

Exploration on path improvement of fire alarm system

Xia Li^{1,*}, Liangwei Zhang², Mingxuan Jiang³

¹College of Business Administration, China University of Petroleum Beijing at Karamay, Karamay, 834000, China

²College of Arts and Sciences, China University of Petroleum Beijing at Karamay, Karamay, 834000, China

³Petroleum Institute, China University of Petroleum Beijing at Karamay, Karamay, 834000, China

*Corresponding author

Abstract: For fire alarm system equipment, we should also strive to achieve a high-level grasp of the early warning situation, so as to better protect the lives and valuable property of the people. This paper mainly focuses on the improvement path of the accuracy of the components of the fire early warning system. Based on this, a comprehensive analysis and research is carried out in combination with the given data set and the preliminary characteristics of the city. Further, to quantify the comprehensive management level, the entropy weight-TOPSIS model was established, and relevant suggestions were put forward for the comprehensive management level.

Keywords: certainty reliability, Z-score processing, Bootstrap simulation, entropy weight TOPSIS evaluation

1. Introduction

In the past few decades, the public's awareness of fire protection has been continuously improved, and the fire alarm system, which is a part of the high-tech industry, has developed rapidly. Due to the expansion of demand and market, foreign products are also pouring into the domestic market, and the competition among fire protection products has intensified, which has put forward higher requirements for fire detection products. Different detectors detect different environmental indicators, and have the same reliability and sensitivity. The sensitivity of the detector determines the sensitivity of the fire protection system to the fire response, but a higher sensitivity may lead to false alarms of fire and poor reliability. Therefore, the sensitivity and reliability of the detector need to reach a certain balance in order to achieve the optimization of fire detection.

By screening the real fire conditions, after excluding the alarm of the same real fire, because there is the possibility of multiple alarms for the same component and multiple real fires, it is determined based on interval estimation that the number of fires is [417,493] times. Based on the relevant technical literature, a brief failure mode and impact analysis is carried out, the design margin is further calculated, the inherent uncertainty and cognitive uncertainty are determined, and the confidence reliability of each component is obtained for evaluation and analysis. By analyzing the obtained results, it is determined that the more reliable components are light beam smoke detection, intelligent photodetector and gas detection.

Based on the confidence reliability results, an intelligent judgment model based on risk assessment and real fire probability estimation is established through Z-score dimensionless processing and Bootstrap sampling method. On the basis of this research and judgment model, parameter estimation is carried out on the alarm conditions of each team and component under each project in the data, and the probability estimation interval is [0.1059, 0.0799] under 95% confidence, that is, the 13 alarms are Treated as an independent event, the probability of a fire per alarm is 9.09%. According to the comprehensive management level of each team, with the help of TOPSIS to establish relevant indicators and establish an evaluation system. The weights in the TOPSIS evaluation model are determined by the entropy weight method. The management and maintenance of each component of the fire alarm system mainly focuses on seasonal factors, sensitivity adjustment, equipment selection, and troubleshooting methods.

2. Reliability model of fire alarm system

In mechanical failure, the fault object may be jointly affected by deterministic causes, inherent uncertainty and cognitive uncertainty. When the relationship between these factors is comprehensively considered, some reliability metrics based on the above factors have been proposed- Be sure of reliability [1]. The specific form is:

$$R_B = \Phi\left(\frac{M_d}{U_a+U_e}\right) \quad (1)$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x \exp\left(-\frac{t^2}{2}\right) dt \quad (2)$$

In the formula, M_d is the design margin, which will be involved in the subsequent failure mode and impact analysis, and mainly reflects the deterministic cause of the failure, U_a represents the inherent uncertainty, which is used to characterize the inherent uncertainty impact on product reliability, while U_e is the cognitive uncertainty, which can be determined by evaluating the activities related to the cognitive uncertainty.

For the convenience of calculation, the inherent uncertainty and the cognitive uncertainty are usually normalized to obtain the inherent uncertainty factor a_a and the cognitive uncertainty factor a_e , respectively:

$$\begin{cases} a_a = \frac{U_a}{|M_d|} \geq 0 \\ a_e = \frac{U_e}{|M_d|} \geq 0 \end{cases} \quad (3)$$

The calculation method of the certainty reliability for evaluating each component is:

$$R_B = \begin{cases} \Phi\left(\frac{1}{a_a+a_e}\right), M_d \geq 0 \\ 1 - \Phi\left(\frac{1}{a_a+a_e}\right), M_d < 0 \end{cases} \quad (4)$$

2.1. Failure mode and impact analysis

Failure mode and effects analysis (FMEA), to determine the impact of failures on the system as a whole by unit, so that improvement measures can be drawn to focus on the right medicine to reduce reliability problems caused by the understanding of unit failure modes [2]. Through the FMEA, we can more objectively understand the cognitive uncertainty, and then grasp the design margin and inherent uncertainty. Although there is still no mature applicable evaluation and analysis method to evaluate and analyze the fire alarm system, it is essentially a type of optoelectronic system. It is also feasible to refer to reliable evaluation methods for such mechanical and complex systems [3].

Combined with FMEA implementation methods [4-6] and common problems [7], the main factors affecting the application effect of FMEA are divided into: failure mode awareness, failure cause awareness, failure impact awareness and the effectiveness of the improvement measures. In this section, the uncertainty inherent in the product as well as the perceived uncertainty is discussed. The cognition and establishment of the two are often closely related, and this part often involves authoritative issues. Most of the studies are evaluated and selected by experts based on the FMEA application effect evaluation criteria. In this question, due to the establishment of the prerequisite assumptions, we temporarily assume that the functional state of the equipment is in good condition and conforms to the specification, and the only uncertain factors are the false alarm rate of each component and the failure rate of each component. The author made an overall analysis of the fire alarm system through the Monte Carlo method [3], and determined the reliability model of the overall fire alarm system as:

$$R(t) = \exp\left(\frac{t}{560.7217}\right)^{1.4835} \quad (5)$$

Where t represents time, that is, it is a function of service life.

In our analysis, the failure mode is often closely related to the service life of the product. Circuit aging and extreme environments for a long time will affect the reliability of the product and lead to its failure. Therefore, in product design, the service life is a crucial part. It not only determines the cycle of the product, but also directly reflects the quality level of the product in most cases. Similarly, most of the improvement measures for faults, if the overall cost allows, are mainly based on replacement of

new products. This shows that in the whole system, the product life of each component can often be used to measure the performance of a product.

2.2. Calculation of certainty reliability

Based on the analysis results of FMEA, we determine the relevant data indicators for our calculation of confidence reliability. The inherent uncertainty factor is the failure rate, the cognitive uncertainty factor is the false alarm rate, and the performance margin of the second product is simulated by the Monte Carlo method. The obtained function, select $t=18$ as the indicator for calculation, that is:

$$M_d = R(18) = \exp\left(-\frac{18}{560.7217}\right)^{1.4835} \quad (6)$$

From this, we got the final calculation result, firstly, the number of real fire occurrences, excluding the alarm conditions of the same fire according to the description, and secondly, counting the number of times, and the final result is in the interval [417,493].

Finally, an evaluation system is constructed based on the certainty reliability. In this evaluation, the reverse ranking of each component is shown in table 1.

Table 1: Ranking of components with assured reliability

Component name	Belief Reliability
Light beam smoke	0.83235
Linear beam smoke detector	0.740607329
Intelligent photoelectric detector	0.739372127
Gas detector	0.739372127
Intelligent temperature sensing	0.739372127
Flame detector	0.73937144
Point type smoke	0.739370753
Point type temperature smoke	0.739365943
Multiple-sensor	0.738291315
.....

It can be seen from table 1 that the reliability of light-sensitive detectors such as light beam smoke detectors and linear beam smoke detectors is higher than that of other types of fire alarm detectors. However, there is not much difference in the confidence reliability of the middle section, which may be due to the fact that the failure rate and the false alarm rate are too small.

3. Judgment model

As a powerful tool for big data, one of the current research hotspots, it has been used in key security fields such as public opinion analysis, public security data research and judgment, and it also has its presence in all walks of life, as shown in Fig. 1.

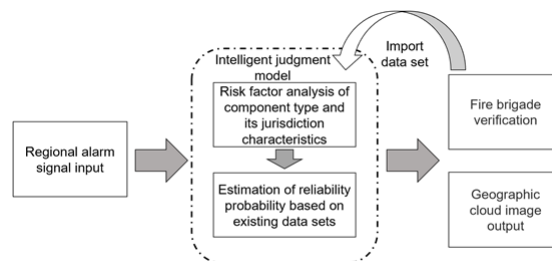


Figure 1: The path diagram of the judgment model

As can be seen from Fig. 1, starting from the input signal of the regional components, it is assumed that the city has established a big data analysis cloud platform and all fire alarm devices are connected to the platform. Then, on this basis, it is time for the judgment model to show its talents. Analysis is carried out by reading the characteristic data of the part type and the jurisdiction of the brigade to which it belongs. In the case of this question, in order to better reflect the characteristics of the components, the obtained confidence reliability is selected for the feature data of the component

category, and the number of fire occurrences per unit area is selected as the regional feature for the feature data of the brigade's jurisdiction.

In order to more clearly characterize the data features, we perform dedimensionalization processing here. In addition to this reason, there are other factors that need to use de-dimensioned data - dimensionless can better compare data, such as the relationship coefficient can actually be regarded as the result of covariance dimensionless. At present, the dimensionless processing methods used in the relevant literature mainly include: min-max normalization, Z-score normalization, regularization, meanization, etc. Among them, Z-score is often used in factor analysis and association analysis [8]. The formula for Z-score normalization is:

$$Z_a = \frac{x_i - \bar{x}}{S_D} \quad (i = 1, 2, \dots, n) \quad (7)$$

where Z_a represents the standard score of the selected analysis feature, x_i is the value of each research object in the feature variable with respect to the feature variable, \bar{x} is the mean of the former, S_D is the standard deviation in the data set of X_i . \bar{x}, S_D calculation method as follows:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^n x_i \quad (i = 1, 2, \dots, n) \quad (8)$$

$$S_D = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{x})^2} \quad (i = 1, 2, \dots, n) \quad (9)$$

where N represents the total number of characteristic variable objects of each research object. For some negative indicators, we have:

$$Z_a = \frac{S_D}{x_i - \bar{x}} \quad (10)$$

It is guaranteed that it is positively related to fire risk in the form of negation. Thereby a preliminary foundation of true fire probability estimates and two characteristic factors is constructed.

Based on the above processed data, it is difficult for us to understand its data distribution, so as to determine which type of distribution it belongs to and then analyze it in depth, but Bootstrap can avoid this problem

The troubles brought about by the interval estimation. The core idea is to put back sampling. By means of replacement sampling, a certain number of samples are obtained based on the original samples, and this type of samples is called Bootstrap samples, or autonomous samples. The relevant parameter estimates can be obtained by repeatedly sampling and constructing the empirical distribution. The essence is the population distribution simulation based on resampling, as shown in Fig. 2.

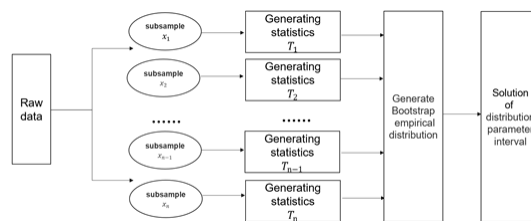


Figure 2: Bootstrap solution flow chart

The pivot method is the basic method for constructing confidence intervals, but it also has limitations. Let φ be a parameter of the sample population, and treat it as a functional of the population, namely: $\varphi = \varphi(F)$. When X is a sample in the population, let (X) be a statistic related to φ . By transforming to have $W + h(G(X), \varphi)$, so that the distribution function of W does not contain any unknown parameters, then for the two quantiles of W we have:

$$P\left(w_{\frac{a}{2}} < h(T, \varphi) < w_{1-\frac{a}{2}}\right) = 1 - a \quad (11)$$

Solving the inequality gives the confidence interval for φ . In the solution, it is easy to encounter complicated and difficult situations. At this time, our Bootstrap method has the opportunity to show its strength. By continuously resampling and estimating φ , a transformation $V = h(g(Y), \hat{\varphi})$, that is close to the W distribution can be obtained, and the obtained score can be used for estimation [9].

In this paper, based on the original data set, the alarm reliability rate of component alarms (the number of real fire occurrences/the number of alarms) is sampled and simulated to determine the

interval estimate. On this basis, combined with the previously obtained dimensionless data for correction, the final obtained probability is determined.

Through analysis, we can obtain that the linear beam smoke detector components belonging to B team and the project name are HFHX1#3#5#CJJYLGQ. Among these 13 alarms, on the basis of our premise that the alarm events are independent. The probability of possibly reflecting a true fire situation is at a 95 confidence interval: [0.1059, 0.0799]. The obtained process is shown in table 2, and the median of the interval estimate is taken as the representative of the estimated value in the table. Round to six decimal places to estimate the resulting probability.

Table 2: True fire probability

Component name	Project name	Affiliated Brigade	True fire probability
Linear Beam Smoke Detector	HFHX1#3#5#CJJYLGQ	Fire brigade B	0.090909
Manual alarm button	CYZBGL、CK	Fire brigade Q	0.043243
Manual alarm button	ATYYXXGS	Fire brigade D	0.02166
Intelligent photoelectric probe	DHZYC17#、18#L	Fire brigade A	0.02
Point temperature detector	ZGYXFXBGL	Fire brigade P	0.015075
Point temperature detector	YZJTGFYXGSGMYZSC	Fire brigade F	0.013953
Intelligent photoelectric probe	ZLRS (SD) YXGSCQXFSS	Fire brigade E	0.011111
Point Type Smoke Detector	1000QFBDZ	Fire brigade C	0.010312
Intelligent photoelectric probe	ZDDXAZ	Fire brigade G	0.008435
Point type smoke detector	QZYFSSZD	Fire brigade L	0.00777
Point type smoke detector	HYBL	Fire brigade J	0.00666
Point type smoke detector	ZBDCF	Fire brigade H	0.005956
Point type smoke detector	ZJSJCXQ	Fire brigade N	0.003984
Point type smoke detector	SGWHJD、LSW	Fire brigade M	0.003276
Point type smoke detector	YYLNGY (YYXQ3#L)	Fire brigade I	0.000044

It is proposed to use the original data to the maximum extent, the entropy weight method and the TOPSIS method with more objective evaluation to establish the evaluation model, determine the weight and evaluation score in the evaluation model respectively, and realize the final evaluation according to the score ranking. At the same time, the quantification of the technical indicators for the evaluation of the comprehensive management level has also been completed.

Four indicators can be found by analyzing the fire protection facilities in a unit area (A_1), the number of fires in a unit area per day (A_2), the number of failures in a unit area (A_3) and the reliability of fire alarms (A_4), among the four indicators, A_1 , A_2 , and A_4 are positive indicators, while A_3 is a negative indicator. In order to facilitate the establishment of an evaluation model for unified evaluation, the A_3 indicator data is set as X_3 , where the samples are x_3 . Forwardization is achieved by the maximum value $\max\{X_3\} - x_3$.

Redundancy of variability for each indicator:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (12)$$

Redundancy of information entropy:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (13)$$

Redundancy of information entropy:

$$g_j = 1 - e_j \quad (14)$$

Where m is the number of evaluation indicators, the weight of each indicator is determined by:

$$w_j = \frac{g_j}{\sum_{j=1}^m g_j} \quad (15)$$

After the standardized matrix and weights are determined, the TOPSIS method is used to calculate the distance between the superior and inferior solutions, and the specific evaluation score is obtained after normalization. Given the standardized matrix Z_{ij} , the maximum value is defined as $Z^+ = \max Z_{ij}$, and the minimum value is defined as $Z^- = \min Z_{ij}$. Compute the distance of the i th

evaluation object from the maximum and minimum values:

$$D_i^+ = \sqrt{\sum_{j=1}^m w_j (Z_i^+ - Z_{ij})^2} \quad (16)$$

$$D_i^- = \sqrt{\sum_{j=1}^m w_j (Z_i^- - Z_{ij})^2} \quad (17)$$

$$S_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (18)$$

Normalizing S_i to get the final score:

$$\tilde{S}_i = \frac{S_i}{\sum_{i=1}^n S_i} \quad (19)$$

Establishing ledger records and distribution diagrams of fire protection components, and use intelligent technology to connect fire protection components with computers to achieve real-time monitoring. When a fire alarm occurs, the location of the alarm components can be quickly located, and the control and management of the fire protection system can be increased. And record each misreporting, fault, etc., collect the specific data and causes of the relevant misreporting and fault, so as to facilitate subsequent analysis and adjustment, and realize feedback and supplement of management methods.

Troubleshoot the cause of false positives to reduce false positives. If it is an occasional false positive, consider the cause of human false positive; if it is a regular false positive, you need to check the environment where the component is located to check whether there is water vapor, dust, smoke, large temperature changes, and electromagnetic interference in the surrounding environment. If it is an environmental problem, it is necessary to change the environment or change the installation position of the components; if it is a non-environmental problem, consider whether the components themselves have faults or design problems [10].

4. Conclusion

This paper analyzes the data through the design margin and inherent uncertainty to obtain the actual number of fire occurrences in the interval of [417, 493]. At the same time, according to the evaluation system constructed by the confidence reliability, and ranking the components, it is found that the confidence reliability of the beam smoke detector and the linear beam smoke detector is relatively high. Then use Bootstrap to obtain samples to estimate and establish a model. The established intelligent judgment model is to sample and simulate the alarm reliability rate of component alarms (the number of real fire occurrences/alarm times) to determine the intelligent judgment model of the interval estimated value, so as to obtain each team. The probability of real fire for different signals. Further, the comprehensive management level of the jurisdictions was quantified by establishing the entropy weight-TOPSIS model, then the scores could be calculated and relevant suggestions were put forward for the comprehensive management level.

References

- [1] Zeng Z, Wen M, Kang R. Belief reliability: A new metrics for products' reliability [J]. *Fuzzy Optimization and Decision Making*, 2013, 12(1): 15-27.
- [2] Fan Mengfei, Zeng Zhiguo, Kang Rui. Reliability evaluation method based on certainty reliability [J]. *Systems Engineering and Electronic Technology*, 2015,37(11):2648-2653.
- [3] Xing Zhixiang, Chen Lu, Zhu Dezhi. Monte Carlo simulation of reliability of fire detection and alarm system based on Matlab [J]. *China Safety Production Science and Technology*, 2012,8(01):47-51.
- [4] Dhillon B S. Failure modes and effects analysis—bibliography[J]. *Microelectronics Reliability*, 1992, 32(5): 719-731.
- [5] Chen Ying, Kang Rui. FMECA technology and its application [M]. 2nd edition. Beijing: National Defense Industry Press, 2014.
- [6] Mckinney B T. FMECA, the right way. 1991.
- [7] Sayareh J, Ahouei V R. Failure mode and effects analysis (FMEA) for reducing the delays of Cargo handling operations in marine bulk terminals[J]. *Journal of Maritime Research*, 2013, 10(2):43-50.
- [8] Zhang Yudong. Research on fire safety risk diagnosis and adaptive mechanism in urban areas [D].

Capital University of Economics and Business, 2019. DOI: 10.27338/d.cnki.gsjmu.2019.001100.

[9] Wang Jinglong, Liang Xiaojun. *Nonparametric statistical analysis [M]. Higher Education Press, 2006.*

[10] Cui Qiming, Guo Zixiang, Zhao Yutong, Pei Kai. *Maintenance and use of fire alarm control system [J]. China Instrument, 2019(12):45-47.*