processed and the indicators were reselected to obtain the weights using the entropy weighting method. Subsequently, TOPSIS model was established to evaluate the comprehensive management level of each fire brigade, and the analysis results can be obtained: the highest rating of K fire brigade is 0.8689, and the lower ratings of F fire brigade, R fire brigade and M fire brigade are 0.3666, 0.3821 and 0.4073, and the improvement plan is proposed for this result. For problem 4: Firstly, analyze the model results of the above problem and put forward suggestions for the maintenance of each component of the fire alarm system from three aspects: reasonable selection of fire detectors, improving the authenticity of alarm signals and effectively improving the comprehensive management level of the fire brigade, taking into account the actual situation. Finally, this paper evaluates and generalizes the model. It is concluded that this model can also be

generalized to other regional or national fire safety system management scoring, component reliability scoring problems.

Keywords

TOPSIS Game Theory Integrated Empowerment Method RUSBoost Entropy Method Evaluation Model.

1. INTRODUCTION

1.1. Background of the Problem

Within the past three decades, China's fire detection alarm industry has developed rapidly and become an integral part of China's high-tech industry, and the number of new fire detectors installed each year is huge, and the industry has a bright future. Fire detection alarm technology and fire alarm system, as an important element of fire prevention technology, has the great significance of timely detection of fire, timely control of fire and protection of life and property [1].

Even though the technology of the fire detection and alarm industry is getting better, the reliability of fire detector alarms needs to be improved and fire alarm system failures occur from time to time. As fire detector sensitivity and alarm reliability compete with each other, the two need to be balanced, fire alarm system failure problems need to be addressed, and the level of comprehensive management of jurisdictions varies. Therefore, it is of great practical importance to evaluate the selection of reliable fire detector types for each type of component, to determine the probability of real fires, to quantify the level of comprehensive management in the jurisdictions to give improvement plans, and to give maintenance advice on component management.

1.2. Presentation of the Problem

The data used in this paper are presented in: annex 1 (alarm dataset); annex 2 (fault dataset); annex 3 (test data); and annex 4 (fire alarm system background information). Combining the data, the problem to be solved is as follows.

(1) Analyze the alarm data set to establish the true number of fires; combine the fault data set and Figure 1 to create a correlation model to evaluate each type of component and select a reliable type of fire detector.

(2) Based on the conclusion of the data in question one, an intelligent research model is established to determine the correctness of the alarm information, evaluate the authenticity of the test data, and determine the true fire probability.

(3) Based on the results of the above questions and combined with Table 1, a model was developed to analyze the comprehensive management level of each fire brigade and to quantify the technical indicators of the three jurisdictions with the lowest management level and give the corresponding improvement plan.

(4) Review the relevant literature in conjunction with the model obtained from the above problem, analyze the model results, and make targeted suggestions for the management and maintenance of each component of the fire alarm system.

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2. ANALYSIS OF THE PROBLEM

2.1. Analysis of Question One

Problem 1 requires analysis of the alarm data set to establish the true number of fires; combined with some of the components in Annex 1 and Figure 1 after model screening, a relevant model is built to evaluate each type of component and select a reliable type of fire detector. In this paper, we first perform data cleaning to eliminate the missing alarm data, screen the real alarm information, compare whether it is the same alarm information, and establish the final real number of fires. Subsequently, a TOPSIS evaluation model is established based on the metrics given in the topic. To ensure the accuracy of the model, this paper decided to use multiple assignment methods to assign weights to the indicators and use the game theory comprehensive assignment model to determine the comprehensive weights. Finally, the TOPSIS evaluation model is used to evaluate each type of component and select the type of fire detector that is more reliable and has a low error reporting rate.

2.2. Analysis of Question Two

Question 2 requires an intelligent research model based on the data findings of question 1 to determine the correctness of the alarm information, evaluate the authenticity of the test data, and determine the true fire probability. Firstly, data cleaning is performed on the data results of problem one to reselect indicators and eliminate irrelevant data to get the data required for this problem. Secondly, multiple prediction models are built and the sample data are trained separately using machine learning, and the prediction algorithm with the highest accuracy is used by comparing the results of the data obtained. Then this model is used to perform target prediction and authenticity evaluation of the data in Annex 3 in order to determine the probability that each alarm signal in Annex 3 is a real fire.

2.3. Analysis of Question 3

Question 3 requires an evaluation model based on the results of the above questions and combined with Table 1 to analyze the comprehensive management level of each fire brigade and to quantify the technical indicators of the three jurisdictions with the lowest management level and give the corresponding improvement plan. In this paper, we first process the data and reselect the indicators. Subsequently, weights are obtained using relevant algorithms to establish an evaluation model. Finally, the established evaluation model is used to score the evaluation of the comprehensive management level of each fire brigade.

2.4. Analysis of Question 4

This paper first describes the model used in the first three questions and analyzes the model results, and then proposes feasible solutions and suggestions in three aspects: reasonable selection of fire detectors, improving the authenticity of alarm signals and effectively improving the comprehensive management of fire brigades. Finally, it is explained that the fire alarm system has the great significance of timely maintenance and management to detect fire, control fire and protect life and property in a more timely manner.

3. BASIC ASSUMPTIONS

1. The number of fires in 2022 by month and the trends are similar to those in 2021.
2. The detector is properly installed and meets the standard assumptions.
3. There are no production quality issues with the detectors.

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4. DESCRIPTION OF SYMBOLS

Table 1. Illustrate

symbolic	Symbol Description	Symbolic unit
H_j	information entropy	
d_i^+	positive ideal solution	
d_i^-	negative ideal solution	
S_i	coefficient of variation	
S_j	volatility	

5. DATA PROCESSING

5.1. Data Pre-processing

5.1.1 Data cleaning

In order to fully and concisely reflect the valid information of the data, this paper pre-processes the data indicators in Annex 1. First, using the filtering function of the EXCEL table, each column of data was ranked for missing data, and finally it was found that there were a few cases of missing data for the machine number, loop number and address indicators, and the sample machine numbers with missing loop numbers and addresses were missing, so the alarm data of the missing machine numbers were retrieved, and the comparison revealed that the alarm data of the missing machine numbers were all false alarms, which were not related to the real number of fires we were seeking, so the the missing values were removed. After eliminating a small amount of data, again using an EXCEL sheet, a total of 499 alarms that were not false alarms were filtered out. These data were then compared and analyzed to see if the codes for address, machine number, and loop were the same. If the same, these alarm data were identified as the same fire alarm message; otherwise, they were different fire alarm messages. Meanwhile, if the data A and B are the same fire alarm message and the number of alarms of A is more than that of B, the number of alarms of A is taken. Finally, this paper concludes that the real number of fires in the city from June 1 to June 18 is 440, and the number of fires in some brigade areas is as follows.

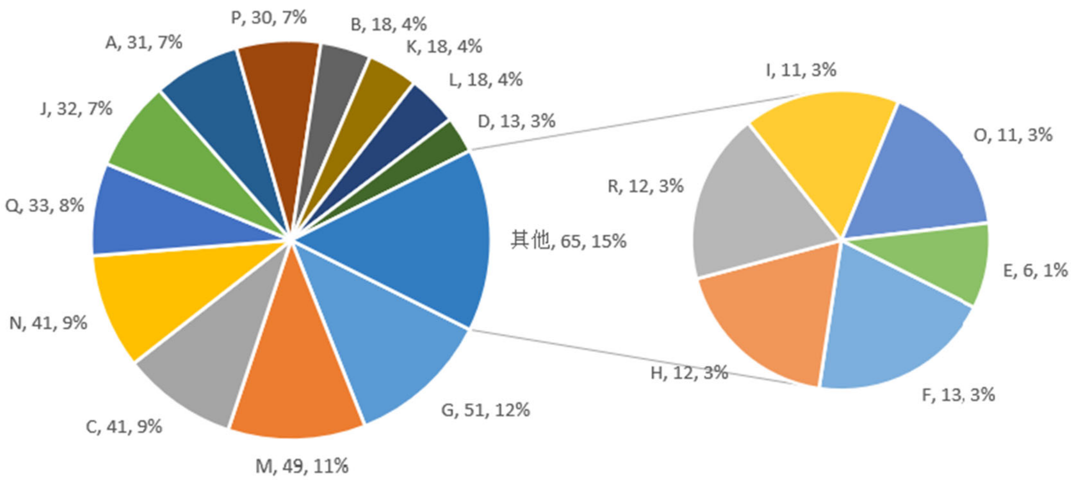

Figure 1. Number of fires in each brigade area

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The labels of the different colored sectors in the above chart indicate the number of fires in a brigade's area from June 1 to June 18, as a percentage of the total number of fires. For example, the orange sector "M, 49, 11%" at the bottom of the graph indicates that the number of fires in the area of Brigade M from June 1 to June 18 was 49, or 11% of the total number of fires.

5.2. Selection of Indicators

According to the review of relevant literature, it is known that the major fire brigades correspond to the corresponding regions, and there are certain differences in the types of regions, such as plains and mountains, etc. The different types of regions also have a certain impact on the performance of detectors. And considering that the sensitivity of the detector determines the sensitivity of the response to fire characteristics, too high sensitivity will lead to the reduction of alarm reliability, while higher reliability requires sacrificing the sensitivity of the detector. Therefore, the sensitivity and reliability of the detector become the key parameters that need to be balanced, and the false alarm rate can better reflect the reliability of the detector. Comprehensive analysis of the above, this paper selects the frequency of component use, the number of alarms per square kilometer, the false alarm rate and the failure rate as evaluation indexes to build the evaluation model [2].

5.3. Weighting of Indicators

5.3.1 CRITIC Empowerment Method

step1: Obtain the data. Suppose a set of data is available, with m objects to be evaluated and n evaluation indicators, forming the original data matrix X :

$$X=\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{1}$$

step2:Data standardization. The main purpose of data standardization is to eliminate the effects of dimensionality so that the data can be measured with a uniform standard.

For positive indicators.

$$x_{ij}'=\frac{x_j-x_{\min}}{x_{\max}-x_{\min}} \tag{2}$$

step3:Calculate the information carrying capacity. C_j is the amount of information, A_j is the conflictiveness, and S_j is the volatility.

$$C_j=S_j\times A_j \tag{3}$$

step4:Calculate the weights.

$$W_j=\frac{c_j}{\sum_{j=1}^{n}C_j} \tag{4}$$

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Based on the above methodology, the weights of the following indicators were obtained in this paper, as shown in the following table.

Table 2. Weights obtained from the CRITIC assignment method

targets	weights
Number of alarms per square kilometre	0.197
frequency of use	0.269
False alarm rate	0.192
failure rate	0.342

5.3.2 Entropy method of assignment

In order to be able to accurately judge the orderliness and the utility of information in information system, this paper negatively deals with information entropy to obtain information. For the evaluation system determined in this paper, the information entropy of an indicator is positively correlated with the value of its information, i.e., the lower the information entropy of an indicator, the smaller the indicator is given a smaller indicator weight; and vice versa.

step1: It may be assumed that the sample distribution has no effect on the model. Let the initial series of each indicator be denoted as x_i , and after the forward normalization process be denoted as y_i

step2: Calculate the weight of the j indicator among the i suppliers p_{ij} with the indicator entropy value H_j

$$p_{ij}=\frac{x_{ij}}{\sum_{i=1}^{m}x_{ij}},0\leqslant p_{ij}\leqslant 1 \tag{5}$$

$$H_j=-\frac{1}{\ln m}\sum_{i=1}^{m}(p_{ij}\cdot\ln p_{ij}),0\leqslant H_j\leqslant 1 \tag{6}$$

step3: And the utility of the first j indicator can be measured by the information entropy H_j. In this paper, the coefficient of variation g_j is derived by calculating the difference between the information entropy H_j and 1 by negativizing the information entropy :

$$g_j=1-H_j \tag{7}$$

step4: Once the coefficient of variation is obtained, the weight of each indicator, i.e. the weight of the coefficient of variation of each indicator in the sum of the coefficients of variation, can be obtained. The weight of the indicator ω_{j1} for item j can be expressed as follows.

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$$w_{j1} = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{8}$$

The above is the principle of the entropy weight method. In this paper, the weights of each of the above four indicators are determined using the entropy weighting method, and then multiplied by the corresponding entropy weighting method weights respectively, and then weighted and normalized to obtain the total comprehensive evaluation score, which is recorded as the weighting sought by the entropy weighting method, as shown in the following table.

Table 3. Weights obtained by entropy weighting method

targets	weights
Number of alarms per square kilometre	0.242
frequency of use	0.228
False alarm rate	0.247
failure rate	0.283

5.3.3 Coefficient of variation method for determining weights

Again, this paper assumes that the sample distribution does not affect the model effect. The standard deviation of the normalized data is first calculated σ_i and the mean $\overline{X_i}$, followed by the coefficient of variation for each indicator S_i.

$$S_i = \frac{\sigma_i}{\overline{X_i}} \tag{9}$$

Finally, the weight of each indicator is derived from the ratio of the coefficient of variation to the total coefficient of variation ω_{j2} :

$$\omega_{j2} = \frac{s_i}{\sum_{i=1}^{n} S_i} \tag{10}$$

Therefore, the following weights for the indicators were obtained in this paper, as shown in the following table.

Table 4. Coefficient of variation method for determining weights

targets	weights
Number of alarms per square kilometre	0.243
frequency of use	0.231
False alarm rate	0.247
failure rate	0.279

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5.3.4 Game theory integrated empowerment method

Game theory integrated assignment weighting method is an algorithm that combines all the weights linearly in order to facilitate obtaining equilibrium weights. The kernel of the operation is to use multiple assignment methods to find the weights, combine them into a weight vector set, and use the basis vectors within the weight vector set to solve for the optimal vector set as the optimal weights.

step1: In this paper, three different weight regrouping methods have been used to derive three different weight regrouping. Namely, $\omega_k = (\omega_{k1}, \omega_{k2}, ..., \omega_{kn}), k = 1, 2, 3$,using these two weight regroups to construct a basis vector group of vector space.

$$\omega = \{\omega_1, \omega_2, ..., \omega_3\} \tag{11}$$

Naturally, the full vector space consists of any combination of the weight vectors in ω .

$$\omega = \sum_{k=1}^{3} \alpha_k \omega_k^T \, (\alpha_k > 0) \tag{12}$$

In the above equation α_k is the weight coefficients and ω is the set of vectors consisting of linear combinations of basis vectors.

step2: In order to determine the optimal set of vectors ω^* , the deviation of the vector set from each ω_k must satisfy the minimization.

$$\min \left\| \sum_{k=1}^{3} \alpha_k \omega_j^T - \omega_i^T \right\|_2 (i = 1, 2, 3) \tag{13}$$

Differentiating the matrix, it is not difficult to find the optimal solution form of the above equation, i.e.

$$\sum_{j=1}^{3} \alpha_j \omega_i \omega_j^T = \omega_i \omega_j^T \, (i = 1, 2, 3) \tag{14}$$

Corresponding linear system of equations.

$$\begin{bmatrix} \omega_1 \cdot \omega_1^T & \omega_1 \cdot \omega_2^T & \omega_1 \cdot \omega_3^T \\ \omega_2 \cdot \omega_1^T & \omega_2 \cdot \omega_2^T & \omega_2 \cdot \omega_3^T \\ \omega_3 \cdot \omega_1^T & \omega_3 \cdot \omega_2^T & \omega_3 \cdot \omega_3^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} \omega_1 \cdot \omega_1^T \\ \omega_2 \cdot \omega_2^T \\ \omega_3 \cdot \omega_3^T \end{bmatrix} \tag{15}$$

Solve for the weighting factors and normalize the scaling factors to.

$$\alpha^* = \frac{\alpha_K}{\sum_{k=1}^{3} \alpha_K} \tag{16}$$

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step3: Finalize the combination weights.

$$\omega^* = \sum_{k=1}^{3} \alpha^* \omega_k^T \tag{17}$$

The weights calculated by the entropy weighting method, coefficient of variation evaluation method and hierarchical analysis method used in the previous section were substituted into the game theory integrated weighting model to obtain the integrated weights as shown in the following table.

Table 5. Game theory integrated assignment method to determine weights

targets	weights
Number of alarms per square kilometre	0.227
frequency of use	0.243
False alarm rate	0.229
failure rate	0.301

The weights of the two indicators were derived using a game theoretic combined weighting model, which indicates the magnitude of the influence of the indicator on the dependent variable, i.e., the indicator with the higher combined weight has a greater effect on forest cover and vice versa.

5.4. TOPSIS Evaluation Modeling

The TOPSI S algorithm is a comprehensive evaluation method that can make full use of the information in the raw data and the results can accurately reflect the gap between the evaluation options. In this paper, the original data matrix is unified by the minimal algorithm to obtain the normalization matrix, and then the normalization matrix is normalized to eliminate the influence of each indicator scale, and finds the best and worst solutions among the finite solutions, and then calculates the distance between each evaluation object and the best and worst solutions respectively to obtain the relative proximity of each evaluation object and the best solution, which is used as the basis of evaluation. The distance between each evaluation object and the optimal solution and the worst solution are calculated separately, and the relative proximity of each evaluation object to the optimal solution is obtained, which is used as the basis for evaluating the superiority and inferiority.

Step1.

Using the normalized decision matrix $B=(Y_{ij})_{m\times n}$ and the weight vector $W=(W_1, W_2, \cdots, W_n)$, the normalized matrix $R=(r_{ij})_{m\times n}=(W_j Y_{ij})_{m\times n}$ is obtained after a weighted average.

Step2: Let the ideal solution vector S^+ and the negative ideal solution vector S^- :

$$\begin{aligned} S^+ &= \{r_j^+\}\,(j=1,2,\cdots,n) \\ S^- &= \{r_j^-\}\,(j=1,2,\cdots,n) \end{aligned} \tag{18}$$

式中$r_j^+ = \max(r_{1j}, r_{2j}, \cdots, r_{mj})$， $r^- = \min(r_{1j}, r_{2j}, \cdots, r_{mj})$

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Step3: Calculate the distance between the evaluated object of this paper to the ideal solution and the negative ideal solution by d_i^+ and d_i^-. The equations are as follows.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (r_{ij} - r_i^+)^2} \quad (i = 1, 2, \cdots, m)$$
$$d_i^- = \sqrt{\sum_{j=1}^{n} (r_{ij} - r_i^-)^2} \quad (i = 1, 2, \cdots, m) \tag{19}$$

Step4: Calculate the distance between the value vector of the evaluated object indicator and the ideal solution.

$$C_i = \frac{100 \times d_i}{d_i^+ + d_i^-} \tag{20}$$

5.5. Solving the Evaluation Model

Once the weights of the indicators are obtained in this paper, the evaluation model for the stability of each detector type can be constructed using MATLAB software.

Step1: Standardization of indicator data, here in this paper we want to evaluate the indicators as large as possible, using positive evaluation indicators, applying the above formula and MATLAB programming for standardization, the results are shown in Table.

Table 6. Standardization results

Part Name	Number of alarms per square kilometre	frequency of use	False alarm rate	failure rate
Spot smoke detectors	0.24589	0.26586	0.26145	0.26562
Linear beam smoke detectors	0.24847	0.26586	0.27266	0.18031
Gas detectors	0.24914	0.26590	0.26705	0.29344
Pressure switches	0.25264	0.26592	0.26145	0.29807
Spot type temperature sensor	0.25668	0.26624	0.27224	0.00000
Composite detector	0.25992	0.26593	0.27266	0.29344
Intelligent photoelectric probe	0.25992	0.26593	0.27266	0.29344
fire hydrant	0.26222	0.26586	0.27266	0.25635
Spot temperature smoke	0.26520	0.26656	0.25727	0.19231
Manual alarm button	0.27164	0.23345	0.25256	0.27443
flame detector	0.27276	0.19419	0.25911	0.29344
Smart Photoelectric Detector	0.27396	0.26588	0.27266	0.29807
Dim Mak	0.28417	0.24195	0.23989	0.19626
Signal Valves	0.28806	0.26619	0.26612	0.29807
intelligent temperature sensing	0.15760	0.00000	0.14376	0.16589
Light beam smoke detection	0.00000	0.26619	0.00000	0.20476

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Step2: Determine the positive ideal solution and negative ideal solution and the results are shown in the table.

Table 7. Positive and negative ideal solutions

item	positive ideal solution	negative ideal solution
Number of alarms per square kilometre	0.28805175	0.00009996
frequency of use	0.2665552	0.00009996
False alarm rate	0.27265395	0.00009996
failure rate	0.2980603	0.00009996

Step3: Calculate the composite score by combining the above formula to calculate the distance between each type of detector and the positive ideal solution and the negative ideal solution, and then calculate the composite score for each type of detector according to the formula, and the results are shown in the table.

Table 8. Positive and negative ideal solution distances and combined scores for each detector

Part Name	Positive ideal solution distance (D+)	Negative ideal distance (D-)	Composite score index
Spot smoke detectors	0.02755	0.25989	0.90416
Linear beam smoke detectors	0.06557	0.24203	0.78684
Gas detectors	0.01950	0.27031	0.93271
Pressure switches	0.01829	0.27118	0.93681
Spot type temperature sensor	0.15922	0.22447	0.58503
Composite detector	0.01406	0.27412	0.95121
Intelligent photoelectric probe	0.01406	0.27412	0.95121
fire hydrant	0.02557	0.26394	0.91169
Spot temperature smoke	0.05785	0.24494	0.80895
Manual alarm button	0.02393	0.25942	0.91554
flame detector	0.03607	0.25980	0.87808
Smart Photoelectric Detector	0.00694	0.27879	0.97571
Dim Mak	0.05776	0.24075	0.80650
Signal Valves	0.00326	0.28073	0.98854
intelligent temperature sensing	0.17130	0.13743	0.44515
Light beam smoke detection	0.20220	0.16731	0.45279

Based on the above combined score ranking and bar graphs, the bars are as follows.

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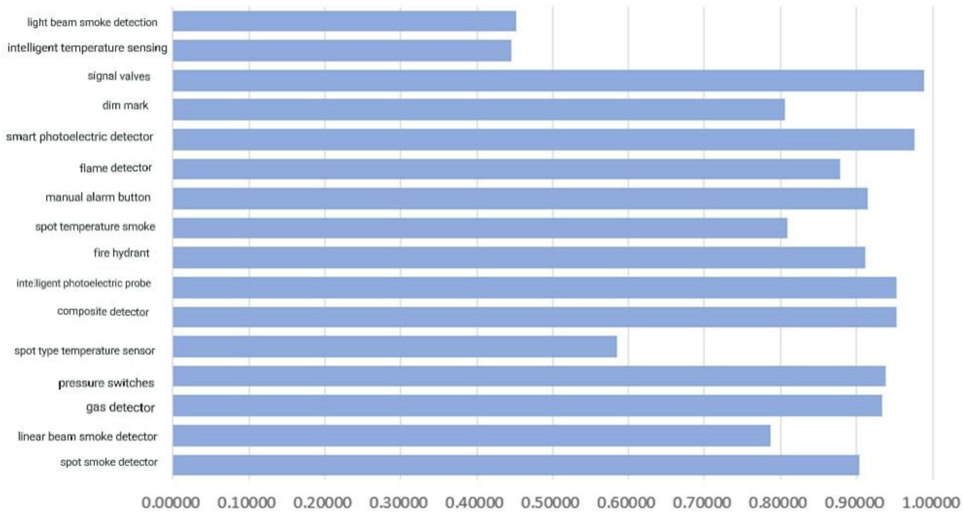

Figure 2. Combined score for each detector type

Based on the analysis of the evaluation results, it can be seen that several detectors are close to each other. Among them, the signal valve detector has the highest comprehensive score of 0.98854, which indicates that the reliability and failure rate of this detector is higher compared to other types of detectors, followed by the intelligent photoelectric detector with a score of 0.97571. Therefore, the optimal detector is the signal valve detector.

6. MACHINE LEARNING BASED MODEL BUILDING

6.1. Data Pre-processing

6.1.1 Data cleaning

Based on the data findings of problem one, this paper ranked the comprehensive score of each type of detector in descending order and ordered the detector score indicator instead of the component name indicator; secondly, this paper considered that the number of fires as a percentage and the cumulative percentage of the number of fires are duplicated with the meaning of the number of fires, so they were deleted. Using MATLAB machine learning toolbox for feature selection of the eight indicators, the selection results are as follows.

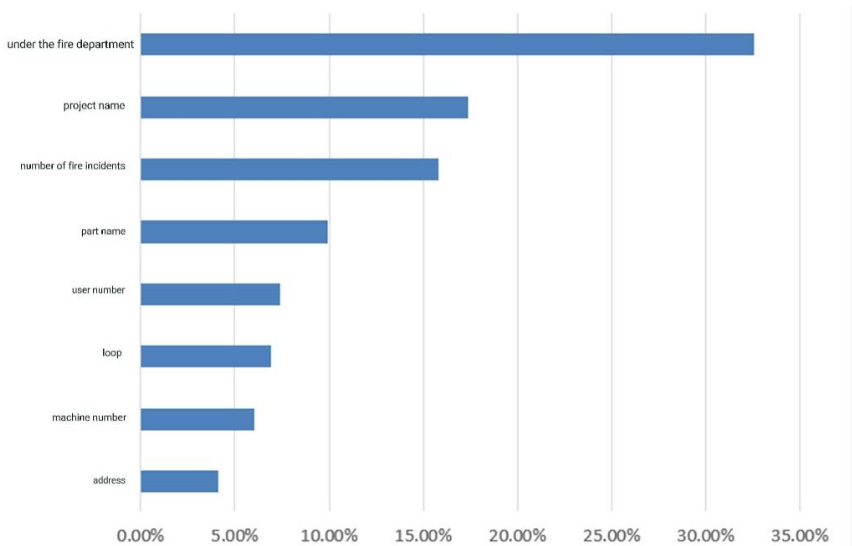

Figure 3. Feature Selection Sorting

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According to the above figure in this paper, we found that the indicators of affiliation with the fire agency accounted for the largest proportion, the project name, the number of fires and component name indicators accounted for a larger proportion, the remaining indicators are not significantly different, that is, the user number, loop, address and machine number indicators are considered to be of low importance and are irrelevant indicators, which do not affect the processing of the model below, so irrelevant indicators and related data are excluded, and the remaining data are required for this question [3].

6.2. Model building with RUSBoost Algorithm as The Core

RUSBoost is an algorithm for unbalanced data and a hybrid algorithm that combines Boosting and undersampling methods. This algorithm is each iteration of the Adaboost.M2 algorithm uses the RUS method to extract the training dataset for weak classifier training before training the weak classifier.The RUS method refers to random undersampling where a certain amount of majority class samples and few classes are randomly selected from the dataset to form a balanced distribution of the training dataset. All samples are set with normalized sample weights $D(i)$

Step1: $for\ t=1,2,\cdots,T$.

A certain number of randomly selected majority class samples, and all minority classes form the training dataset S, and the weights of the samples in S SD,will be normalized to SD .

Step2: Using the training dataset S, a weak classifier $h(t)$ is trained based on the weights SD, and the output of $h(t)$ is the probability of awarding two classes , which class is awarded with high probability in the final decision. Let the probability of $h(t)$ judging the first i sample as the actual class of the sample be P_1（i）, and the probability of judging the opposite class of the sample as the actual class be P_2（i）.

Step3: Let have the probability that the $h(t)$ i th sample is judged to be the actual category of the sample as P_1（i） and the probability that it is judged to be the opposite category of the actual category of the sample as P_2（i）. Calculate the error e .

$$e=\sum D（i）\times[1-P_1(i)+P_2(i)] \tag{21}$$

The summation formula here is only for the misclassified sample.

$$a(t)=\frac{e}{1-e} \tag{22}$$

Step4: Update the weights and normalize them.

$$D（i）=D(i)\times a(t)^{\frac{1}{2}[1+P_1(i)-P_2(i)]} \tag{23}$$

Step5: Output integrated classifier

$$H=\sum h(t)\times\log\left(\frac{1}{a(t)}\right) \tag{24}$$

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6.2.1 Random Forest Modeling

Random forest is a parallel integrated learning method based on Bagging strategy. It obtains N different training sets by N random sampling, and trains the corresponding base learners based on each training set, and finally integrates the output of the above N base learners by voting or averaging.

Set $H(x)=\frac{1}{k}\sum_{i=1}^{k}h_i(x)$ to be the regression model results for a single decision tree, and $\{h(X,\theta_i), i=1,2,\dots,k\}$ to be the predicted value of the random forest regression obtained by averaging the regression results of k decision trees, i.e.:

$$H(x)=\frac{1}{k}\sum_{i=1}^{k}h_i(x) \tag{25}$$

where $H(x)$ denotes the result of the combined classification model.

6.2.2 Modeling of the Adaboost algorithm

AdaBoost is an iterative algorithm whose core idea is to train different classifiers, i.e., weak classifiers, for the same training set and then to aggregate these weak classifiers to construct a stronger final classifier.

Each iteration of the algorithm produces a weak learner h_j, the performance of h_j is determined by the training error rate ε_j, the lower the training error rate means the better the classification effect, so its weight coefficient ∂_j will also be higher, the principle of ∂_j is selected so that the loss function of the weak learner on the training samples is minimized in each round, the loss function of Adaboost is an exponential function defined as:

$$F(\partial)=\sum_{i=1}^{m}\exp\{-y_i(\partial h_j(x_i))+y_i\sum_{\gamma=1}^{j-1}\partial_\gamma h_\gamma(x_i)\} \tag{26}$$

Accordingly, the weights for each round can be obtained from ∂_j, and the training sample weights are updated according to ∂_j.

6.3. Solving the Prediction Model

In this paper, three algorithms were chosen to build the prediction model for Annex 1 (test data), where it is easy to find that Annex 1 (alarm data set) has three indicator variables, namely "Yes (True)", "No (False)" and "No, one of them was a real fire (False, one of them was a real fire)". The number of samples with "Yes (True)" is much more than the number of samples with the other two items. Therefore, although the random forest algorithm and adaboost algorithm in this paper can predict the number of samples with "Yes (True)" more accurately, they are weak in dealing with the problem of sample imbalance. Our RUSboosted algorithm is more accurate in predicting the number of samples with less data than other algorithms in solving the sample imbalance problem.

Step1: Use RUSboosted to make predictions on the Annex 1 data and verify the correctness of the predictions against the original data. The confusion matrix obtained is shown in the figure.

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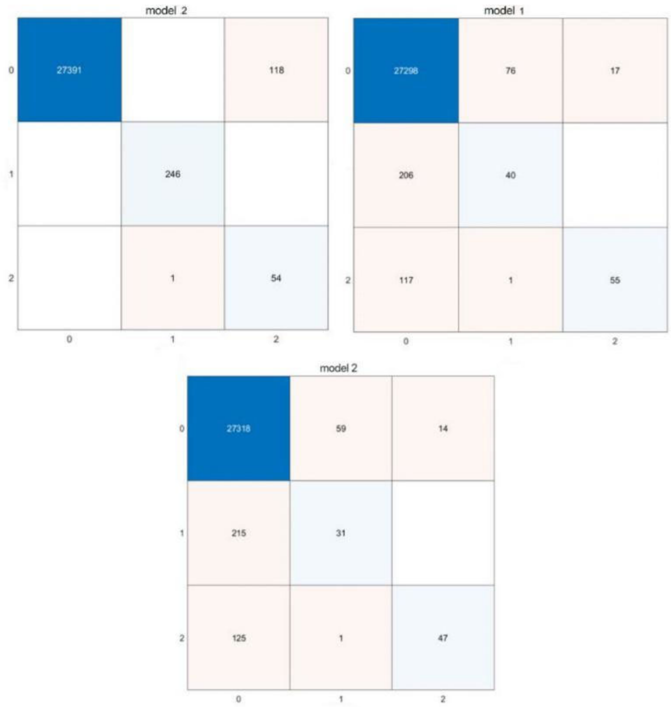

Figure 4. RUSBoost algorithm, Random Forest algorithm, Adaboost algorithm confusion matrix

where 0, 1 and 2 stand for "Yes (True)", "No, one of them was a real fire (False, one of them was a real fire)" and "No (False)". From the figure, it can be seen that only 118 samples with a prediction result of 0 are predicted incorrectly, which does not have much influence on the final prediction compared to the 27391 samples that are predicted correctly. Therefore, this paper considers that the RUSboost model is successfully established. The confusion matrix derived using the random forest algorithm is significantly less effective than the RUSboost algorithm in predicting the categories "1" and "2".

Step2: We use MTALAB software to derive the ROC curves for the three prediction models.

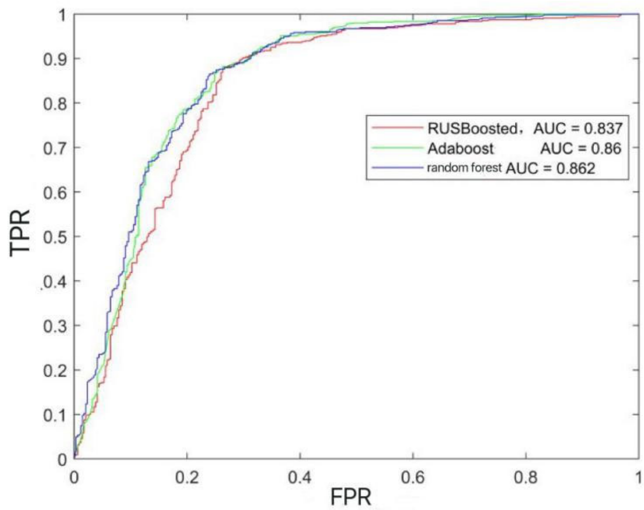

Figure 5. ROC curves for the three prediction models

In this paper, we can see that the curve represented by Random Forest is closest to the upper left corner of the plane, while the curves represented by RUSboost and Adaboost are entangled

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with each other and located at the lower right. The calculated AUC values are 0.837, 0.860, and 0.862, respectively, which shows that the line random forest works best. However, since RUSBoost is better at dealing with sample imbalance, it has better results in predicting data with relatively small samples compared to the other two algorithms. Therefore, RUSBoost algorithm is selected as the prediction model.

Step3: The same performance evaluation metrics for multiple classifications are measured by calculating F1 scores.

Table 9. F1 scores obtained by RUSboost algorithm

name	Classes			macroAVG	microAVG
TP	23123	246	173	7847.3300	7847.3333
FP	0	3304	964	1422.6600	1422.6667
TN	4268	0	0	1422.6600	1422.6667
FN	419	24260	26673	17117.3300	17117.3333
tracking accuracy	1	0.0693	0.1522	0.8072	0.8465
survey completion rate	0.8442	1	1	0.9481	0.8465
idiosyncrasy	1	0.8801	0.9651	0.9484	0.9233
Classification accuracy	0.8465	0.8465	0.8465	0.8465	0.8465
F1 score	0.9155	0.1296	0.2641	0.8364	0.8465

In the prediction of the multiclassification model, we introduced the concepts of macroAVG macro-averaging and microAVG micro-averaging, and the values of both types of F1 scores can be calculated to be closer to 1, further confirming the correctness of the model selection in this paper.

Step4: Determine the probability of each alarm signal in Annex 3 being a real fire by RUSboost.

Table 10. Probability of whether a real fire occurred in each brigade

Attached to the firefighting agency	0	1	Attached to the firefighting agency	0	1
G Brigade	0.5833	0.4167	M Brigade	0.8414	0.1586
J Brigade	0.7254	0.2746	P Brigade	0.8854	0.1146
N Brigade	0.6758	0.3242	Brigade A	0.8787	0.1213
H Brigade	0.5799	0.4201	Brigade B	0.6112	0.3888
Q Brigade	0.1772	0.8228	E Brigade	0.8707	0.1293
Brigade C	0.8787	0.1213	F Brigade	0.8667	0.1333
L Brigade	0.6982	0.3018	I Brigade	0.6884	0.3116
Brigade D	0.6653	0.3347			

In the table, 0 represents the probability of no fire and 1 represents the probability of a fire.

Based on the data in the table we can conclude that the probability of fire in the areas under the jurisdiction of brigades J, N, C, D, M, P, A, B, E, F, and I is greater, while the probability of fire in the areas under the jurisdiction of brigade Q is smaller, and the probability of whether fires occur in the areas under the jurisdiction of brigades G and H is not very different, which indicates that we need to increase fire control in the areas under the jurisdiction of brigades J, N, C, D, M, P, A, B, E, F, and I in order to reduce the probability of fire in these areas. This suggests

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that we need to increase fire control in the areas under the jurisdiction of J, N, C, D, M, P, A, B, E, F, and I brigades in order to reduce the probability of fire in these areas.

7. RE-APPLICATION OF THE EVALUATION MODEL

7.1. Indicator Selection and Data Processing

In question 1, the number of fire occurrences in each jurisdiction has been obtained in this paper, in order to further evaluate the comprehensive management level of each fire brigade in the city, this paper needs to reassess the value of indicators and select indicators in order to establish an evaluation model. According to the area of each brigade, the number of fires, false alarm rate and failure rate can be derived from the number of fires per square kilometer, false alarm rate and failure rate respectively, that is, the average false alarm rate and failure rate of the components used by each brigade divided by the area of the jurisdiction, which can effectively avoid the influence of the area of the jurisdiction on the evaluation results; based on the results of problem two, it can be seen that some fire brigades have adopted more reliable detectors alarm may not be accurate In order to solve this problem, this paper selects the average component score index, that is, for each fire brigade jurisdiction, all the components used are averaged to obtain a comprehensive component score. With the above four indicators to establish a comprehensive management level evaluation model, the data and indicators after processing are as follows.

Table 11. Results of the treatment of indicators

Attached to the firefighting agency	Combined component score	Number of fires	False alarm rate	failure rate
Brigade A	0.6	0.1	4503.9	35605.2
Brigade B	0.7	0.1	34036.5	375786.1
Brigade C	0.6	0.1	8489.1	604587.5
Brigade D	0.6	0.1	1623.6	80780.1
E Brigade	0.6	0.1	6006.2	109403.1
F Brigade	0.6	0.1	4095.0	210683.1
G Brigade	0.7	0.4	1128908.6	10505919.9
H Brigade	0.6	0.1	10203.5	1359174.8
I Brigade	0.7	0.1	3239559.2	268904.3
J Brigade	0.8	0.6	260336.8	31484474.8
K Brigade	0.7	0.1	2044.3	33098.9
L Brigade	0.7	0.1	4187.7	186373.0
M Brigade	0.6	0.1	15930.1	645853.0
N Brigade	0.7	0.2	66348.6	2737692.0
Brigade O	0.7	0.1	7126.6	104046.9
P Brigade	0.7	1.3	175925.9	5830729.2
Q Brigade	0.7	0.1	1950.0	173832.8
R Brigade	0.6	0.9	55733.6	409188.0

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The data units under the false alarm rate and failure rate indicators in the above table are both "$/(one\ million\ hours \cdot square\ kilometers)$" and under the number of fires occurring indicator. The highest number of fires per square kilometre was 1.3 for P Brigade, the highest false alarm rate was 3239559.2 per million hours for I Brigade, and the highest failure rate was 268904.3 per million hours for J Brigade.

7.2. Entropy Method Weights

In this question we use the entropy weighting method already used in problem one to assign weights to each of these four indicators. The weights can be calculated directly from the step-by-step characteristics of the entropy weighting method, and the weights are shown in the following table.

Table 12. Weights obtained from the entropy weighting method

targets	weights
Average rating using detectors	0.450
Number of fires per square kilometre	0.230
False alarm rate	0.159
failure rate	0.160

7.3. TOPSIS Evaluation Model Reapplication

Since the TOPSIS model has the feature of accurately reflecting the gap between each evaluation program . Therefore, the TOPSIS model was also used to evaluate the comprehensive management level of each fire brigade in this question, and the results are presented in the following table.

Table 13. Overall management level scores for each consumption brigade

Attached to the firefighting agency	Positive ideal solution distance (D+)	Negative ideal distance (D-)	Composite score index	sorted
Brigade A	0.2314	0.2132	0.4796	10
Brigade B	0.1908	0.2333	0.5501	8
Brigade C	0.2392	0.2077	0.4648	12
Brigade D	0.2405	0.2099	0.4660	11
E Brigade	0.2451	0.2074	0.4583	13
F Brigade	0.3286	0.1902	0.3666	18
G Brigade	0.1835	0.2014	0.5232	9
H Brigade	0.2436	0.2056	0.4578	14
I Brigade	0.1808	0.2352	0.5654	5
J Brigade	0.1157	0.3485	0.7508	2
K Brigade	0.0508	0.3367	0.8689	1
L Brigade	0.1066	0.2922	0.7328	3
M Brigade	0.2820	0.1938	0.4073	16
N Brigade	0.1804	0.2294	0.5597	7
Brigade O	0.1467	0.2625	0.6415	4
P Brigade	0.2388	0.1787	0.4280	15
Q Brigade	0.1860	0.2374	0.5608	6
R Brigade	0.2659	0.1645	0.3821	17

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According to the above table it can be seen that K Fire Brigade has a higher rating of 0.8689 and F, R and M Fire Brigade have lower ratings of 0.3666, 0.3821 and 0.4073 respectively, this paper concludes that F, R and M Fire Brigade have a low level of comprehensive management. The data for each indicator after processing were standardized and the line statistical graphs were drawn as follows.

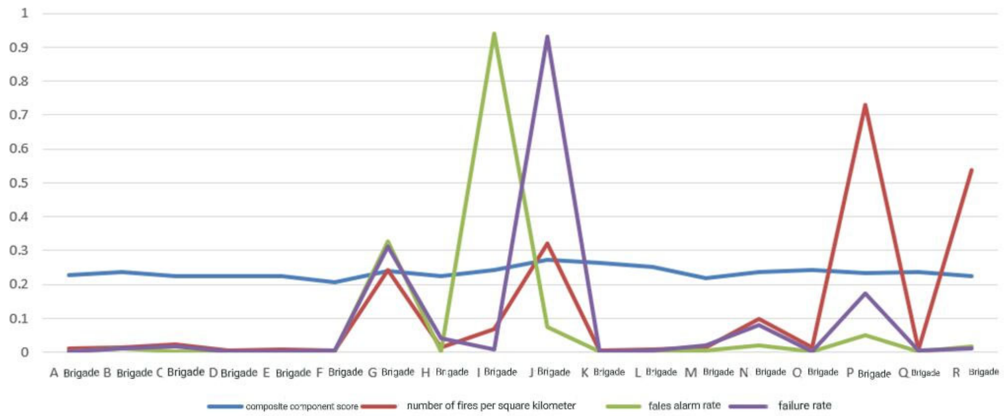

Figure 6. Level of integrated fire brigade management

The graph observes that the false alarm rate is higher in G and I brigades, especially in I brigade, which is close to 0.95, much higher than the rest of the fire brigades; J and G brigades have relatively high failure rates; and P and R brigades have a higher number of fires per square kilometer, 0.72 and 0.55.

7.4. Improvement Programmes

According to the above chart, it is easy to find that the component scores used by F, R and M fire brigades are low among the 18 fire brigades, especially the number of fires per kilometer in F and R fire brigades is not high, and it is very easy for sudden fires to be detected in time, so proper consideration can be given to replacing some of the poorer components with more reliable components such as signal valves and intelligent photoelectric detectors. For the R brigade the number of fires per kilometer in the area is more prominent, the reason may be that the region's climate and other drier, should be appropriate to strengthen fire prevention knowledge publicity, improve the public awareness of disaster prevention.

7.5. Suggestions Related to The Management and Maintenance of The Components of The Fire Alarm System

From the models established in the first three problems, it can be seen that: the model established in problem one is an evaluation model for the type of fire detectors; the model established in problem two is a prediction model for judging the probability of real fires; the model established in problem three is an evaluation model for the comprehensive management level of each fire brigade. Analyzing the characteristics of these three models, this paper will put forward suggestions for the management and maintenance of each component of the fire alarm system from three aspects: reasonable selection of fire detectors, improving the authenticity of alarm signals and effectively improving the comprehensive management level of fire brigades .Proper selection of fire detectors is one of the most noteworthy aspects of maintaining and managing a fire alarm system. From the analysis of the data results obtained from question 1, it can be seen that the TOPSIS evaluation model scores various types of fire detectors: intelligent temperature detectors have the highest score of 1; point type smoke detectors and point type temperature detectors have much lower scores than other detectors, with scores of

0.73274 and 0.88301 respectively; the rest of the detectors have similar scores. Fire detectors are products directly related to the safety of people's lives, as the "sense organ" of the fire alarm system, and assume the role of a pioneer. In the installation environment is suitable, the alarm function is not damaged, the major fire alarm systems should give priority to highly reliable fire detectors such as intelligent temperature detectors, try to avoid the use of low reliability of fire detectors such as point smoke detectors and point type temperature detectors, for the frequent false alarms alarm, to identify the causes and to maintain and replace, to prevent paralysis. Reasonable choice of fire detectors is conducive to timely and accurate detection of fire, reducing the loss of life and property.Improving the authenticity of the alarm signals of each component is significant for managing and maintaining the fire alarm system. From the prediction results of the prediction model established in Problem 2, it can be seen that Q brigade, H brigade and G brigade have the highest authenticity of each component alarm information with 0.8228, 0.4201 and 0.4167 respectively; while P brigade, C brigade and E brigade have the lowest authenticity of each component alarm information with 0.1146, 0.1213 and 0.1293 respectively.From the prediction results, it is easy to see that each brigade's Different parts alarm authenticity varies greatly, in this case, there will be parts alarm authenticity low brigade waste time to check the authenticity of the alarm, reducing the efficiency of the fire brigade. Improving the authenticity of the alarm signal of each component is conducive to reducing the waste of unnecessary time and improving the efficiency of the fire brigade, so as to facilitate faster and more accurate police dispatch, timely suppression of fire and reduction of losses.Effectively improving the level of integrated management of fire brigades is the most practical and efficient method of change. The TOPSIS evaluation model established by question three scores each fire brigade's comprehensive management level: K fire brigade has the highest score of 0.8689; while F, R and M have lower scores of 0.3666, 0.3821 and 0.4073. there is a huge difference in the comprehensive management level of each brigade, which is not conducive to the improvement of the level of fire alarm systems in the whole city. According to the model scoring index, we can area selection specialization that is, different areas of the fire alarm system to choose the most appropriate components, the high fire-prone areas should actively carry out fire propaganda, popularize firefighting knowledge, improve the public awareness of firefighting. And the division of responsibility should be specific and strictly implemented to stimulate the awareness of staff responsibility [4].

These are the observations and recommendations related to the management and maintenance of each component of the fire alarm system in this paper.

8. MODEL EVALUATION, IMPROVEMENT AND REPLICATION

8.1. Evaluation of the Model

In question one, by assigning weights to the indicators using three different methods, followed by a comprehensive calculation of the weights using game theory, the importance of the indicators is objectively and accurately shown, and each object is evaluated and scored by the TOPSIS evaluation model, which is objective and highly accurate.

In problem 2, the models of three different algorithms are first trained on the given data using three different algorithms to measure the accuracy between the three and find the winner, which in turn predicts the results in Annex 3.

8.2. Extension of the Model

TOPSIS model has the feature of accurately reflecting the gap between each evaluation scheme. This model can find the best and worst solutions among a limited number of solutions, calculate the distance between each evaluation object and the best and worst solutions

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respectively, and obtain the relative proximity of each evaluation object to the best solution, which is used as the basis for evaluating the advantages and disadvantages.

The model is general and applicable to other evaluation type problems, this model can also be extended to other regional or national fire safety system management scoring, component reliability scoring problems.

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