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Research Article

Electrical Fire Dynamic Risk Assessment for High-Rise Buildings Based on Variable Fuzzy Set Theory and Bayesian Network

Lei Su,[1] Chongwen Wei,[2] Fan Yang,[1] Lei Zhang ,[2] Yu Shen,[1] Fan Zhang,[2] and Zhichun Yang[1]

[1]*State Grid Hubei Electric Power Company Electric Power Research Institute, Wuhan 430077, China*
[2]*College of New Energy, China University of Petroleum Huadong, Qingdao 266580, China*

Correspondence should be addressed to Lei Zhang; zl@upc.edu.cn

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High-rise buildings fires are far more harmful than ordinary fires. In this regard, fire risk assessment is an important way to control fire risk and reduce losses. This study presents a comprehensive model to electrical fire dynamic risk assessment of high-rise buildings based on a Bayesian network (BN) and a variable fuzzy set theory (VFST). Firstly, electric system, safety management, and other factors were comprehensively analyzed based on three categories: hazard sources identification (HSI), fault tree (FT) analysis, and VFST. A high-rise building electrical fire dynamic risk assessment model was established based on a BN. Secondly, the prior probability of BN root nodes was determined by VFST, and the conditional probability table (CPT) was determined by the analytic hierarchy process (AHP) and decomposition method. On that basis, the quantitative inference and sensitivity analysis can be performed on the electrical fire risks of high-rise buildings in combination with the variable fuzzy Bayesian network (VFBN) inference. Finally, a high-rise building in Wuhan, China, was used as an example for verification. The results show that the proposed method can realize dynamic risk assessment of electrical fires in high-rise buildings. This study provides a new method for fire risk assessment of high-rise buildings to reduce the possibility of fire.

1. Introduction

A growing number of high-rise buildings have been constructed in recent years, due to the increasing scarce land for urban construction. These buildings are characterized by multiple floors, high height, large volume, and concentrated personnel, making them exposed to higher fire risk than normal buildings [1–3]. Meanwhile, high-rise buildings are multifunctional, highly electrified and automated, equipped with lots of electrical facilities, and consume a large amount of power, making them vulnerable to electric leakage, short circuit, and other faults and prone to fire accidents [4, 5]. According to the statistics of high-rise buildings fire cases in the recent decade, the fires caused by electrical system faults accounted for about 31% [6]. For example, the fires of Windsor Tower [7], the Plasco building [8], and the Grenfell Tower [9] were due to a short circuit, which resulted in severe human injuries and property damage. Therefore, it is necessary to establish an electrical fire risk assessment system for high-rise buildings and quantify the electrical fire risk level.

To reduce the hazards and economic losses caused by fires, a number of scholars have carried out research in this field [10–13]. In general, fire risk assessment methods are based on a particular application scenario. For different assessment scenarios, some assessment methods based on system theory have been proposed previously. For example, Liu et al. established a fire risk assessment system for large-scale commercial buildings to evaluate the risk of fire protection system [14]. Li et al. analyzed fire characteristics of high-rise buildings under construction and put forward a fire risk assessment method for high-rise buildings under construction based on unascertained measure theory [15].

Aiming at the difficulty in carrying out effective rescue in case of fire in super high-rise buildings, Sun and Luo evaluated the risk of fire in super high-rise buildings [16].

Their research results indicate that fire accidents in super high-rise buildings are mainly caused by electrical fire. Therefore, in order to reduce fire accidents, it is of great importance to assess the risk of electrical fire. Li and Zhu proposed a method for quantitatively detecting electrical fire hazards in high-rise buildings based on a modified interpretive structural model (ISM) [4]. The research works of electrical fire risk assessment mainly focus on two aspects: electrical fire risk assessment and electrical fire early-warning algorithm. For instance, Wang et al. improved the accuracy of electrical equipment detection, as well as smoke and flame detection in the warning system, by using convolutional neural network fire early-warning algorithm [17]. Consequently, the studies of electrical fire risk assessment failed to focus on buildings fire risk assessment, particularly in high-rise buildings where fire accidents are frequent due to electrical factors. The occurrence of electrical fires involves an extremely complex process, and the electrical fire risk factors have considerable uncertainty. In addition, there is a certain interaction relationship between fire risk factors. More importantly, many electrical parameters associated with fire risks in the electrical system are time varying, which poses a challenge for quantitative assessment methods dominated by expert opinion.

BN can be employed to handle multistate variables and dependencies between variables and update probabilities based on new evidence and reasoning in case of uncertainty [18–20]. Thus, it can be considered a robust risk assessment technique [21]. Given the influence of uncertainty, Pei and Wang proposed a revised BN assessment model and applied it to high-rise buildings fire risk assessment [22]. Under the circumstances of lacking detailed data and complete knowledge, it is difficult to utilize the traditional BN to perform accurate quantitative analysis, especially for high-rise buildings projects that are seriously damaged. Furthermore, it is also impossible to adopt the traditional BN to obtain accurate data. Therefore, many scholars have applied fuzzy logic in combination with the BN theory to risk assessment projects on uncertain occasions. For example, Zarei et al. put forward a fuzzy Bayesian network (FBN) method for the safety assessment of process systems [23]. Zhang et al. performed a risk assessment for pit collapse in subway stations based on FBN and fuzzy hierarchy analysis [24]. Due to the fact that the advantages of fuzzy set theory (FST) and BN are integrated into FBN, it can clearly represent the complex relationship between each risk factor, deal with the uncertainty of risk data more effectively, and obtain more accurate quantitative assessment results [25]. However, whether FBN or BN, obtaining the prior probability and CPT under the circumstances of lacking detailed data and complete knowledge is one of the key challenges that needs to be eliminated [24].

With the advancement of electrical monitoring and Internet of Things (IoT) technologies, a lot of technical support has been provided for intelligent detection, information monitoring, and personnel positioning. Hence, a method for dynamic risk assessment of electrical fires in high-rise buildings was proposed in this study by combining engineering applications of electrical monitoring and IoT technology. Specifically, the electrical fire risk factors were determined based on three categories of hazard sources and FT analysis, and a high-rise building FT assessment model was established by combining dynamic risk factors and static risk factors. Besides, the FT assessment model was integrated into the BN model for risk inference. In addition, the prior probability of root nodes was determined based on the VFST. Compared with the fuzzy analytic hierarchy process (FAHP) [26], this method could reduce the subjectivity of expert assessment to some extent. Meanwhile, the membership function of the variable fuzzy set has a correspondence with the actual physical quantity, which improves the credibility that it is not an a priori condition under the circumstances of lacking detailed data and complete knowledge. Moreover, the decomposition method was adopted to determine the CPT of intermediate nodes, which could reduce the subjectivity of experts in multistate assessment. Finally, a sensitivity analysis based on indicators identified the key risk factors for electrical fires in high-rise buildings.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical background of BN and VFST. Section 3 describes the procedure of the proposed method. Section 4 combines a case study to demonstrate the risk assessment process for electrical fires in high-rise buildings. The discussion and conclusions are presented in Sections 5 and 6, respectively.

2. Preliminaries

2.1. Bayesian Network. BN is a modeling method based on a probability graph model. In this method, qualitative analysis methods are combined with quantitative analysis methods to make effective inferences, and objective evidence and prior probabilities are employed to analyze uncertain problems in complex systems. This method enables the study of causal relationships among several factors as a research objective, and the degree of dependence among these factors, reflected by the conditional probability distribution, has been widely used in many fields. Electrical fires in high-rise buildings are highly complex and uncertain. Therefore, the risk of electrical fires for a characterized building cannot be predicted with the assessment based on a frequency interpretation approach. In this study, the dynamic assessment model of electrical fire risks in high-rise buildings based on BN combined with VFST can be used to analyze the uncertainty in electrical fires and identify the relationship between each risk factor.

The whole concept of BN is built on Bayesian theorem, which indicates the relationship between the prior probability and the posterior probability of an event through Bayesian formula as follows:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}, \quad (1)$$

where $P(A)$ and $P(B)$ are the prior probabilities, $P(A) > 0$, $P(A|B)$ is the conditional probability, and $P(B|A)$ is the posterior probability.

Suppose, there is a BN node x_i and $Pa\ [x_i]$ is the parent node set of x_i. The number of BN nodes is n. The calculation formula of the BN joint probability distribution function can be expressed as follows:

$$P(x_1, x_2, \ldots x_n) = \prod_{i=1}^{n} P[x_i | Pa(x_i)]. \tag{2}$$

The probability that system A occurs can be calculated directly by utilizing the joint probability distribution through prior probabilities and conditional probabilities in the network.

2.2. Variable Fuzzy Set Theory. In view of the uncertainty and fuzziness of electrical fire in high-rise buildings, this study adopts VFST method for risk assessment [27, 28]. At present, VFST has been applied in many fields and has broad application prospects [29–31]. The details are as follows:

(1) Each index of the assessment system was divided into assessment intervals according to m levels, with 1 level as the worst level and m level as the best level. Ranking the interval values at each level in turn results in a matrix of indicator evaluation intervals [32].

$$I_{ab}([a,b]_{ik}) = \begin{bmatrix} [a,b]_{11} & [a,b]_{12} & \cdots & [a,b]_{1m} \\ [a,b]_{21} & [a,b]_{22} & \cdots & [a,b]_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ [a,b]_{n1} & [a,b]_{n2} & \cdots & [a,b]_{nm} \end{bmatrix}, \tag{3}$$

where $[a_{nm}, b_{nm}]$ is the standard value interval of index n under the m level; a_{nm} and b_{nm} represent the upper and lower limits of the interval, respectively.

$$I_{cd}([c,d]_{ik}) = \begin{bmatrix} [c,d]_{11} & [c,d]_{12} & \cdots & [c,d]_{1m} \\ [c,d]_{21} & [c,d]_{22} & \cdots & [c,d]_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ [c,d]_{n1} & [c,d]_{n2} & \cdots & [c,d]_{nm} \end{bmatrix}, \tag{4}$$

where $[c_{nm}, d_{nm}]$ is the variable range value interval of index n under the m level. c_{nm} and d_{nm} represent the upper and lower limits of the interval, respectively.

$$[c_{ik}, d_{ik}] = \begin{cases} [a_{ik-1}, b_{ik+1}], k-1 > 0, k < m, \\ [a_{ik}, b_{ik+1}], k-1 = 0, \\ [a_{ik-1}, b_{ik}], k = m. \end{cases} \tag{5}$$

(2) According to matrix I_{ab}, the point matrix of index i corresponding to $[a, b]_{ik}$, whose relative membership degree is equal to 1 is expressed as follows:

$$\mathbf{M} = \begin{bmatrix} M_{11} & M_{12} & \cdots & M_{1m} \\ M_{21} & M_{22} & \cdots & M_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ M_{n1} & M_{n2} & \cdots & M_{nm} \end{bmatrix}, \tag{6}$$

where,

$$M_{ik} = \begin{cases} a_{i1}, h = 1, \\ \dfrac{a_{ik} + b_{ik}}{2}, 1 < k < m, \\ b_{ik}, k = m. \end{cases} \tag{7}$$

It is assumed that the actual grade of electrical fire assessment index of high-rise buildings is $X = [x_1, x_2, \ldots, x_n]$, and compare the actual score x_i with the corresponding point-value matrix M_{ik} $(k = 1, 2, 3, 4, 5)$ [33].

If $x_i \le M_{ik}$, the membership formula is as follows:

$$\begin{aligned} u_A(x_{ij})_k &= 0.5\left(1 + \frac{x_i - a_{ik}}{M_{ik} - a_{ik}}\right), x_i \in [a_{ik}, M_{ik}], \\ u_A(x_{ij})_k &= 0.5\left(1 - \frac{x_i - a_{ik}}{c_{ik} - a_{ik}}\right), x_i \in [c_{ik}, a_{ik}]. \end{aligned} \tag{8}$$

If $x_i > M_{ik}$, the membership formula is as follows:

$$\begin{aligned} u_A(x_{ij})_k &= 0.5\left(1 + \frac{x_i - b_{ik}}{M_{ik} - b_{ik}}\right), x_i \in [M_{ik}, b_{ik}], \\ u_A(x_{ij})_k &= 0.5\left(1 - \frac{x_i - b_{ik}}{d_{ik} - b_{ik}}\right), x_i \in [b_{ik}, d_{ik}]. \end{aligned} \tag{9}$$

Using (8) and (9), the relative membership matrices of assessment index in different levels were obtained as follows [34]:

$$\mu_A(u) = \begin{bmatrix} \mu_A(x_1)_1 & \mu_A(x_1)_2 & \cdots & \mu_A(x_1)_m \\ \mu_A(x_2)_1 & \mu_A(x_2)_2 & \cdots & \mu_A(x_2)_m \\ \cdots & \cdots & \cdots & \cdots \\ \mu_A(x_n)_1 & \mu_A(x_n)_2 & \cdots & \mu_A(x_n)_m \end{bmatrix}, \tag{10}$$

3. The Proposed Assessment Methodology

3.1. Risk Assessment Process. Based on VFST and BN, a dynamic risk assessment method for electrical fires in high-rise buildings was proposed in this study. The overall procedure of assessment is shown in Figure 1. During the application of this method, the risk factor analysis is performed firstly to identify the risk factors of electrical fires in high-rise

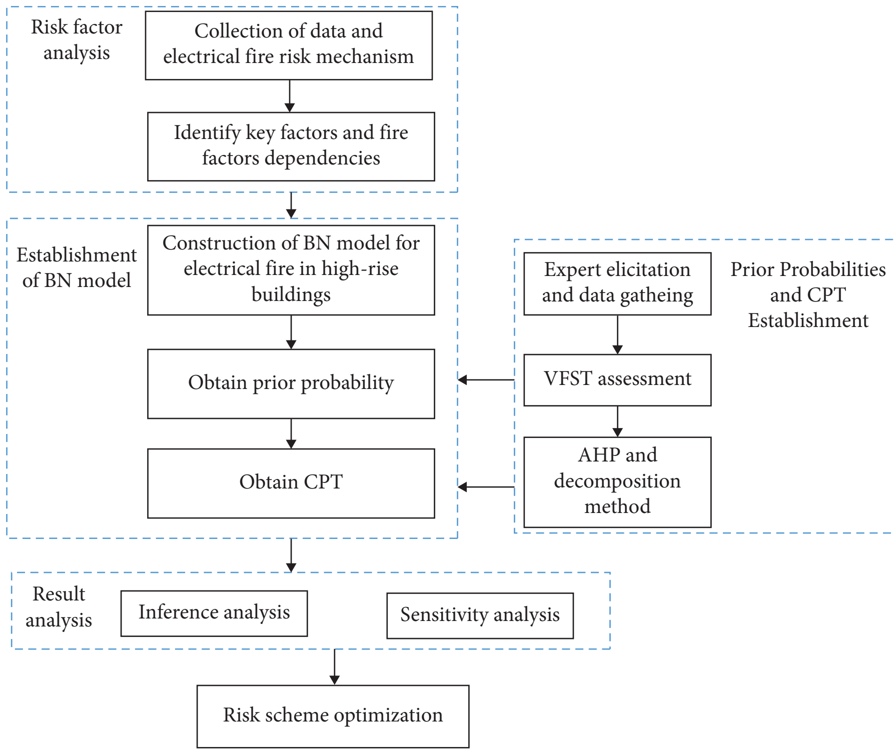


Figure 1: The overall procedure for risk assessment approach based on VFBN.

buildings and the dependency of each factor. Secondly, a BN model is constructed based on the identified fire risk factor correspondence. Thirdly, the prior probability and CPT are established by expert scoring, electrical parameter monitoring, variable fuzzy probability calculation, and CPT calculation with the decomposition method and AHP.

3.2. Risk Factor Analysis. Electrical fire accidents in high-rise buildings involve complex risk factors that are somewhat relevant and fuzzy. To realize the dynamic risk assessment of electrical fires, this study analyzes the high-rise buildings electrical fire risk mechanism in terms of both dynamic risk factors (electrical line risk) and static risk factors (electrical equipment, fire protection facilities, and building fire prevention capacity). According to the characteristics of electrical systems and high-rise buildings, three categories of hazard sources are proposed in the literature [1]. Figure 2 shows three categories of hazard sources in high-rise electrical systems. Based on the HIS technology of electrical fire in high-rise buildings, combined with the buildings fire protection standards and fire risk assessment guidelines of the United States, Britain, and China [35–38], referenced from the previous research results [39] and real fire case investigation reports [7–9, 40], the main risk factors and the FT model can be determined.

3.3. Establishment of BN Model. Establishing BN structure directly from existing fire case data is difficult. Fortunately, transformation methods based on FT or event tree to BN structure have been applied in engineering [41]. After the key risk factor of electric fires were identified and the FT relationships were established in the previous step, a BN risk assessment model was established based on the combination of dynamic and static assessment indexes by FT. FT was directly converted to the equivalent BN model according to the transformation relationship between FT and BN, as listed in Table 1 [19]. In the numerical transformation principle, the probability for the occurrence of a major event serves as the prior probability at the root node. CPT was obtained by Boolean gate of FT [24].

3.4. Variable Fuzzy Prior Probabilities and CPT. After a BN assessment model is established, the model parameters, including the prior probability of root nodes and the CPT of intermediate nodes, need to be imported. If enough available data are collected, the prior probability and CPT of BN can be obtained based on shrinkage methods [42] or hill climbing algorithms [43]. However, due to the severe loss caused by high-rise buildings fires, it is difficult to provide enough available data for the construction and parameterization of BN models in engineering practice. Therefore, during BN modeling, the establishment of probabilistic parameters of BN still relies on the inspiration of experts. However, the involvement of human judgment inevitably brings subjectivity and ambiguity. To date, many scholars have introduced fuzzy BN for risk assessment analysis. However, there are some deficiencies in the BN based on the fuzzy set theory, such as membership function fixation and poor adjustability. In this study, a VFST was adopted to deal with the uncertainty and ambiguity of the criteria and judgment process. Through combining VFST,

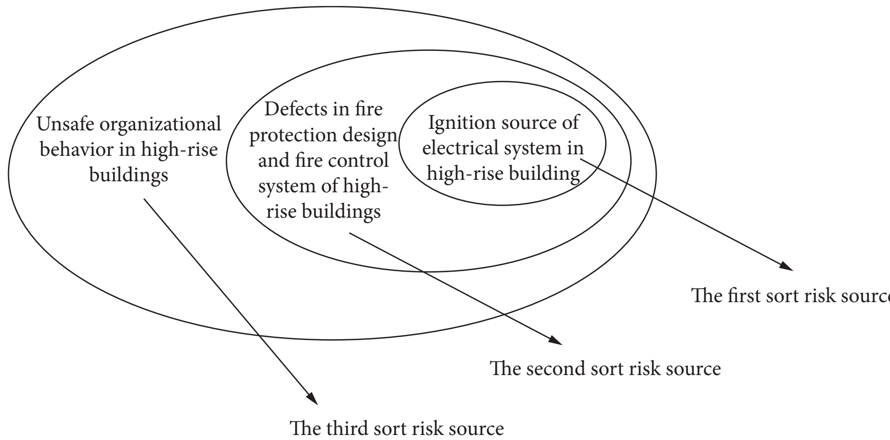


Figure 2: Electrical fire risk identification of high-rise buildings.

Table 1: Mapping relationship from a FT to a BN.

Assessment method	Mapping relationship		
FT	Primary events	Intermediate events	Top event
BN	Root nodes	Intermediate nodes	Leaf node

decomposition methods, and improved weight calculations, the prior probability and CPT of BN can be established as follows.

3.4.1. Generation of Root Nodes' Prior Probabilities. Assume that the root node N has n states, S_1, S_2, ..., S_n, the probability of the occurrence of state S_i is P (S_i). In the traditional risk assessment methods, P (S_i) is usually obtained from FAHP or AHP by expert assessment, which is limited by the effect of the number of states. Under the circumstances of a large number of states and a complex BN model structure, the accuracy of the assessment results cannot be ensured. Given the subjective assessment of experts, there would also be strong subjectivity for the risk factor parameters in an assessment model. In this study, root node correspondence bottom factor are assessed by VFST to determine the probabilities of each state of root nodes.

Each basic event corresponds to each root node, and the factors contributing to the occurrence of that event can be subdivided, namely bottom risk factor. Besides, objectivity shall be considered for risk factors, which preferably correspond to the actual physical quantities. It is also an advantage of VFST compared with FST. Assume that the root node n corresponds to m assessment factors D_1, D_2, ..., D_{m}, the weight coefficients of each assessment factor can be expressed as $w_1, w_2, \ldots, w_m\,(w_1 + w_2, \ldots + w_m = 1)$. The weight calculation by AHP is a common method used in quantitative risk assessment [44], but this method yields a weight value that is constant and subjective. Therefore, the variable weight comprehensive theory with equilibrium function is adopted to optimize the weight coefficient [45], and the formula for calculating variable weights can be expressed as follows:

$$w_i\left(x_1, x_2, \cdots, x_m\right) = \frac{w_i^0 x_i^{\alpha-1}}{\sum_{i=1}^m w_i^0 x_i^{\alpha-1}}, \tag{11}$$

where α reflects the equilibrium of variable weight theory and it is generally determined according to practical engineering experience. A large amount of engineering experience indicates that $\alpha = 0.2$ is suitable for general engineering [46]. w_i^0 is the constant weight of the i-th index; x_i is the standardized score corresponding to the i-th index, and standardized index scores used extreme value method [47]; m is the number of assessment indexes.

After the variable weight coefficient is calculated, the risk score criteria for each factor can be divided into k ($k = n$) levels, which is the same as the number of states at the root node. Specific division boundaries refer to industry specification standards with the incorporation of expert experience. Then, the factors are scored by some experts according to the established risk score criteria. After the means are counted, the eigenvalues of each factor can be obtained. Combined with the variable fuzzy set principle introduced in Section 2.2, the eigenvalues of each index are calculated sequentially corresponding to I_{ab}, I_{cd}, m, and μ_A. The affiliation vector R of each index can be obtained by normalizing μ_A. According to the univariate assessment model of fuzzy integrated risk assessment, R can be substituted into (12) to obtain a comprehensive risk vector as follows:

$$B = w \circ R = \left[w_1, w_2, \cdots, w_n\right] \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1k} \\ r_{21} & r_{22} & \cdots & r_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nk} \end{bmatrix} = \left[b_1, b_2, \cdots, b_k\right], \tag{12}$$

where "∘" is weighted average fuzzy composition operator [48] and $[b_1, b_2, \ldots b_k]$ is the probability of each state of root node N.

3.4.2. CPT for a Node with One Parent. Similarly, for a node N ($S_{N1}, S_{N2}, \ldots, S_{Nn}$) with n states, it can be assumed that it has only one parent node T ($S_{T1}, S_{T2}, \ldots, S_{Tm}$) with m states. Under this circumstance, the main idea is based on T state of each node to estimate the probability of each state of node N, namely, $P(S_{Ni}|S_{tm})$ ($i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$). Based on the idea of AHP, experts are asked to determine which state S_{Ni} and S_{Nk} ($k = 1, 2, \ldots, n$) corresponding to N node is more likely to occur in state S_{Mj}. Meanwhile, the 1–9 scale of AHP was used for comparison. After the comparison matrix is obtained, $P(S_{Ni}|S_{Tn}) = w_{ij}$ can be further calculated. The calculation process and the commonly used AHP to calculate index weights are the similar as reference [49]. Since node M has m states, M matrices should be constructed to obtain all wij ($i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, m$), and the CPT of the single parent node can be obtained.

3.4.3. CPT for a Node with Multiple Parents. Under the condition that one node has multiple parents, the results of estimating multiple states by experts are extremely inaccurate. In this study, a method proposed in a previous literature [49] is adopted. AHP and decomposition can be combined to calculate the CPT for cases with multiple parents, and the basic idea of this method is to decompose the multiple parent nodes into multiple CPTs for single parent nodes, as described in Section 3.4.2.

According to the method proposed in a previous research [49], for a node N with n states ($S_1, S_2, \ldots, S_n$), it has a parent node count of m ($m \geq 2$), that is, ($T_1, T_2, \ldots, T_j, \ldots, T_m$). Among them, the parent T_j has k states, namely, $S_{Tj}^{(1)}$, $S_{Tj}^{(2)}, \ldots, S_{Tj}^{(k)}$. The prior probability that each state of n is conditional on the different state combinations of its parent nodes can be expressed as follows:

$$\begin{aligned} &P\left(N = S_i \mid T_1 = S_{T_1}^{(q)}, T_2 = S_{T_2}^{(q)}, \ldots, T_n = S_{T_m}^{(q)}\right) \\ &(i = 1, 2, \ldots, n; q = 1, 2, \ldots, k). \end{aligned} \tag{13}$$

For a node A, which has two parent nodes B and C, its conditional probability on B and C can be approximated according to (14) as follows:

$$P(A|B, C) = \alpha P(A|B)(A|C). \tag{14}$$

Combined with (13), it can be simplified as follows:

$$\begin{aligned} &P\left(N = S_i \mid T_1 = S_{T_1}^{(q)}, T_2 = S_{T_2}^{(q)}, \ldots, T_n = S_{T_m}^{(q)}\right) \\ &= \alpha \prod_{j=1}^{m} P\left(X = S_i \mid T_n = S_{T_m}^{(q)}\right) (i = 1, 2, \ldots, n; q = 1, 2, \ldots, k;\ j = 1, 2, \ldots, m. \end{aligned} \tag{15}$$

where α is a normalized constant to ensure that

$$\sum_{i=1}^{n} P\left(X = S_i | T_1 = S_{T_1}^{(q)}, T_2 = S_{T_2}^{(q)}, \ldots, T_n = S_{T_m}^{(q)}\right) = 1. \tag{16}$$

3.5. Risk Analysis Based on VFBN

3.5.1. Inference Analysis. The assessment results based on BN can be mainly analyzed by the forward inference and backward inference methods. In terms of the forward inference method, the probability that a leaf node corresponds to the occurrence of a risk event can be calculated by the joint probability distribution, as (2) described in Section 2.1, which can be used to perform a quantitative assessment for the overall risk level of high-rise buildings. The backward inference calculation for the BN model is fault diagnosis, which is the calculation of the posterior probability of each risk factor by (1) described in Section 2.1. When an outcome event is bound to occur, the key factors that lead to the occurrence of a disaster can be derived. Based on that, critical risk factors for the occurrence of an electrical fire can be identified scientifically.

3.5.2. Sensitivity Analysis. Sensitivity analysis, which is performed to determine the contribution rate of each risk factor to a risk event, plays an important role in probabilistic risk assessment. In actual fire risk assessment, it is often required to identify the most important factors, which conduces to further fire risk control. The sensitivity analysis of the BN model could identify the most important factors. Li et al. proposed the calculation method of sensitivity indicators based on the risk achievement worth (RAW) and the risk reduction worth (RRW) [50]. In this study, this method was adopted to analyze sensitivity factors. If a risk factor C_i has a large impact on fire risks, it corresponds to a larger RAW (C_i). Similarly, a larger RRW (C_i) indicates that smaller changes in the indicator C_i can significantly change a fire event. Birnbaum measure (BM) is the mean of RAW and RRW. These three indicators can be obtained by the following formulas:

$$\mathrm{RAW}(C_i) = \frac{\max\left\{P\left(T = S_t \mid C_i = c_j\right)\right\} - P(T = S_t)}{P(T = S_t)},$$

$$\mathrm{RRW}(C_i) = \frac{P(T = S_t) - \min\left\{P\left(T = S_t \mid C_i = c_j\right)\right\}}{P(T = S_t)},$$

$$\mathrm{AVG}(C_i) = \frac{\mathrm{RAW}(C_i) + \mathrm{RRW}(C_i)}{2}. \tag{17}$$

4. Case Study

4.1. Background. An office building in Wuhan, China, with a height of 32 m and a total of 9 floors, is selected as a case sample. The main function of the building is to conduct power testing and to provide power advisory services. On the first floor, there is a high-voltage power distribution room with an area of 60 m^2, and a low-voltage power distribution room with an area of 115 m^2, 3 administrative power distribution rooms with an area of 19 m^2, and two laboratories with high-power electric equipment. The rest of rooms are regular offices, and the whole floor can be regarded as a fire prevention zone, as shown in Figure 3. All floors of the office building are equipped with automatic sprinkler systems, fire alarm devices, and fire hydrants. Case buildings part actual situation is shown in Figure 4; Figure 4(a) shows the overall structure of the building. The high-voltage supply cable and the low-voltage distribution cabinet are, respectively, shown in Figures 4(b) and 4(c). A high voltage laboratory in the case is shown in Figure 4(d). This office building is located in a transportation hub, with convenient transportation, humid, and hot climate. Within 2 km, there are two fire brigades with perfect firefighting equipment.

4.2. Fire Risk Factor Analysis. There are many risk factors for electrical fires in high-rise buildings, and there is also a certain interaction relationship between various fire risk factors that affect fire risks. Li et al. analyzed the coupling relationships among various factors of electrical fires in high-rise buildings by ISM [4], including the source of fire, the fire environment, the victims, and the fire drivers. To realize the dynamic risk assessment in this paper, based on Li's study results and fire accident investigations [7–9], the electrical fire risk factors in high-rise buildings are identified from the aspect of the failure of electrical lines, the failure of electrical equipment, and the fire protection ability of building by using FT analysis. Electrical fire risk factors are mainly classified into two categories:

(1) Dynamic risk factors: Through the analysis of data from cases of electrical fire accidents, abnormal sign information such as increased current, voltage fluctuation, and temperature rise will occur before the occurrence of electrical fire. Therefore, the dynamic risk factors select electrical line failure (B_1) as the risk factor, which specifically includes four types of electrical failure that mainly lead to the formation of an ignition source: line short circuit (C_1), overload (C_2), ground failure (C_3), and failure arc (C_4). Electrical failure (C_1, C_2, . . ., C_4) occurrence is the result of the combination of factors, and fire can only be stated if there is a certain degree of abnormality in multiple parameters. To achieve a dynamic risk assessment in conjunction with the electrical fire monitoring system, the occurrence of an electrical failure was associated with a bottom risk factor (D_1, D_2, . . ., D_7) as shown in Table 2. The bottom risk factors are correspond to electrical parameters, and the specific descriptions and risk states divisions are given in Table S1 (Supplementary Materials). Dynamic bottom risk factor eigenvalues are obtained through the electrical fire monitoring system and served as an evaluation indicator for the probability of risk factors (C_1, C_2, . . ., C_4) quantified by VFST. The specific process will be discussed in the following section.

(2) Static risk factors: For static risk factors, which are characterized by no alteration in the short term and are partly related to the physical attributes of the building, a portion is determined by expert field evaluation of characteristic values. Based on the Plasco building findings, it was pointed out that changes in the use function of the building without appropriate adjustments can lead to more severe fires [8]. Therefore, in the electrical equipment operation risk (C_6), the ratio of the maximum workload to the designed load of the electrical equipment (S_6) is important. According to the investigations of Windsor tower and Grenfell tower fire accidents, the fire resistance grade of steel structure and fire resistance grade of concrete structure are the major causes for the collapse of a building during the fire [7, 9]; the building envelope poses a significant hazard to the spread of fire using flammable insulating materials. Based on the cases analysis, fire resistance grade of steel structure (S_{10}), fire resistance grade of concrete structure (S_{11}), and fire resistance grade of the building envelope structure (S_{12}) were selected as bottom factors to the building structure risk (C_8). Similarly, other factors were obtained based on fire case analysis and will not be detailed here. The basic events of static risk factors and the specific descriptions of static bottom risk factors (S_1, S_2, . . ., S_{27}) are shown in Table 2 and S2.

4.3. Establishment of BN Model. After the establishment of the risk factor FT, there are a total of 14 root risk factors (C_1, C_2, . . ., C_{14}) listed in the FT assessment model of electrical fire risks in high-rise buildings, which correspond to the root

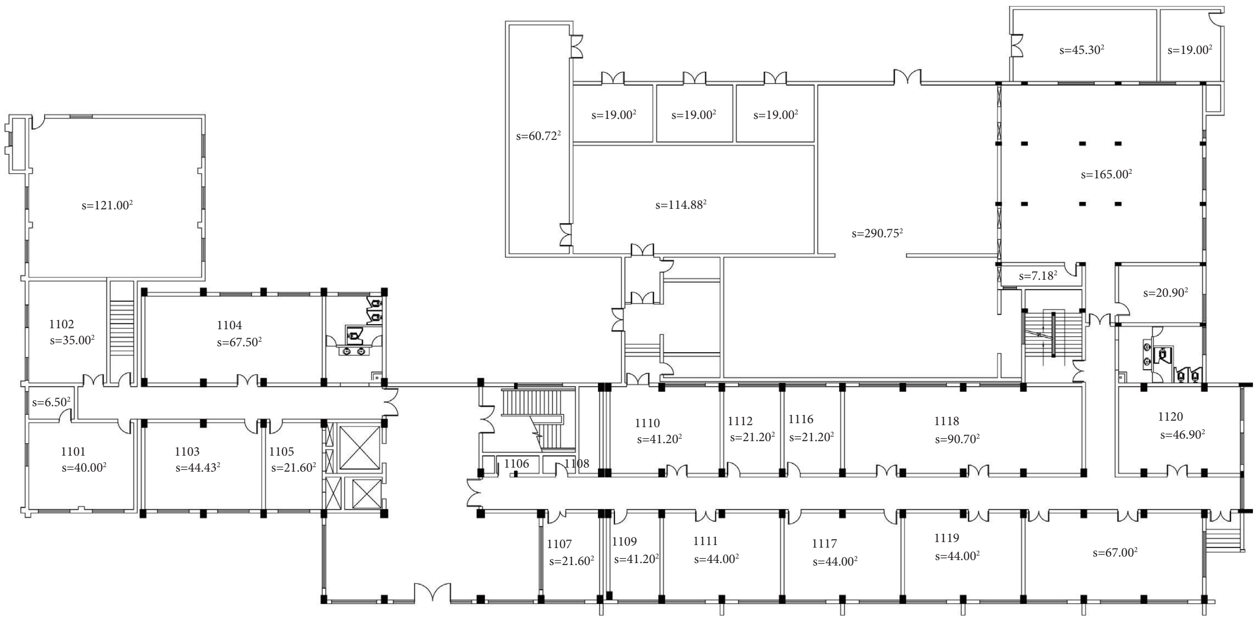
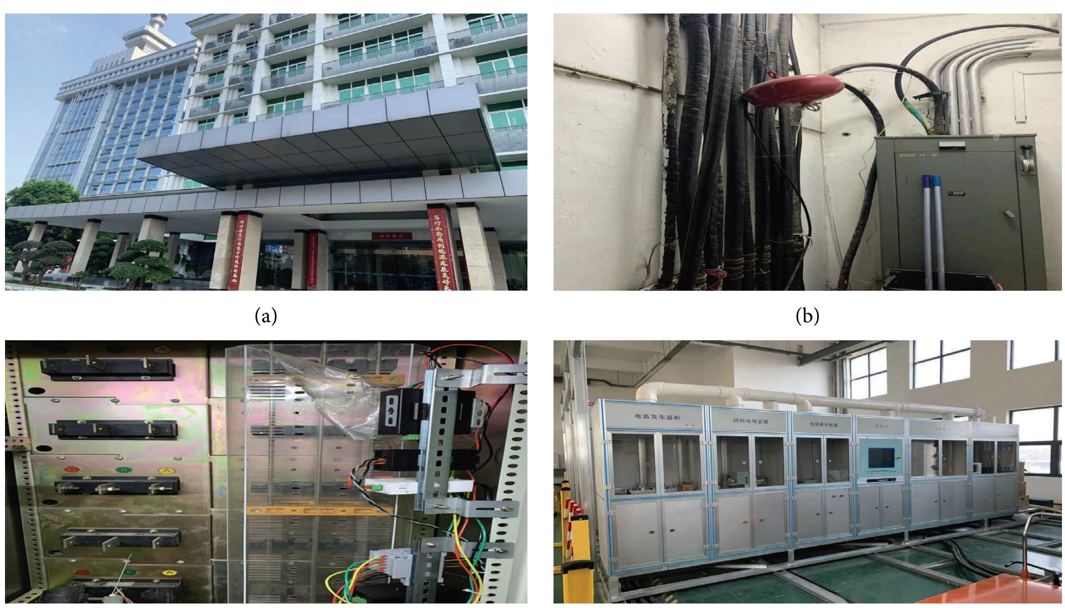


Figure 3: Layout of the building.



(a) (b)

(c) (d)

Figure 4: Case building situation: (a) the overall structure of the building; (b) high-voltage power supply line; (c) low-voltage distribution cabinet; (d) high-voltage laboratory.

node of the BN model. The 5 factors categories correspond to intermediate nodes (B_1, B_2, ..., B_5), and the top event A corresponds to the leaf node. To present the advantages of flexible and variable membership functions of VSFT, the risk status of each root node can be divided into four levels: H (high), M (medium), L (low), and S (safe); each intermediate node can be divided into two levels: H (high) and L(low). The dynamic risk assessment BN model of electrical fire risks in high-rise buildings established in this study is shown in Figure 5.

4.4. Variable Fuzzy Prior Probabilities and CPT. In terms of dynamic root nodes (C_1, C_2, . . ., C_4), the electrical system design and electrical equipment information for evaluating high-rise buildings are collected firstly to determine the risk states division of bottom risk factors. The number of level intervals is the same as the number of states of the root node. Standard interval divisions for the assessment of the dynamic bottom risk factors (D_1, D_2. . ., D_7) are shown in Table S1. It can be seen that the dynamic bottom risk factors are all physical quantities related to electrical faults, which

Table 2: Basic events for electrical fire risk assessment of high-rise buildings.

Top event	Factors categories	Root event	Bottom factors
Electrical fire risk A	Electrical line failure B_1	Line short circuit risk level C_1	D_1, D_2, and D_3
		Line overload risk level C_2	D_1, D_4, and D_5
		Risk level of line grounding fault C_3	D_2 and D_6
		Hidden danger of line fault arc C_4	D_2 and D_7
	Electrical equipment failure B_2	Operation risk of distribution equipment C_5	S_1, S_2, and S_3
		Operation risk of electrical equipment C_6	S_4, S_5, and S_6
		Risk of electrical equipment placement C_7	S_7, S_8, and S_9
	Building fire prevention capacity B_3	Building's structure risk C_8	S_{10}, S_{11}, and S_{12}
		Plane layout risk C_9	S_{13}, S_{14}, S_{15}, and S_{16}
	Fire protection facilities capability B_4	Fire station risk C_{10}	S_{17} and S_{18}
		Reliability risk of fire protection system C_{11}	S_{19}, S_{20}, and S_{21}
	Ability of evacuation safety management B_5	Safety management system C_{12}	S_{22} and S_{23}
		Evacuation routes and evacuation facilities C_{13}	S_{24}, S_{25}, and S_{26}
		Fire emergency plan and exercise C_{14}	S_{23} and S_{27}

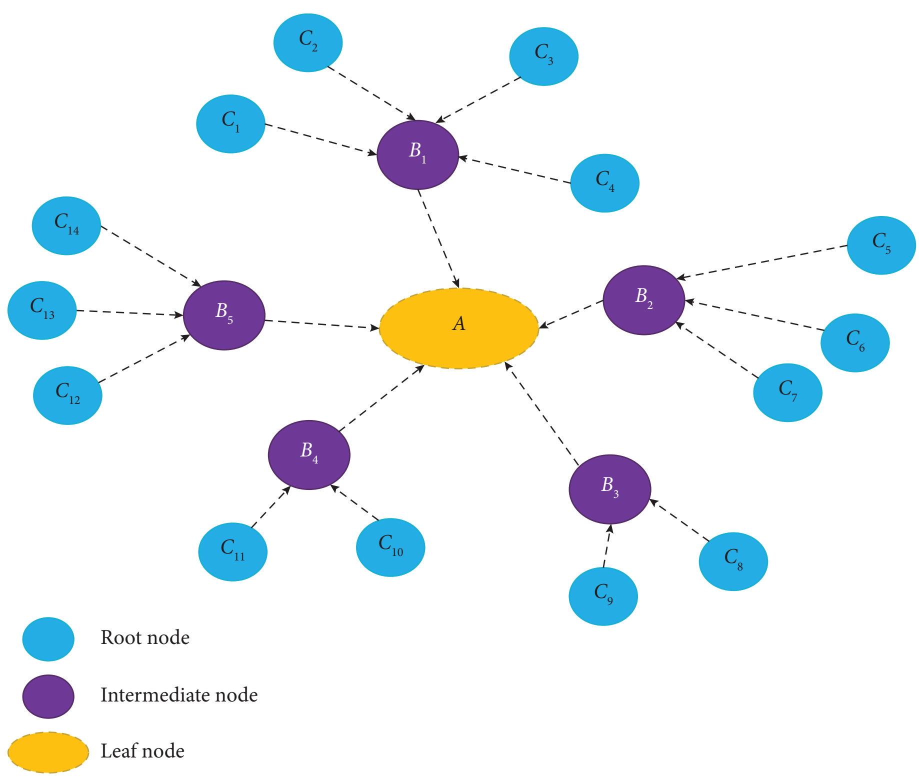


Figure 5: VFBN model diagram of electrical fire dynamic risk assessment for high-rise building.

can be found by the feedback of the electrical fire monitoring system. To enable the generalizability of assessment methods, the eigenvalues of these dynamic risk factors are set as the ratio of real values to baseline values (rated values).

Since static risk factors nodes would not be changed in a short period, static nodes are mainly dominated by expert assessment. First, the risk states division of the VFST of static bottom risk factor can be established based on the analysis of electrical fire cases in recent years, relevant specifications in the electrical industry and construction industry, and the survey of previous studies (Table S2). Then, the bottom risk factors corresponding to each static node can be scored by domain experts on site. In this study, the prior probabilities and CPT for VFBN are derived by three domain experts based on the collected information and their experience.

Taking dynamic root node C_1 as an example, based on the measured data of the electrical fire monitoring system, it can be obtained that the eigenvalue of the dynamic risk factor C_1 corresponding to the bottom factors (D_1, D_2, and D_3) are $X_1 = [0.88,\ 0.9,\ 1.4]$. The index scores are standardized, and the standard rank intervals in Table 3 can be applied to extreme value normalization. Eventually, $x_1 = [0.824,\ 0.45,\ 0.72]$ can be obtained.

(1) Based on the AHP, the constant weight coefficients $w^0 = [0.523, 0.186, 0.291]$ can be obtained for D_1, D_2,

Table 3: Prior probabilities of each root node.

Root node	H	M	L	S
C_1	0.0563	0.3287	0.3600	0.2549
C_2	0.0458	0.3473	0.3937	0.2130
C_3	0.0805	0.4536	0.3895	0.0761
C_4	0.0890	0.4813	0.3577	0.0718
C_5	0.0364	0.3806	0.4547	0.1282
C_6	0.0702	0.4528	0.3165	0.1603
C_7	0.0241	0.3071	0.4863	0.1822
C_8	0.0453	0.3895	0.3961	0.1689
C_9	0.0430	0.2720	0.4614	0.2235
C_{10}	0.0387	0.3099	0.4145	0.2367
C_{11}	0.0309	0.2823	0.4716	0.2149
C_{12}	0.0258	0.3921	0.5018	0.0802
C_{13}	0.0317	0.2870	0.4677	0.2133
C_{14}	0.0253	0.3317	0.4174	0.2254

and D_3. According to equation (11) and x_i, the improved variable weight coefficient can be obtained as $w = [0.4553, 0.2626, 0.2821]$. It can be seen that the improved variable weight value becomes larger for D_2 with lower eigenvalues, which indicates that the impact of D_2 on fires becomes greater under this eigenvalue. It is obviously more consistent with the practical situation.

(2) According to the risk states division of dynamic risk factors of high-rise buildings in Table S1, the risk assessment standard interval matrix I_{ab} can be expressed as follows:

$$I_{ab1} = \begin{bmatrix} [5, 1.5] & [1.5, 1.3] & [1.3, 1] & [1, 0] \\ [0, 0.7] & [0.7, 1] & [1, 1.2] & [1.2, 2] \\ [5, 1.8] & [1.8, 1.3] & [1.3, 1) & [1, 0] \end{bmatrix}. \quad (18)$$

(3) The variable interval matrix I_{cd} can be expressed as follows:

$$I_{cd1} = \begin{bmatrix} [5, 1.3] & [5, 1] & [1.5, 0] & [1.3, 0] \\ [0, 1] & [0, 1.2] & [0.7, 2] & [1, 2] \\ [5, 1.3] & [5, 1] & [1, 1.8) & [1.3, 0] \end{bmatrix}. \quad (19)$$

(4) According to (7), the point-value matrix M_{ik} of the membership degree of 1 of each assessment interval of the secondary risk factors is as follows:

$$M = \begin{bmatrix} 5 & 1.4 & 1.15 & 0 \\ 0 & 0.85 & 1.1 & 2 \\ 5 & 1.55 & 1.15 & 0 \end{bmatrix}. \quad (20)$$

(5) The relative membership matrix of the grade of the secondary risk factors can be calculated based on (8) and (9) and then normalized to obtain the membership matrix of the secondary risk factors of the assessment system as follows:

$$R\left(u_{C_1}\right) = \begin{bmatrix} 0 & 0 & 0.44 & 0.56 \\ 0.125 & 0.625 & 0.25 & 0 \\ 0.083 & 0.583 & 0.333 & 0 \end{bmatrix}. \quad (21)$$

Finally, after the variable weight coefficient is obtained by Step (1) and equation (12), the coupling factor weight with the membership matrix is selected as a fuzzy operator, and the prior probability under the feedback value corresponding to the dynamic node C_1 can be obtained as follows:

$$\begin{aligned} P\left(C_1 = H\right) &= 0.0563, \\ P\left(C_1 = M\right) &= 0.3287, \\ P\left(C_1 = L\right) &= 0.3600, \\ P\left(C_1 = S\right) &= 0.2549. \end{aligned} \quad (22)$$

Based on that, the prior probabilities of other root nodes can be provided specifically in Table 3.

As described in Section 3.4.3, the method combining AHP with the decomposition method can be used to calculate the CPT of each node. The comparison matrix can be derived by opinion assessment from 3 experts. The first expert is a senior engineer at Hubei Academy of Electric Power Sciences, the second one is a professor at China Petroleum University, and the third one is an associate professor at China Petroleum University. Examples would not be provided for calculations due to space limitations. The specific calculation process of determining CPT based on the combination of the decomposition method and AHP can be consulted in the previous literature [49].

4.5. Case Result Analysis

4.5.1. Inference Analysis Result. After the prior probability and CPT of nodes are calculated, Bayesian inference is performed with Netica. As shown in Figure 6, the probability

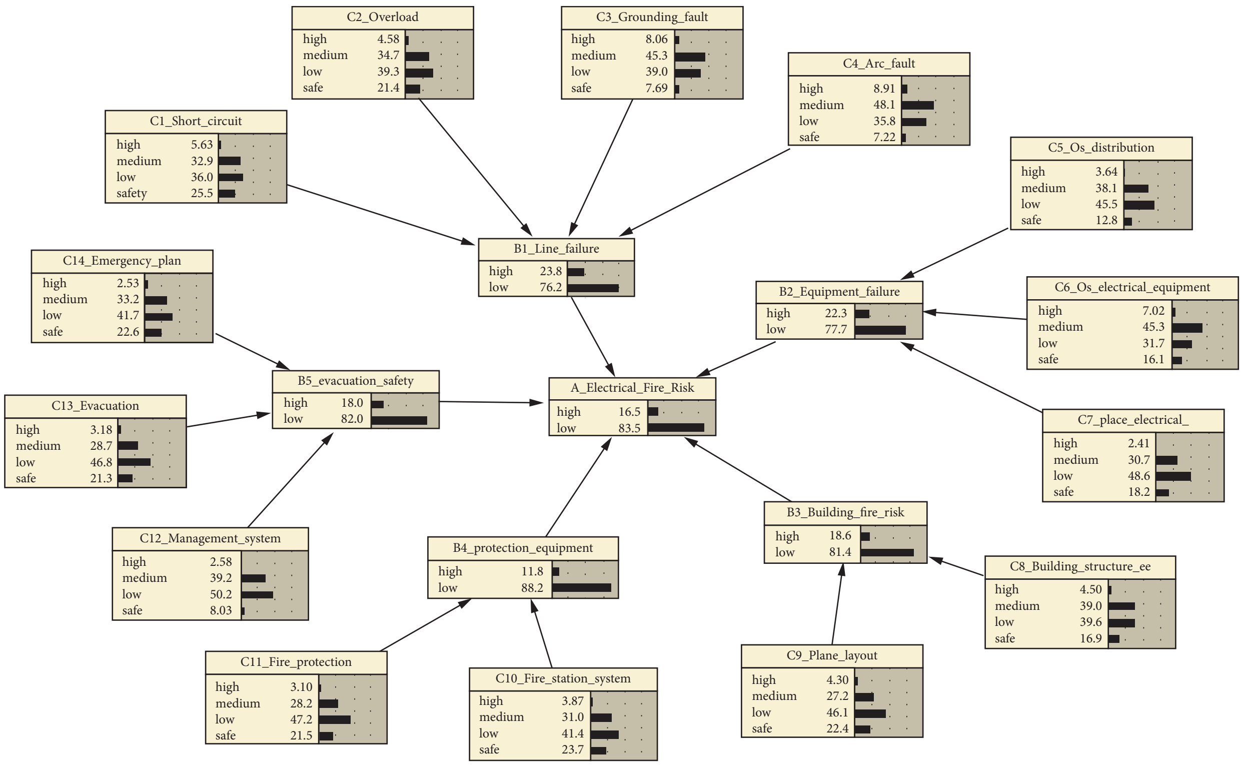


Figure 6: BN of electrical fire risk for high-rise building under prior conditions.

of an electrical fire in a high-rise building is P (A = high) = 16.5%, which is higher than 10%. Therefore, it can be argued that there are some risks for the occurrence of electrical fires in this high-rise building and decision makers should take measures to conduct risk containment. With rather limited posterior knowledge, one can use forward inference to make a preliminary judgment on the overall risk of an electrical fire in a high-rise building and then determine the optimal plan to eliminate fire hazards.

In the event of an electrical fire accident in a high-rise building, it is common to cut the whole power supply system firstly, and then, the concerned department immediately organizes experts to perform an on-site analysis to determine the causes inducing the fire.

Due to a larger variety of features in a high-rise building, too long assessment time also causes certain economic losses. With the help of the inference of the posterior probability, the reverse inference analysis is conducted for electrical fire accidents to realize the dynamic detection of the accident cause. Meanwhile, the posterior probability can also be used to determine the important influence degree of each fire risk factor on the occurrence of electrical fires. The posterior probability of each risk factor can be calculated with (1) under the electrical fire occurrence condition of P (A = High) = 1. As shown in Figure 7, the top six fire risk factors can be ranked as $C_4 > C_6 > C_3 > C_1 > C_2 > C_5$ based on their posterior probabilities. C_4 (arc fault), C_6 (operation risk of electrical equipment), and C_3 (grounding fault) are the causes with the largest possibility inducing electrical fires. Therefore, safety inspection and risk management should be performed on arc faults, line-to-ground faults, and electrical equipment operation faults. Through inspection, it is found that there are some problems of excessive contact resistance at the connection points of electrical lines and some non-standard grounding. In the static risk assessment methods based on traditional expert experience, it is difficult to identify these dynamic risk factors with physical quantity changes. In addition, buildings structure risk (C_8) and plane layout risk (C_9) are factors with a large posterior probability among nonelectrical factors, which is the same as the building's findings in a recent fire inspection report. Therefore, the risk assessment method proposed in this study can be used to scientifically and reasonably assess the real-time changing electrical system.

4.5.2. Critical Analysis. During quantitative risk assessment, the analytical identification of significance for the basic event C_i is an important step. Obtaining critical parameters of risk factors through sensitivity analysis of the BN model is an important step during risk assessment. Therefore, sensitivity analysis is required in identifying the most critical variables or factors. With the sensitivity analysis technique of BN, the risk factors affecting electrical fires in high-rise buildings can be adjusted and optimized in real time, which contributes to fire risk control. The RAW, RRW, and AVG for each basic event of an electrical fire can be obtained according to equations (11)–(13). The calculation results are shown in Figure 8. As can be seen from the rank results of AVG values in Figure 8, faults arc (C_4) and electrical equipment operation faults (C_6) are the top two risk factors. Based on this rank, fire digital simulation analysis can be conducted on

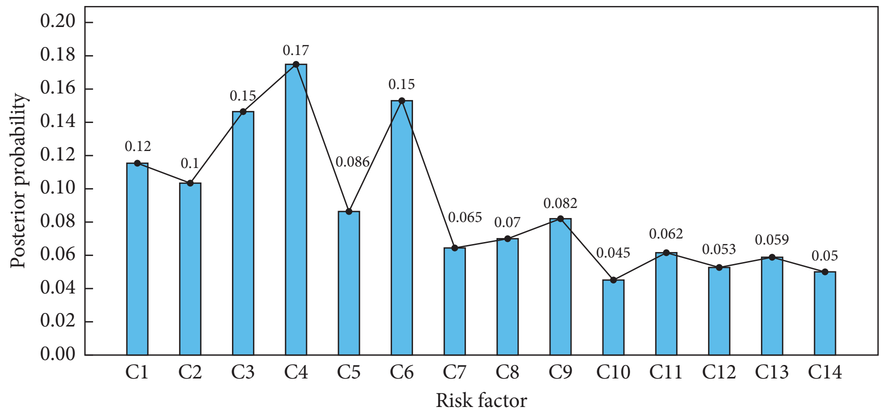


FIGURE 7: Posterior probability of fire risk factors ($P(C_i = H)$).

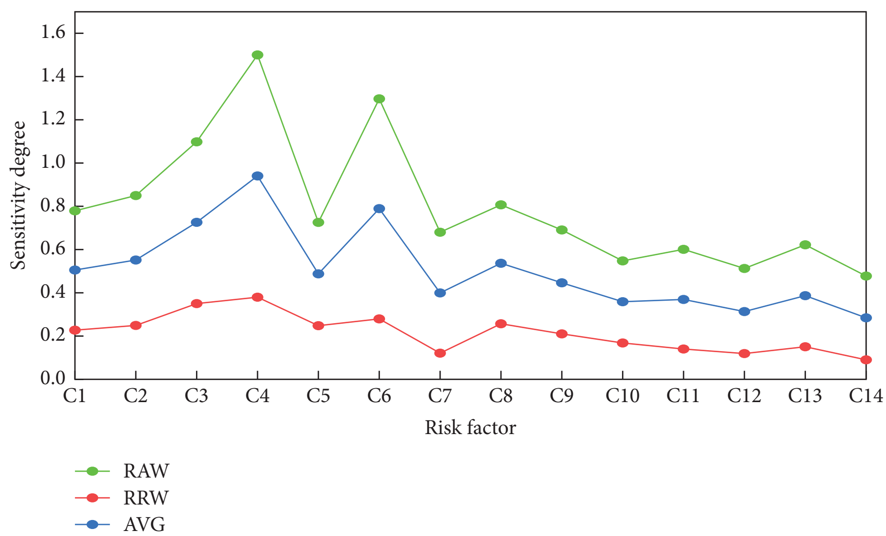


FIGURE 8: Risk importance of each risk factor.

four common electrical fire risk factors: short circuit, overloaded circuit, arc fault, and ground fault. After the effects of thermal release rate, smoke density transformation, CO concentration change, and CO_2 concentration change are considered comprehensively, the simulation results can be obtained, as shown in Figure 9. As shown in Table 4, it can be concluded that the four common electrical faults can be ranked based on their hazards: arc fault (C_4) > ground fault (C_3) > short circuit (C_1) > overload (C_2), which is different from those in Figure 8 ($C_4 > C_3 > C_2 > C_1$). The reason is that the overloaded circuit in Figure 8 is associated with the electrical device state, which would cause their corresponding AVG bigger. Therefore, the risk assessment model proposed in this study is verified to be objective and reasonable.

5. Discussion

Electrical fires have been the leading cause of fire outbreaks in high-rise buildings. However, it is difficult to perform an accurate quantitative risk assessment for electrical fires due to the complexity and uncertainty of causes. FBN, which combines the uncertainty of BN and the ambiguity and uncertainty of FST, has been widely used in the safety assessment of engineering. In this paper, a combination of VFST and BN, in which membership function can be adjusted and correspond to the physical meaning of risk factors, is applied to the dynamic risk assessment of electrical fires in high-rise buildings. Based on the variable fuzzy probabilities and electrical quantity monitoring values from expert assessment, this method can be used for electrical fire risk assessment. Besides, it can also be employed to quantify electrical fire risk probabilities and identify the most sensitive cause for the occurrence of electrical fires. Some questions would be discussed as follows.

5.1. Dynamic Uncertainty Assessment. For an electrical fire, it is common that an electrical fault occurs in conjunction with a mutation in the electrical quantity in the circuit. That is to say, the electrical fire risk is variable in real time. Meanwhile, it is difficult to collect the risk data from electrical fires in high-rise buildings, which causes a blockage

Table 4: Rank of importance of influence.

Electrical line failure	Fire impact category				
	Heat release rate (45%)	Smoke density change (25%)	CO concentration change (10%)	CO_2 concentration change (20%)	Finally
Short circuit	3rd	2nd	1st	4th	3rd
Overload	4th	3rd	2nd	3rd	4th
Ground fault	2nd	4th	3rd	2nd	2nd
Fault arc	1st	1st	4th	1st	1st

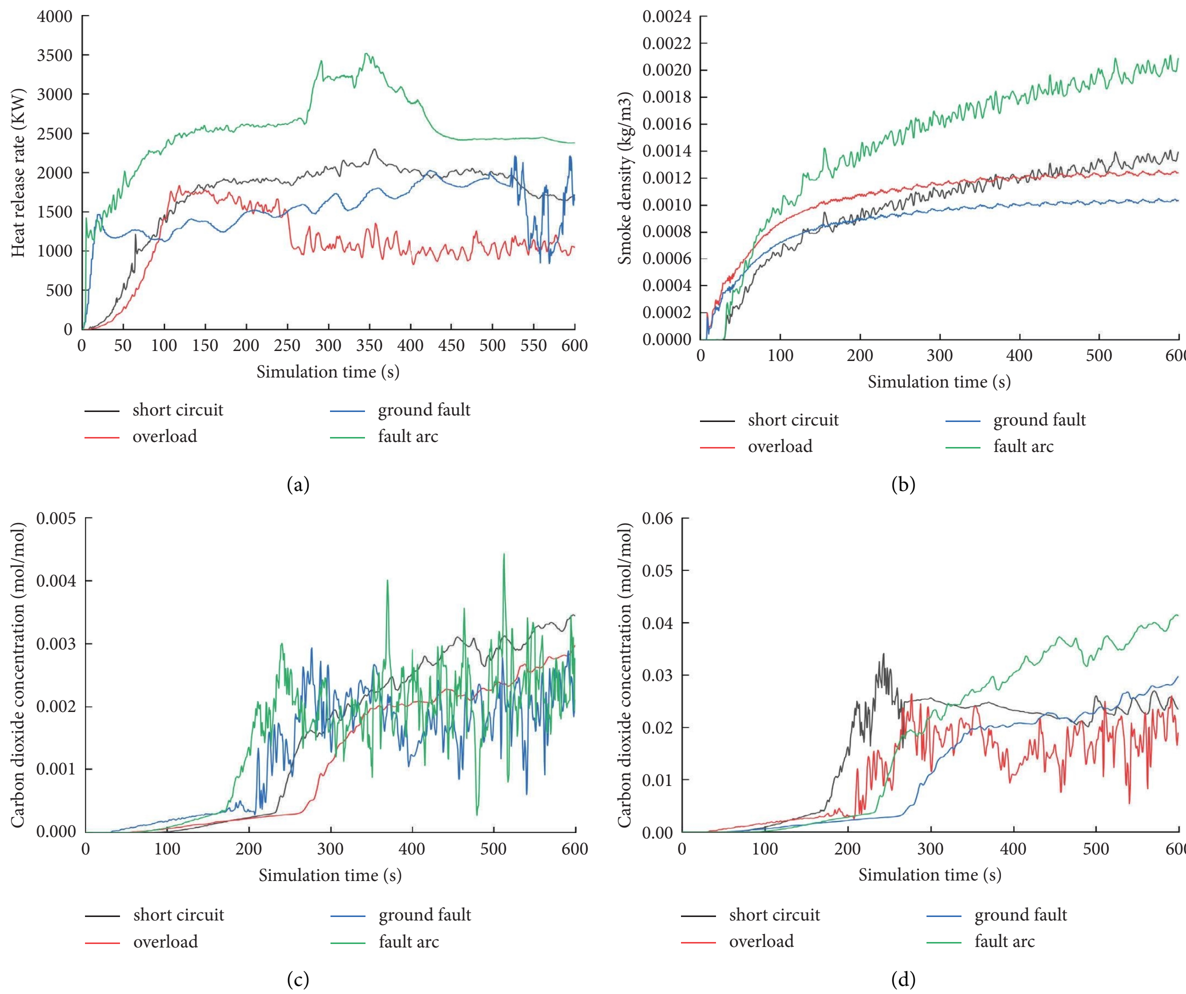


Figure 9: Results of electrical fire simulation: (a) heat release rate change curve; (b) smoke density change curve; (c) CO concentration change curve; (d) CO_2 concentration change curve.

in logistic analysis calculations. In this study, a BN risk assessment model is established based on the combination of dynamic and static assessment risk factor. For the dynamic risk factors, the electrical fire risks in high-rise buildings can be dynamically assessed through the monitoring, state identification, and inference of medium electrical information by an electrical fire monitoring system. For static risk factors, the eigenvalues of bottom risk factors can be judged based on the knowledge and experience of domain experts, and a few indicators are related to building physical properties. Based on that, the same reasoning and inference algorithm as conventional BN is adopted for predictive analysis and probability update in this paper. Through Bayesian inference, the probability of an electrical fire and the probability distribution of fire risk factors can be calculated in real time based on prior knowledge and evidence updates. Furthermore, the static node will not change in a short period after the prior probability is obtained through expert assessment, and VSFT assessment does not need to change in a short period. Hence, dynamic risk factor can be identified through the real-time monitoring of the electrical fire monitoring system. Moreover, this method can realize real-time evolutionary inference, dynamic risk assessment, and management.

5.2. Risk Factor Inference. BN risk analysis features that it yields a posterior probability based on the actual observation of the root node. Different from the prior probability, the posterior probability could exert an important impact on differentiating the extent to which individual essential events contribute to this top event in electrical fire accidents. The current investigative diagnosis of electrical fire accidents highly relies on the experience and knowledge of experts. Once an electrical fire occurs, the power supply system of the entire high-rise building would be typically cut off, and then, experts would be organized for site survey analysis. This presents a certain hazard to the personal safety of experts. In addition, prolonged power outages time would affect the daily use of high-rise buildings and cause more economic losses. With the assistance of the reverse inference technique of BN, fire risk factors can be reversely analyzed and the posterior probability of each risk factor can be calculated. Furthermore, fire risk control can be performed by prioritizing diagnoses for those influencing factors with large posterior probabilities and quickly determining the source of fires. This improves the accuracy of identifying the fire source, accelerates the recovery in the normal operation of high-rise buildings, and reduces the loss caused by fires.

5.3. Key Factor Identification. In electrical fire risk assessment, decision makers usually pay more attention to which factors play a crucial role in the occurrence of electrical fires in high-rise buildings. However, key factor identification is often dominated by the subjective judgment of experts. The assessment method proposed in this paper can quickly identify the most dangerous fire factors and facilitate the adjustment and optimization of fire protection measures in real time by calculating the extent to which each fire risk factor has an impact on fire accidents. Thus, the method can identify key sensitive risk factors, which would facilitate real-time adjustment and optimization by measuring the impact of each risk factor C_i on the top risk event A.

6. Conclusions

To reduce the hazards of electrical fires in high-rise buildings, a quantitative analytical model combining VFST and BN is proposed in this study to assess the risk probability of electrical fires in high-rise buildings. A BN risk assessment model based on dynamic risk factors and static risk factors is also established. The prior probability of root nodes can be calculated with the membership function, a more flexible VFST method instead of the traditional FBN. Besides, the decomposition and hierarchical analysis methods are employed to determine the CPT. The electrical fire cases in high-rise buildings are also analyzed, and the results verify the feasibility of the proposed method in engineering practice. The prediction results of electrical risk probability in high-rise buildings by Bayesian forward inference demonstrate that electrical fires have a certain probability during their occurrence, and the overall risk level of electrical fires in high-rise buildings can be quantitatively assessed. By backward inference, the diagnosis can be made for the factors with larger effects that cause electrical fires, which can quickly strengthen the preparedness and control for these risk factors and lower the probability of an electrical fire accident. In addition, sensitivity analysis is conducted to identify key influencing factors, as an attempt to control the risk of electrical fires in advance, and to ensure the safety of people in tall buildings.

Nevertheless, there are still several limitations in the methodology of this study. For example, this method relies heavily on domain experts in establishing prior probabilities of VFST and CPT. Although the subjective bias and uncertainty have been reduced to some extent by VFST-based risk states division, the effects of subjectivity cannot be eliminated. Moreover, the dynamic risk factors of electrical fire in high-rise buildings among the risk factors considered in this study are limited by the influence of electrical monitoring technology. Electrical equipment-related dynamic risk factors were not considered, and more electrical fire cases are required for improvement.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Supplementary Materials

Table S1: dynamic bottom factors descriptions and risk states division. Table S2: static bottom factors descriptions and risk states division. (*Supplementary Materials*)

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