World Journal of Innovation and Modern Technology, Vol. 7, Issue 2, (Apr) **2024**
ISSN 2682-5910
DOI: 10.53469/wjimt.2024.07(02).16

Research on Fire Alarm System Issues Based on Grey Theory

Fengjiao Gong[1], Yixuan Cui[2], Hang Zuo[3]

[1,2,3]School of Mathematics, Chengdu Normal University, Chengdu, Sichuan, China
[1]2894387399@qq.com, [2]1584912243@qq.com, [3]1595286958@qq.com

Abstract: ***In recent years, the fire detection and alarm industry in China has been growing rapidly. This paper provides a comprehensive evaluation of components within the fire protection system and fire organizations from the perspective of the grey theory. It also predicts the probability of real fire incidents based on alarm data from detectors. Methods: Grey comprehensive correlation is used to evaluate the components of fire detectors and fire brigades in various regions. A decision tree model is employed to analyze the alarm system. Conclusions: (1) There were a total of 497 real fire incidents, with intelligent photoelectric detectors, manual alarm buttons, and pressure switches being the top 3 rated components. (2) One data point had a 100% probability of being a "one-time fire incident," while 10 data points had a probability greater than 10% of being "one-time fire incidents." (3) The three regions with the lowest overall management level are J Brigade, H Brigade, and M Brigade.***

Keywords: Fire detection and alarm system; Grey comprehensive correlation; Decision tree model.

1. INTRODUCTION

Since the 1990s, China's fire detection and alarm industry has experienced rapid growth, with numerous companies engaged in the production of fire-related products, resulting in a production value of several billion. The fire alarm industry has become an essential part of China's high-tech industry. Sousa Tomé Emanuel and others [1] proposed a smoke sensor anomaly detection method based on online data-driven approaches. This method models the behavior of these systems over time and detects abnormal patterns that may indicate potential faults. Junyan Tian and colleagues [2] established a comprehensive evaluation model based on entropy weighting to score various key components, identifying the two most reliable components of the fire alarm system: intelligent photoelectric detectors and manual alarm buttons. Andreev A and others [3] assessed the prospects of fire alarm systems based on neural network principles. Klimczak Tomasz and others [4] provided an overview of issues related to electronic fire alarm systems (FAS). Abdusalomov Akmalbek Bobomirzaevich and others [5] introduced the development of a vision-based early flame recognition and notification method using artificial intelligence to assist visually impaired individuals. He Xi and colleagues [6] conducted a comprehensive review of the latest advancements in intelligent FAS, summarizing their operation principles, mainstream manufacturing methods, and addressing challenges and future research directions. Xia Li and others [7] conducted research on improving the accuracy of various components of fire warning systems. Li Mengjie and others [8] compared the CART and ID3 algorithms using C4.5 to analyze the accuracy of multi-sensor intelligent fire alarm data in terms of F1 value. Zhiyu Chen [9] evaluated the overall management level of different regions using the fuzzy comprehensive evaluation method and ranked their management scores. Paś Jacek and others [10] proposed an operation process evaluation method for civil building fire alarm systems (FAS) based on the use of analysis. Li Xiaolu and others [11] designed a new type of fire alarm using flame-retardant cellulose paper with load-bearing graphene oxide (GO) and two-dimensional titanium carbide (Ti_3C_2, MXene). Steven Heckman [12] believed that as the benefits of fire alarm systems expand, we will see improvements in reliability, signal initiation, and early warning. Gupta Surbhi and others [13] determined the reliability of fire alarm systems using algebraic logic. Jakubowski Krzysztof and others [14] discussed the impact of operating conditions on the reliability of representative fire alarm systems in selected critical infrastructure buildings (CIB). Li Hao and others [15] addressed the low detection accuracy and high false alarm rate of current intelligent camera-based fire incident alarm systems by designing a fire incident alarm system based on fuzzy recognition algorithms.

2. METHODS

2.1 Fire Detection Device Component Evaluation Model

2.1.1 Selection of Evaluation Metrics

Definition 1: $X_i = \{x_i(k)\}$, where $k = 1, 2, ..., 8$, represents the i-th alarm data, where $x_i(k)$ represents the k-th indicator of the i-th alarm data. $x_i(1)$ represents "Unit Number," $x_i(2)$ represents "Loop," $x_i(3)$ represents "Address," x_i (4) represents "Component Name," x_i (5) represents "Fire Alarm Count," x_i (6) represents "Subordinate Fire Department," x_i (7) represents "False Alarm," and x_i (8) represents "Real Fire Count."

Definition 2: $E_i = \{e_i(k)\}$, where $k = 1, 2, ..., 6$, represents the i-th fault data, where $e_i(k)$ represents the k-th indicator of the i-th fault data.

Definition 3: $X^{(k)} = \{X_i|x_i(4) = k, k = 1, 2, ..., 16\}$ represents the alarm data set for the k-th type of component, denoted as $X^{(k)} = \{X_i(k)\}$, where $X_i(k)$ represents the i-th alarm data in $X(k)$, and $|X^{(k)}|$ represents the number of elements in $X(k)$.

Definition 4: $E^{(k)} = \{E_i|e_i(4) = k, k = 1, 2, ..., 16\}$ represents the fault data set for the k-th type of component, denoted as $E^{(k)} = \{E_i^{(k)}\}$, where $E_i^{(k)}$ represents the i-th fault data in $E(k)$, and $|E(k)|$ represents the number of elements in $E(k)$.

(1) Average False Positive Rate ($AFPR$) in a Unit Time

The formula for calculating the average false positive rate ($AFPR$) for the k-th type of component is as follows:

$$AFPR_k = \frac{\sum_{i=1}^{|X^{(k)}|}\left(x_i^{(k)}(5) - x_i^{(k)}(8)\right)}{|X^{(k)}| \times t} \tag{1}$$

(2) Total Duration for t = 18-24

The total duration for June 1st to the 18th is represented by t = 18-24. This metric can describe the average false alarm rate of various components within a unit of time. It reflects the sensitivity and reliability of the components.

(3) Number of Distribution Areas

The formula for calculating the number of distribution areas (NAD_k) for the kth type of component is as follows:

$$NAD_k = \left|\{x_i^{(k)}(6)\}\right| \tag{2}$$

Where $x_i^{(k)}(6)$ represents the 6th item of the indicator $x_i^{(k)}$, which is composed of "affiliated fire departments." $|x_i^{(k)}(6)|$ represents the number of elements in $x_i^{(k)}(6)$. This metric reflects the extent of the component's distribution across various areas and to some degree, its universality and reliability.

(4) Success Alarm Rate

The formula for calculating the success alarm rate (SAR_k) for the kth type of component is as follows:

$$SAR_k = \sum_{i=1}^{|X^{(k)}|} \frac{x_i^{(k)}(8)}{x_i^{(k)}(5)} \tag{3}$$

This indicator represents the proportion of successful component alarms to the total number of alarms, reflecting the sensitivity and reliability of the component to fire signals.

(5) Successful Alarm Areas

The formula for calculating the number of successful alarm areas $NSAA_k$) for the k-th component is as follows:

$$NSAA_k = \left|\{X_i^{(k)} \mid x_i^{(k)}(7) \neq 0\}\right| \tag{4}$$

Where Ω is a subset of elements from X(k), and |Ω| is the number of elements in Ω. This indicator describes the number of areas where the component can effectively operate, to some extent reflecting the component's reliability.

(6) Unit Time Average Failure Rate

The formula for calculating the unit time average failure rate (AFR_k) for the k-th component is as follows:

$$AFR_k = \frac{\sum_{i=1}^{\left|E^{(k)}\right|} e_i^{(k)}(5)}{\left|E^{(k)}\right| \times t} \tag{5}$$

Where t has the same meaning as in formula (1), representing the total duration from June 1st to the 18th. This metric represents the number of failures of various components within a unit time and can directly reflect the failure rate.

(7) Failure Frequency Ratio

The formula for calculating the failure frequency ratio (RFT_k) for the k-th component is as follows:

$$RFT_k = \frac{AFR_k}{\sum_{i=1}^{16} AFR_i} \tag{6}$$

This metric can horizontally reflect the proportion of failures among different components, allowing for a comparison of failure rates between different components.

(8) Number of Failure Areas

The formula for calculating the number of failure areas (NFA_k) for the k-th component is as follows:

$$NFA_k = \left|\{e_i^{(k)}(6)\}\right| \tag{7}$$

Where Ψ represents the set composed of the 6th indicator "Belonging to the Fire Department," and |Ψ| represents the number of elements in that set. This indicator reflects the number of areas where the component is prone to failure, indicating the extent of the component's reliability and failure rate.

(9) Percentage of Failed Devices

The formula for calculating the percentage of failed devices (PFD_k) for the k-th component is:

$$PFD_k = \frac{|E^{(k)}|}{\sum_{i=1}^{16} |E^{(i)}|} \tag{8}$$

This metric reflects the proportion of failed devices for various components and can reflect the failure rate based on the component's performance. Using the above eight indicators, a dataset of indicators for 16 components can be constructed.

2.1.2 Gray Absolute Relevance

Definition 5: $Y_i = \{y_i(k)|k = 1, 2, ..., 8\}$ represents the dataset of "component indicators" for the i-th component, where $y_i(k)$ represents the value corresponding to the k-th indicator of the i-th component object. Specifically, $y_i(1) = AFPR_i$;$y_i(2) = NAD_i$;$y_i(3) = SAR_i$;$y_i(4) = NSAA_i$;$y_i(5) = AFR_i$;$y_i(6) = RFT_i$;$y_i(7) = NFA_i$;$y_i(8) = PFD_i$.

(1) Construct an ideal object $Y_0=\{y_0(k)|k = 1, 2, ..., 8\}$.

The ideal object is constructed from the optimal values of various indicators of existing objects, representing the best performance of various components in each indicator. Based on the definitions of the eight indicators, it can be concluded that the ideal object should take the maximum values of existing objects in "number of distribution zones," "successful alarm rate," and "number of successful alarm zones," while taking the minimum values of existing objects in other indicators. Therefore, the formula for constructing the ideal object is as follows:

$$y_0(k) = \begin{cases} \min\{y_i(k) \mid i = 1, 2, ..., 16\} & , k = 1, 5, 6, 7, 8 \\ \max\{y_i(k) \mid i = 1, 2, ..., 16\} & , k = 2, 3, 4 \end{cases} \tag{9}$$

From formula (9), we can obtain Y_0 = (0.0023, 18, 0.0833, 18, 0, 0, 0, 0).

(2) Calculate the starting zero-integrated image for each object $Y_i^{(0)}=\{y_i^{(0)}(k)|k=1,2,...,8\}$.

The formula for calculating the starting zero-integrated image is as follows:

$$y_i^{(0)}(k) = y_i(k) - y_i(1) \tag{10}$$

Where i = 0, 1, 2, ..., 16. Formula (10) provides the starting zero-integrated images for each object.

(3) Calculate the zero-integrated image integral s for each object.

The formula for calculating the zero-integrated image integral is as follows:

$$s_i = \int_1^8 y_i^{(0)}(k)\mathrm{d}k = \sum_{k=2}^{7} y_i^{(0)}(k) + \frac{1}{2}\left(y_i^{(0)}(1) + y_i^{(0)}(8)\right) \tag{11}$$

Formula (11) is used to calculate the zero-integrated image integrals for each object.

(4) Calculate the gray absolute ϵ_{0i} relevance between object Y_i and the ideal object Y_0.

The formula for calculating the gray absolute relevance between object Y_i and the ideal object Y_0 is as follows:

$$\epsilon_{0i} = \frac{1 + |s_0| + |s_i|}{1 + |s_0| + |s_i| + |s_0 - s_i|} \tag{12}$$

Formula (12) is used to calculate the gray absolute relevance between each object and the ideal object.

2.1.3 Gray Relative Relevance

The gray relative relevance is the gray absolute relevance corresponding to the initial values of various objects. It reflects the degree to which each object approaches the ideal object in terms of the rate of change from the initial point.

To calculate the initial value Y_i' image of each object $Y_i' = \{y_i'(k) \mid k = 1, 2, ..., 8\}$, use the following formula (13):

$$y_i'(k) = \frac{y_i(k)}{y_i(1)} \tag{13}$$

Calculate the initial value image for each object. Subsequently, plug the initial value images of various indicators into formulas (10), (11), and (12) one by one to calculate the gray relative relevance (r0i) of each object with the ideal object.

2.1.4 Gray Comprehensive Relevance

The formula to calculate the gray comprehensive relevance of each object with the ideal object is as follows (14):

$$\rho_{0i} = \theta\epsilon_{0i} + (1-\theta)r_{0i} \tag{14}$$

Here $\theta \in [0,1]$, in this paper, $\theta = 0.5$.

2.2 Decision Tree Model

In this section, we discuss the decision tree model used for the analysis. We first extract four key indicators from the collected alarm data: "Component Name," "Number of Fire Alarms," "Affiliated Fire Department," and "False Alarm Status." Subsequently, we randomly split the data into training and testing sets in a 7:3 ratio.

For this study, we employ the ID3 decision tree algorithm, which is based on "information gain" as the criterion for splitting the sample sets. The algorithm steps are outlined in Table 1.

Table 1: Decision Tree Construction Process

Step	Operation
SETP1	Input the training set Train. If Train is empty, the algorithm terminates
SETP2	If it is not possible to select a suitable indicator and information gain, create a leaf node, and end the algorithm
SETP3	Create an internal node based on the chosen feature and its corresponding information gain.
SETP4	Divide Train into two subsets based on Step 3, and apply this algorithm to each subset.

The formula for information content is as follows:

$$I(x) = \log_a\left(\frac{1}{p}\right) = -\log_a p \tag{15}$$

Where *x* represents the event specified in the message, *p* is the prior probability of *x*, and '*a*' is generally set to 2, making the unit of measurement bits.

Based on this information content formula, the formula for information entropy is as follows:

$$H(X) = E[I(x_i)] = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{16}$$

Where *X* is a specific event class, *xi* represents specific events within *X*.

The information entropy formula for data set *A*, divided into two subsets A_1 and A_2 by the decision value '*f*' of the *j*-th indicator $F^{(j)}$, is as follows:

$$H(A, F^{(j)} = f) = \frac{|A_1|}{|A|}H(A_1) + \frac{|A_2|}{|A|}H(A_2) \tag{17}$$

Where $|A|$,$|A_1|$, and $|A_2|$ represent the sample counts in sets A, A_1, and A_2, respectively. Information gain, which is the reduction in information entropy before and after data set division, can be defined as:

$$Gain(A, F^{(j)} = f) = H(A) - H(A, F^{(j)} = f) \tag{18}$$

According to Equation (18), we select the indicator and corresponding decision value that maximize $Gain(A,F^{(j)}=f)$ as the splitting point.

Following the steps outlined in Table 1, we construct a decision tree model, train it with the training set Train, and obtain the decision tree. When we apply the testing set Test to the decision tree, we achieve an accuracy score of 0.9818. This suggests that the decision tree is reasonably accurate for making predictions on the test set.

2.3 Evaluation Model for the Management Level of Each Fire Brigade

2.3.1 Selection of Management Level Indicators

To better reflect the management level of each jurisdiction, the management level needs to be subdivided into quantifiable indicators. Based on the collected data, the following definitions are provided for alarm data and fault data in each jurisdiction.

Definition 5: $Z^{(k)}=\{X_i|x_i(6)=k,k=1,2,...,18\}$为is the alarm data set for the k-th fire brigade's jurisdiction, denoted as $Z^{(k)}=\{Z_i^{(k)}\}$, where $Z_i^{(k)}$ represents the i-th alarm data in $Z^{(k)}$. $Z^{(k)}$ is a subset of the set $\{X_i\}$. $|Z^{(k)}|$ represents the number of elements in $Z^{(k)}$.

Definition 6: $M^{(k)}=\{E_i|e_i(6)=k,k=1,2,...,18\}$ is the fault data set for the k-th fire brigade's jurisdiction, denoted as $M^{(k)}=\{M_i^{(k)}\}$, where $M_i^{(k)}$ represents the i-th fault data in $M^{(k)}$. $M^{(k)}$ is a subset of the set $\{E_i\}$. $|M^{(k)}|$ represents the number of elements in $M^{(k)}$.

Definition 7: $T=\{t(k)|k=1,2,...,18\}$ is the set of fire occurrence frequencies in all regions. Where $t(k)$ represents the number of fire occurrences in the k-th region from June 1st to June 18th. $k = 1,2,...,18$ corresponds to the jurisdiction of Brigade A to Brigade R.

Definition 8: $S=\{s(k)|k=1,2,...,18\}$ is the set of jurisdictional areas for all regions. Where $s(k)$ represents the jurisdictional area of the k-th region. $k = 1,2,...,18$ corresponds to the jurisdiction of Brigade A to Brigade R.

(1) Fire Occurrence Frequency

The fire occurrence frequency FOF_k for the k-th jurisdiction is calculated as:

$$FOF_k = \frac{t(k)}{day} \tag{19}$$

Where day=18 represents the number of days from June 1st to June 18th. This indicator reflects the average number of fire occurrences per day in each jurisdiction, indicating the fire situation in the jurisdiction and indirectly reflecting the management level of the fire brigade in that jurisdiction.

(2) Component Fault Frequency

The component fault frequency FCF_k for the k-th jurisdiction is calculated as:

$$FCF_k = \frac{\left|\{m_i^{(k)}(5)\}\right|}{day} \tag{20}$$

Where day=18 has the same meaning as in equation (19), and $m_i^{(k)}(5)$ represents the data of the 5th item indicator of $m_i^{(k)}$, which is the "number of faults." $\{m_i^{(k)}(5)\}$ is the set formed by all $m_i^{(k)}(5)$, and $|m_i^{(k)}(5)|$ is the number of elements in it.

(3) Percentage of Effective Components

The percentage of effective components PEC_k for the k-th jurisdiction is calculated as:

$$PEC_k = \frac{\left|Z^{(k)}\right|}{\left|Z^{(k)}\right| + \left|M^{(k)}\right|} \tag{21}$$

This indicator reflects the proportion of effective components within the jurisdiction, indicating the maintenance of components in the jurisdiction and indirectly reflecting the management level of the fire brigade in that area.

(4) Fire Occurrence Density per Unit Area

The fire occurrence density per unit area NFA_k for the k-th jurisdiction is calculated as:

$$NFA_k = \frac{t(k)}{s(k)} \tag{22}$$

This indicator reflects the fire situation in the jurisdiction from the perspective of the area and can reflect the fire management situation of the fire brigade in that area.

(5) Number of Effective Components per Unit Area

The number of effective components per unit area NEA_k for the k-th jurisdiction is calculated as:

$$NEA_k = \frac{\left|Z^{(k)}\right|}{s(k)} \tag{23}$$

This indicator reflects the number of components working effectively per unit area and to some extent, reflects the attention of the fire brigade in that area to fires, demonstrating the level of fire control by the fire brigade.

(6) Number of Faulty Components per Unit Area

The number of faulty components per unit area NTA_k for the k-th jurisdiction is calculated as:

$$NTA_k = \frac{\left|M^{(k)}\right|}{s(k)} \tag{24}$$

This indicator reflects the number of faulty components per unit area and indicates the maintenance status of faulty components by the fire brigade, expressing the management level of the fire brigade with regard to fire components.

2.3.2 Evaluation of the Comprehensive Management Level of Each Fire Brigade

Definition 9: $P_k=\{p_k(n)|n=1,2,...,6\}$ represents the indicator data for the k-th fire brigade. Where $p_k(n)$ represents the data represented by the n-th indicator in p_k. $p_k(1) = FOF_k$, $p_k(2) = FCF_k$, $p_k(3) = PEC_k$, $p_k(4) = NFA_k$, $p_k(5) = NEA_k$, $p_k(6) = NTA_k$.

(1) Constructing the Ideal Fire Brigade P_0

Based on the descriptions of the various indicators in 2.3.1, the formula for constructing the ideal fire brigade P0 can be obtained as:

$$p_0(k) = \begin{cases} \min\{p_i(k) \mid i = 1,2,...,18\}, & k = 1,2,4,6 \\ \max\{p_i(k) \mid i = 1,2,...,18\}, & k = 3,5 \end{cases} \tag{25}$$

According to formula (25), it is evident that the indicators of the ideal fire brigade P0 represent the best performance of each fire brigade on each indicator. Based on calculations, P_0 = (0.4444, 127.6666, 0.5991, 0.0079, 56.5862, 1.1747) can be derived.

(2) Calculating the Grey Comprehensive Association Degree between Each Brigade and the Ideal Fire Brigade

By using equations (10) to (13), the grey absolute association degree and the grey relative association degree between each brigade and the ideal brigade can be calculated. Substituting the grey absolute association degree and the grey relative association degree into equation (14) will yield the grey comprehensive association degree.

3. RESULTS AND ANALYSIS

3.1 Fire Detector Component Evaluation Model

The gray comprehensive correlation between each object and the ideal object can be calculated. The calculation results are shown in Table 2.

Table 2: Gray Comprehensive Correlation between Each Object and the Ideal Object

Object	Comprehensive	Object	Comprehensive	Object	Comprehensive	Object	Comprehensive
Y_1	0.7589	Y_5	0.8053	Y_9	0.5439	Y_{13}	0.6970
Y_2	0.5939	Y_6	0.8372	Y_{10}	0.7060	Y_{14}	0.5351
Y_3	0.7740	Y_7	0.5135	Y_{11}	0.5274	Y_{15}	0.5327
Y_4	0.6343	Y_8	0.5171	Y_{12}	0.7708	Y_{16}	0.6250

The gray comprehensive correlation reflects the degree of similarity between each object and the ideal state, providing a comprehensive representation of how closely the objects are related to the ideal object. According to Table 2, the top three objects with the highest comprehensive correlation scores are Y_6,Y_5, and Y_3, corresponding to the components "Intelligent Photoelectric Probe," "Manual Alarm Button," and "Pressure Switch," respectively.

From the results, "Intelligent Photoelectric Probe," "Manual Alarm Button," and "Pressure Switch" exhibit high reliability and low failure rates. The areas under the jurisdiction of G Brigade, M Brigade, and A Brigade are prone to frequent fires, and the government should increase the number of "Intelligent Photoelectric Probes," "Manual Alarm Buttons," and "Pressure Switches" in the corresponding regions to ensure timely fire detection.

3.2 Decision Tree Model

By inputting the prediction dataset into the decision tree, we can obtain the probabilities for various alarm data being "false alarms," "non-false alarms," and "only one fire occurrence," as shown in Table 3.

Table 3: Probability Prediction Results

False Alarm	Non-False Alarm	Only One Fire Occurrence	False Alarm	Non-False Alarm	Only One Fire Occurrence
0.9	0	0.1	0.8965	0	0.1034

1	0	0	0.8965	0	0.1034
0.8965	0	0.1034	1	0	0
0	0	1	1	0	0
0.8965	0	0.1034	0.8393	0	0.1607
0.8393	0	0.1607	0.8393	0	0.1607
0.8965	0	0.1034	1	0	0
0.8393	0	0.1607			

From Table 3, we can see that one alarm data will definitely result in one fire occurrence, and ten alarm data have a probability greater than 10% of leading to one fire occurrence. All other alarm data are false alarms.

3.3 Evaluation Model for the Management Levels of Various Brigades

The gray comprehensive correlation between each brigade and the ideal brigade is shown in Table 4.
Table 4:

Table 4: Gray Comprehensive Correlation between Each Brigade and the Ideal Brigade

Brigade Name	Comprehensive Correlation	Brigade Name	Comprehensive Correlation	Brigade Name	Comprehensive Correlation
A Brigade	0.6753	B Brigade	0.525	C Brigade	0.5185
D Brigade	0.5383	E Brigade	0.5848	F Brigade	0.5172
G Brigade	0.514	H Brigade	0.5066	I Brigade	0.6748
J Brigade	0.5054	K Brigade	0.6033	L Brigade	0.5223
M Brigade	0.5135	N Brigade	0.5186	O Brigade	0.6052
P Brigade	0.5625	Q Brigade	0.5271	R Brigade	0.8135

According to Table 4, the top three firefighting brigades in terms of comprehensive management ability are R Brigade, A Brigade, and I Brigade. The three brigades with the lowest comprehensive management ability are J Brigade, H Brigade, and M Brigade. The data is as shown in Figure 1.

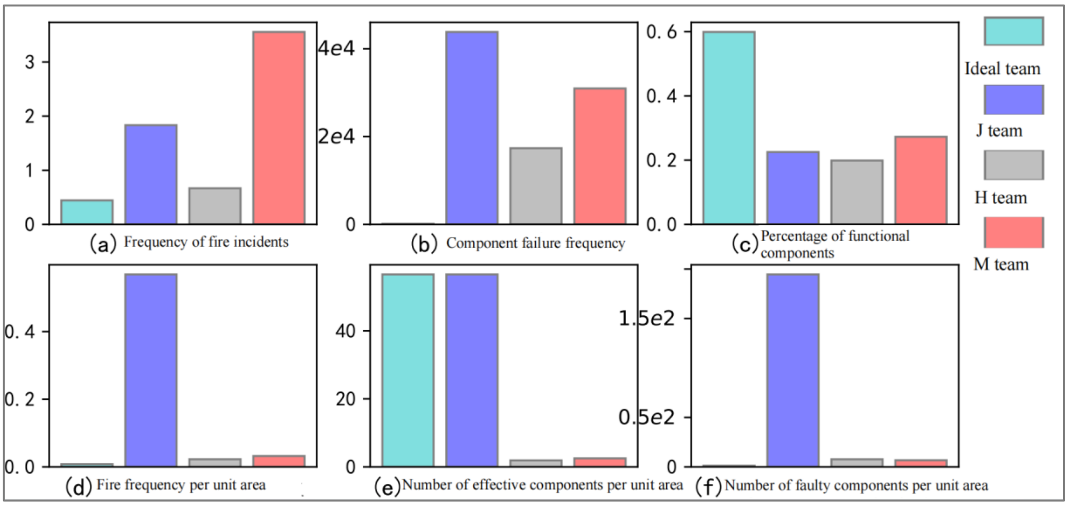

Figure 1: Visualization of Comprehensive Management Indicators for Each Team

From Figure 1, it can be seen that Teams J, H, and M have a higher "component failure frequency" and a lower "proportion of effective components." Therefore, these three teams need to strengthen their management of regular maintenance and updates for the components.

4. CONCLUSION

Priority should be given to the use of "intelligent point detectors," "manual alarm devices," and "pressure sensors" for component usage. In terms of overall performance, "intelligent point detectors," "manual alarm devices," and "pressure sensors" demonstrate higher reliability and lower failure rates. Areas with lower management levels generally exhibit higher "component failure frequencies" and lower "proportions of effective components." Consequently, it is necessary to perform regular maintenance and updates for existing components and replace easily damaged and prone-to-failure components with more durable ones to enhance component reliability. Four key points need to be considered in the inspection of fire alarm systems, which are "improving the overall fire resistance level," "rationally dividing fire compartments," "raising fire safety facility standards," and "enhancing water supply conditions."

REFERENCES

[1] Sousa Tomé Emanuel,Ribeiro Rita P,Dutra Inês,Rodrigues Arlete. An Online Anomaly Detection Approach for Fault Detection on Fire Alarm Systems.[J]. Sensors (Basel, Switzerland),2023,23(10).
[2] Junyan Tian,Zhijing Wu,Xin Qu. Research on Fire Alarm System Based on Entropy Power Method and Topsis Superiority and Inferiority Solution Distance Method[J]. International Journal of New Developments in Engineering and Society,2023,7(2).
[3] Andreev A.,Doronin A.,Kachenkova V.,Norov B.,Mirkhasilova Z.. Fire alarm systems construction on artificial intelligence principles[J]. E3S Web of Conferences,2023,365.
[4] Klimczak Tomasz,Paś Jacek,Duer Stanisław,Rosiński Adam,Wetoszka Patryk,Białek Kamil,Mazur Michał. Selected Issues Associated with the Operational and Power Supply Reliability of Fire Alarm Systems[J]. Energies,2022,15(22).
[5] Abdusalomov Akmalbek Bobomirzaevich,Mukhiddinov Mukhriddin,Kutlimuratov Alpamis,Whangbo Taeg Keun. Improved Real-Time Fire Warning System Based on Advanced Technologies for Visually Impaired People[J]. Sensors,2022,22(19).
[6] He Xi,Feng Yitong,Xu Fuli,Chen Fei-Fei,Yu Yan. Smart fire alarm systems for rapid early fire warning: Advances and challenges[J]. Chemical Engineering Journal,2022,450(P1).
[7] Xia Li,Liangwei Zhang,Mingxuan Jiang. Exploration on path improvement of fire alarm system[J]. International Journal of New Developments in Engineering and Society,2022,6.0(2.0).
[8] Li Mengjie,Liu Chao. Design of Intelligent Fire Alarm System Based on Multisensor Data Fusion[J]. Mobile Information Systems,2022,2022.
[9] Zhiyu Chen. Research on Fire Alarm System[J]. Advances in Computer, Signals and Systems,2022,6(2).
[10] Paś Jacek,Rosiński Adam,Wiśnios Michał,Stawowy Marek. Assessing the Operation System of Fire Alarm Systems for Detection Line and Circuit Devices with Various Damage Intensities[J]. Energies,2022,15(9).
[11] Li Xiaolu,Sánchez del Río Saez José,Ao Xiang,Yusuf Abdulmalik,Wang De-Yi. Highly-sensitive fire alarm system based on cellulose paper with low-temperature response and wireless signal conversion[J]. Chemical Engineering Journal,2022,431(P2).
[12] Steven Heckman. Understanding Fire Alarm Systems: The Benefits of an Unwanted Alarm[J]. Fire Engineering,2022,175(1).
[13] Gupta Surbhi,Kanwar Shefali,Kashyap Manju. Performance characteristics and assessment of fire alarm system[J]. Materials Today: Proceedings,2022,57(P5).
[14] Jakubowski Krzysztof,Paś Jacek,Duer Stanisław,Bugaj Jarosław. Operational Analysis of Fire Alarm Systems with a Focused, Dispersed and Mixed Structure in Critical Infrastructure Buildings[J]. Energies,2021,14(23).
[15] Li Hao,Yang Jie,Zhou Shengzong. Design of fire alarm system of intelligent camera based on fuzzy recognition algorithm[J]. Journal of Intelligent & Fuzzy Systems,2021,41(3).