Research on Fire Risk Assessment in Machining Workshop Based on Bayesian Network

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Abstract. In mechanical processing workshops, fire hazards gravely threaten safety and property. Existing assessment methods fail to comprehensively account for multi-factor interactions. This study innovatively applies the Bayesian network model to this field for the first time. The model, featuring 20 tertiary and 5 secondary nodes, covers hazardous gas storage, operational norms, and equipment conditions. Empirical analysis reveals a 0.16 probability of fire due to improper hazardous gas cylinder storage at the secondary level. Sensitivity analysis shows that "uninspected oxygen and acetylene cylinders upon entry" significantly impacts "non-standard gas welding operations", while hose aging and backfire preventer damage also strongly influence risks. Forward inference identifies key fire-causing factors, with probabilities up to 0.22 at the tertiary level and 0.3 at the secondary level. Reverse inference indicates improper hazardous chemical cylinder storage as the most likely cause during a fire. This study confirms that non-standard operations and equipment aging are pivotal. The Bayesian network's multi-level design and bidirectional inference enable precise risk quantification, offering a scientific basis for safety management and paving the way for dynamic evaluations.

Keywords: Bayesian Network, Machining Workshop, Fire, Risk Assessment, Sensitivity Analysis.

1. Introduction

Jiang Fuchuan et al. [1] analyzed national industrial safety accidents, showing production and processing workshops are high - risk for fire and explosion, accounting for 32.7%. Through scientific statistics, they found such accidents' destructive power and harm far exceed expectations. Involving intense energy release and complex chain reactions, they have severe consequences [2]. These accidents damage equipment, halt production, and endanger personnel, causing casualties and trauma. Macroscopically, their impact extends beyond enterprises, affecting industries and the national economy [3]. Public concern and psychological impacts raise expectations for safe production. Thus, this study urges us to prioritize safety management in workshops, adopt comprehensive preventive measures, mitigate accident risks, safeguard lives and property, and promote sustainable economic and social development [4].

Wang Qiang et al. [5] studied multi - source data fusion using sparse Bayesian learning and improved D - S evidence theory, revealing the diverse and complex nature of global mechanical processing workshop accidents, which involve a complex interplay of human, equipment, and environmental factors. Song Yinghua et al. [6] simulated chemical industrial park fire and explosion accidents via fuzzy Bayesian networks and, based on OSHA statistical methods, found that although fire and explosion accidents accounted for only 18% of workshop accidents, they caused 65% of economic losses. This highlights their high destructiveness despite low occurrence frequency. Consequently, researching fire and explosion accidents is of great practical value [7]. It deepens understanding of high - risk incidents, offering scientific support for preventive and emergency strategies [8]. By analyzing accident causes and mechanisms, it can reduce threats, protect personnel, and minimize economic losses, benefiting not only the mechanical processing industry but also other related fields [9].

In the field of risk assessment, various methods, ranging from qualitative to quantitative, have been widely applied, integrating systematic thinking to address real - world challenges. The Analytic Hierarchy Process (AHP), a classic multi - criteria decision - making method, decomposes complex problems hierarchically, integrates qualitative and quantitative analysis via judgment matrices, and calculates index weights. However, its heavy reliance on expert subjective judgment may introduce biases, as Xu Jianqiang et al [10]. found in building fire risk studies.The fuzzy comprehensive evaluation method, discussed by Junyung Kim et al. uses fuzzy mathematics to transform hard - to - quantify factors into numerical indicators, offering new perspectives on risk management. Yet, it faces the "rule explosion" problem during multi - factor coupling analysis, increasing computational complexity and limiting practical use [11]. In recent years, Bayesian Networks (BN) have emerged as innovative risk assessment tools [12]. As Guo Chuijiang et al. [13] reviewed, BNs use directed acyclic graphs to represent variable dependencies and probabilistic reasoning for quantitative analysis [14-16]. By integrating prior knowledge and data, BNs infer probabilities of unknown events, providing scientific decision - making bases. BNs thus bring both theoretical innovation and practical value to risk assessment [17-20].

This paper’s research framework consists of two major modules: theoretical modeling and empirical analysis. Chapter 2 constructs a Bayesian network theoretical model, focusing on the method of building conditional probability tables and the fusion mechanism of DS evidence theory. Chapter 3 conducts an empirical study in a precision machining workshop, sequentially carrying out initial risk assessment, sensitivity analysis, forward accident deduction, and reverse root cause diagnosis. Chapter 4 summarizes the application value of the model in risk early warning accuracy and prevention measure optimization, and discusses the improvement direction of multi-source data fusion algorithms. This structural design realizes a complete closed-loop from theoretical innovation to engineering application, providing new methodological support for fire prevention and control in mechanical machining workshops.

2. Bayesian Networks and Related Theoretical Foundations

2.1. The Principles of Bayesian Networks

A Bayesian network is a powerful tool based on probabilistic graphical models, primarily used for handling uncertain reasoning problems. Its core idea is to describe and capture conditional dependencies between variables by constructing a directed acyclic graph (DAG). In this network structure, each node represents a random variable, while the directed edges between nodes indicate possible causal relationships or statistical correlations between these variables. Additionally, each node is accompanied by a conditional probability table (CPT), which quantifies the probabilistic influence of parent nodes on the current node. In other words, the conditional probability table specifies the probability distribution of the current node taking various possible values given different values of its parent nodes. The theoretical foundation of Bayesian networks is the famous Bayes’ Theorem, which provides a method for inferring the probability of unknown events from known information. Its mathematical expression is as follows:

$$P(A \mid B)=\frac{P(B \mid A)P(A)}{P(B)} \tag{1}$$

where $P(A \mid B)$ represents the posterior probability, $P(B \mid A)$ represents the likelihood probability, $P(A)$ and $P(B)$ represent the prior probability and marginal probability respectively. For a network containing N variables, its joint probability distribution can be decomposed into:

$$p(X)=\prod_{i=1}^{N} p(X_i \mid Par_G(X_i)) \tag{2}$$

where $p(X)$ is the joint probability distribution of the set of random variables $X=\{X_1, X_2, \cdots, X_N\}$, X_i is an individual random variable among them $(i=1,2,\cdots,N)$, $Par_G\left(X_i\right)$

is the set of parent nodes of X_i in the probabilistic graphical model's graph G, and $p\left(X_i \mid Par_G\left(X_i\right)\right)$ is the conditional - probability distribution of X_i given its parent nodes $Par_G\left(X_i\right)$.

For complex systems involving N variables, a key feature of Bayesian networks is that they can decompose joint probability distributions into a series of simpler conditional probability distributions. This decomposition not only greatly simplifies high-dimensional probability modeling tasks but also significantly reduces computational complexity, making originally intractable large-scale problems feasible. In practical applications of fire risk assessment in mechanical processing workshops, Bayesian networks can effectively integrate heterogeneous data from multiple sources, such as equipment condition monitoring data, environmental parameter measurement results, and compliance with operating standards, thereby building a dynamic risk evolution network and providing decision-makers with more comprehensive and accurate risk assessment basis.

2.2. Acquiring Conditional Probability Distribution in DS Evidence Theory

In practical applications, especially in complex environments such as mechanical processing workshops, the problem of incomplete data is often encountered, which poses significant challenges to traditional modeling methods based on complete data. To address this issue, researchers have introduced Dempster-Shafer (DS) evidence theory as an effective solution. The core of DS evidence theory lies in obtaining conditional probability distributions by fusing multi-source information, thereby overcoming the limitations of traditional methods' strong dependence on prior probabilities. Under the DS evidence theory framework, the first step is to define a frame of discernment

$$\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\} \tag{3}$$

Basic probability assignment function

$$m: 2^{\Theta} \to [0,1] \tag{4}$$

satisfy:

$$\begin{cases} m(\varnothing) = 0 \\ \sum\limits_{A \subseteq \Theta} m(A) = 1 \end{cases} \tag{5}$$

$$(m_1 \oplus m_2 \oplus \cdots \oplus m_n)(A) = \begin{cases} 0, & A = \varnothing \\ \dfrac{1}{K} \sum\limits_{A_1 \cap A_2 \cap \cdots \cap A_n = A} m_1(A_1) \cdot m_2(A_2) \cdots m_n(A_n), & \text{otherwise} \end{cases} \tag{6}$$

$$K = 1 - \sum_{\cap A_i = \varnothing} \prod m_i(A_i) \tag{7}$$

Where K is used to ensure that the final obtained probability values have reasonable ranges and interpretative significance. By transforming expert judgments, historical data records, and experimental monitoring results into corresponding mass functions, Dempster-Shafer (DS) evidence theory can effectively combine multiple information sources to form more reliable and comprehensive conditional probability estimates. This method not only enhances the robustness of the model but also improves its adaptability and accuracy in practical application scenarios, providing new ideas and tools for solving uncertainty problems in complex systems.

3. Results

3.1. The establishment of Bayesian network

In the process of constructing risk nodes, it is necessary to fully combine the actual operation of the mechanical processing workshop and relevant safety standards to clarify each node in the Bayesian network based on this. As shown in Table 1, the design of secondary parent nodes covers multiple key risk factors, including but not limited to improper storage of hazardous gas cylinders (R1), non-standard behavior during welding operations based on gas cylinders (R2), non-compliant operation of electrical equipment (R3), non-standard phenomena in processing technology implementation (R4), and unreasonable storage methods of flammable and explosive substances (R5). The setting of these nodes aims to comprehensively cover various potential risk sources that may cause fires in the workshop. Taking R1 as an example, this node is further divided into several tertiary parent nodes, such as the lack of necessary inspections during the storage of oxygen and acetylene gas cylinders (A), and gas leakage or rupture due to cylinder damage (B), etc. Through this step-by-step refinement, not only can specific hidden danger points be more accurately captured, but it also provides a solid foundation for building the entire Bayesian network architecture. The establishment of this architecture enables us to conduct comprehensive analysis of risk factors in the workshop from multi-dimensional and multi-level perspectives. To ensure the rationality of the network structure, we determined the connection relationship between nodes based on the workshop's production process and the causal relationship between various risk factors, which can be specifically referred to in Figure 1. In addition, in determining conditional probabilities, we adopted a strategy combining multiple methods, including expert experience judgment, statistical analysis of historical data, etc. The application of these methods not only improves data reliability but also provides strong data support for subsequent risk assessment work. Through such comprehensive analysis, we can more accurately identify and quantify various risks in the workshop, thereby laying the foundation for developing effective safety management measures.

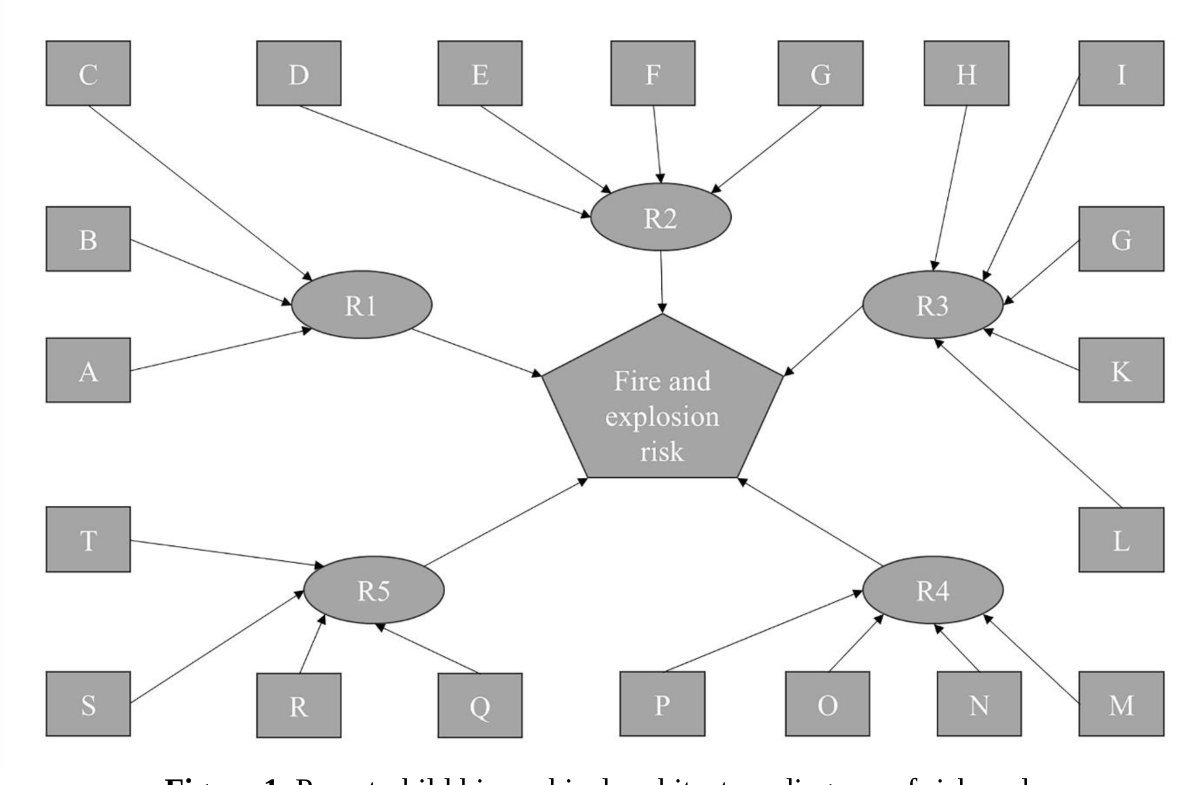

Figure 1. Parent-child hierarchical architecture diagram of risk node

Table.1. Three-level parent of the Bayesian network

Secondary parent node	Tertiary parent node (Root node)
R1. Improper storage of Hazard gas cylinders	A. Failure to inspect oxygen and acetylene cylinders upon storage B. Gas cylinder damage causing leakage or rupture C. Gas cylinders tipping and rolling leading to leakage and rupture
R2. Non - standard operation of gas cylinder - based electric welding	D. High - temperature debris from operation igniting objects E. Aging and damage of hoses causing leakage F. Damage of flashback arresters in acetylene cylinders G. Improper placement of on - site gas cylinders causing rupture
R3. Non - standard use of electrical equipment	H. Wear, aging and short - circuit of wire insulation layer I. High - load operation of electrical equipment causing overheating J. Illegal use of temporary wires causing wear and short - circuit K. Poor grounding of electrical equipment L. Discharge due to static electricity accumulation on objects
R4. Non-standard processing operations	M. No fire - prevention measures during hot work N. Equipment temperature control system failure causes overheating O. Hot workpieces being close to flammable materials P. Local overheating due to equipment component wear
R5. Improper storage of flammable and explosive substances	Q. Leakage during storage or use of flammable liquids R. Accumulation of flammable gases due to poor workshop ventilation S. High concentration of processing dust in the air T. Reactions caused by mixed storage of flammable items

In the process of constructing a Bayesian network, we can visualize the distribution of risk states for each node, as shown in Figure 2. In this diagram, each node's state is clearly divided into two categories: one represents the occurrence of risk, denoted by symbol V1; the other represents the non-occurrence of risk, denoted by symbol V2. Taking node R1 as an example, in certain specific areas, V1 accounts for 16%. This data clearly indicates that in these areas, the likelihood of fire caused by R1 is relatively high, showing significant safety hazards in these areas. By comprehensively analyzing the data information of all nodes in the Bayesian network, we can fully grasp the overall situation of initial fire risk in the workshop from a macro perspective. This method not only helps identify specific areas or key links with high fire risk but also provides important data support and theoretical basis for subsequent in-depth research and precise intervention. In other words, with this systematic analysis tool, we can more accurately locate potential risk points and develop targeted preventive measures based on this, thereby effectively improving overall safety management levels.

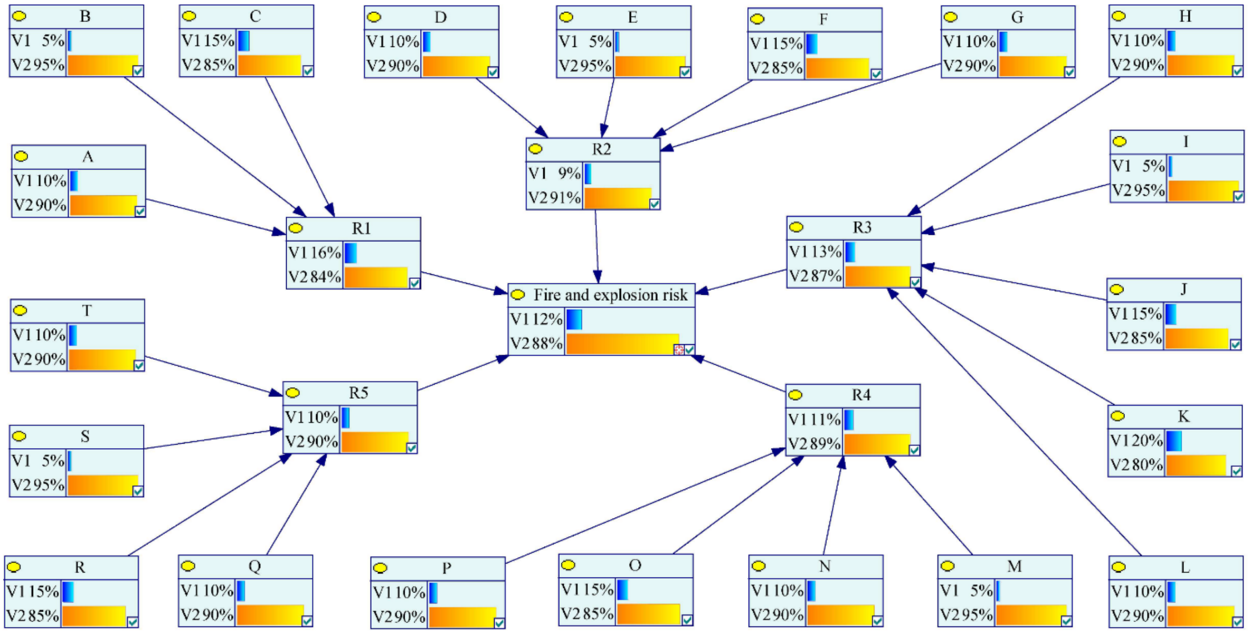

Figure 2. Bayesian Network Initial State

3.2. Sensitivity analysis

Sensitivity analysis is an important tool used to deeply explore the degree of influence of parent nodes on specific child nodes. As shown in Table 2, this analytical method not only reveals the influence relationships between parent nodes and various secondary parent nodes, but also further refines the weighted influence proportions of secondary parent nodes on the specific child node "fire and explosion risk". Through this multi-level quantitative analysis, we can more clearly understand the interaction mechanisms between different nodes. The core principle of this analysis is based on the conditional probability distribution model in Bayesian networks. Specifically, researchers can artificially adjust the state parameters of parent nodes, observe and record how these changes are transmitted to child nodes, thereby evaluating the specific impact of parent node state changes on child node behavior patterns. In this process, the so-called "weighted influence proportion" actually reflects the relative magnitude of the influence of parent nodes on child nodes. If a parent node has a higher proportion value, it indicates that the parent node has a more significant dominant role in the behavior or state of the child node Conversely, if the proportion value is lower, it shows that its influence is relatively limited. Therefore, through this method, we can more comprehensively and accurately grasp the dependency relationships and dynamic change rules between nodes within complex systems.

Table.2. Weighted influence proportion

Parent	Child	Weighted
A	R1	0.325
B	R1	0.315
C	R1	0.265
D	R2	0.254
E	R2	0.291
F	R2	0.291
G	R2	0.254
H	R3	0.189
I	R3	0.202
J	R3	0.208
K	R3	0.196
L	R3	0.208
M	R4	0.254
N	R4	0.241
O	R4	0.279
P	R4	0.241
Q	R5	0.229
R	R5	0.279
S	R5	0.229
T	R5	0.291
R1	Fire and explosion risk	0.233
R2	Fire and explosion risk	0.239
R3	Fire and explosion risk	0.171
R4	Fire and explosion risk	0.233
R5	Fire and explosion risk	0.196

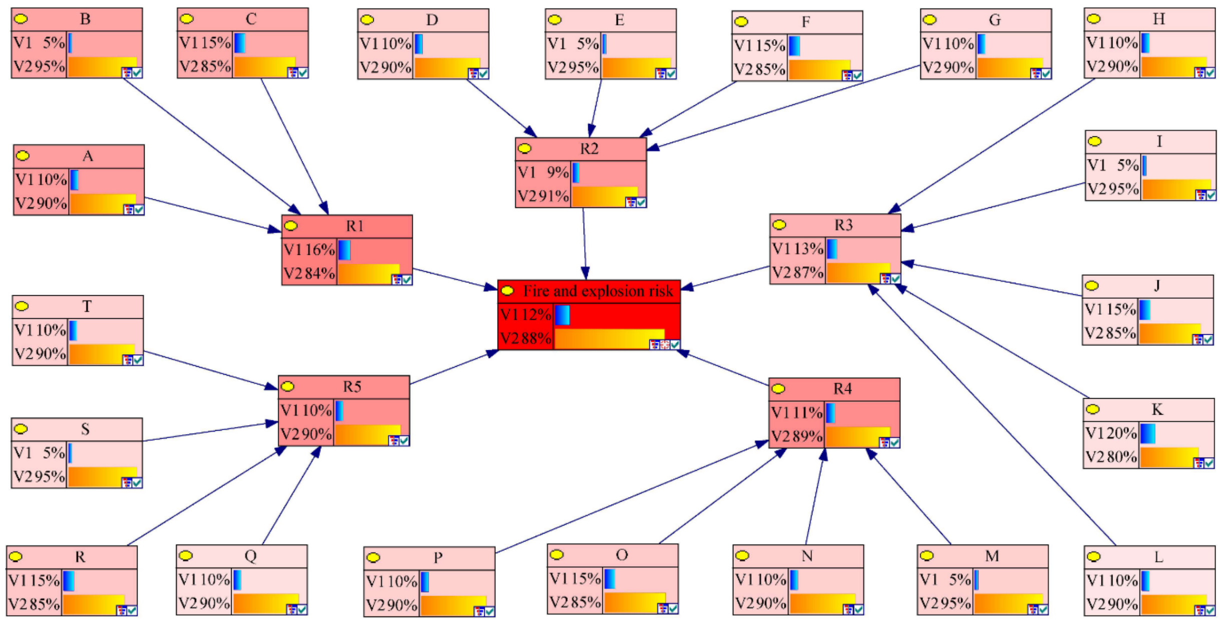

Figure 3. Sensitivity analysis

From the data analysis in Table 2, it can be clearly observed that the weight distribution of various factors at different nodes in the risk assessment model shows significant differences. Specifically, at node R1, factor A has a weight value of 0.325, indicating that A occupies a relatively high proportion in the risk composition of R1 and has a significant impact on the overall risk level. At node R2, factors E and F both have weight values of 0.291, almost at the same level, suggesting that they jointly constitute the core influencing factors at node R2 and play a crucial supporting role in the risk assessment of this node. Further observation shows that the performance of the "fire and explosion risk" sub-node is also noteworthy. According to the data, R2 has a weight value of 0.239 for this sub-node, although slightly lower compared to some factors of other nodes, its influence cannot be ignored, demonstrating the importance of R2 in "fire and explosion risk" assessment. By analyzing the risk distribution variation of nodes in the entire risk network, it can be found that when the state of node B changes, not only does the risk state of node R1 show obvious fluctuations, but also the risk level of the "fire and explosion risk" sub-node changes significantly. This phenomenon fully demonstrates the core position of node B in the entire risk system. It is not only a key variable controlling the risk of node R1 but also an important entry point for preventing fire accidents in the workshop. In summary, through in-depth analysis of the weight of each node and risk distribution, we can clearly identify the factors that play decisive roles in risk prevention and control. In particular, the role of node B is particularly prominent, providing clear direction for formulating scientific and reasonable fire prevention strategies, and laying a solid foundation for subsequent risk management practices. This conclusion not only helps improve the accuracy of risk assessment but also provides strong support for reducing fire and explosion risks at the operational level.

3.3. Positive inference

From the data analysis in Table 3, we can extract the corresponding fire occurrence probabilities when nodes A, B, C, etc. occur. Through detailed comparison and analysis of these probability values, we find that among all listed nodes, nodes A and B have the highest fire occurrence probabilities, reaching 0.22. This result reveals an important fact: among various risk factors covered by the third-level nodes, when nodes A or B experience anomalies, their likelihood of causing fires is significantly higher than other nodes. Specifically, nodes A and B mainly involve situations where oxygen and acetylene gas cylinders were not strictly inspected during storage, as well as risks of gas leakage or rupture due to cylinder damage. Therefore, when formulating fire prevention measures, the focus should be placed on strengthening regular inspection and maintenance of gas cylinders to ensure their safety, thereby effectively reducing potential fire threats. Furthermore, among the risk factors covered by the second-level nodes, we also observe similar phenomena. When nodes R1, R4, or R5 occur, their probabilities of causing fires are also high, reaching 0.3. This indicates that on a broader level, certain specific risk factors play a crucial role in fire occurrence. Specifically, nodes R1, R4, and R5 correspond to issues such as improper storage of hazardous gas cylinders, non-standard processing operations, and improper storage of flammable and explosive substances. If these issues are not properly handled, they are highly likely to become triggers for fire accidents. Therefore, when conducting fire prevention work, stricter control measures must be taken against these high-risk factors, such as optimizing gas cylinder storage environments, standardizing processing operation procedures, and strengthening management of flammable and explosive substances, in order to minimize the possibility of fire occurrence. In summary, through in-depth analysis of risk factors at all levels of nodes, we can not only identify potential causes of fire occurrence but also provide important basis for formulating scientific and effective prevention strategies. Whether it is for nodes A and B in the third-level nodes or nodes R1, R4, and R5 in the second-level nodes, targeted improvement measures need to be taken to comprehensively enhance fire prevention and control levels and ensure production safety and personnel life and property safety.

Table.3. Probability of Final Event When Factors Happen

Parent	Probability
A	0.22
B	0.22
C	0.20
D	0.16
E	0.16
F	0.15
G	0.16
H	0.15
I	0.15
J	0.15
K	0.15
L	0.14
M	0.17
N	0.16
O	0.17
P	0.16
Q	0.15
R	0.17
S	0.16
T	0.17
R1	0.30
R2	0.29
R3	0.27
R4	0.30
R5	0.30

3.4. Reverse inference

Through comprehensive analysis of the detailed data in Tables 2 and 3, combined with the changing trends of risk states at each node in Figure 3, we conducted in-depth calculations and evaluations of the conditional probabilities for each parent node. After a series of rigorous derivations and verifications, we found that P(R1|fire) had a significantly higher value than other nodes, reaching 0.46, in the conditional probability distribution corresponding to the secondary parent nodes. This result indicates that under fire scenarios, R1 (i.e., improper storage of hazardous gas cylinders) is highly likely to be one of the key causes of fires, with a particularly prominent probability contribution. To further explore the underlying disaster-causing factors behind R1, we conducted a detailed analysis of its child nodes A, B, C, etc. The results showed that among all child nodes of R1, node C had the highest conditional probability, reaching 0.25. This suggests that leakage or rupture caused by cylinder tipping and rolling is one of the most representative specific disaster-causing factors within R1 and a high-risk trigger for fires. In other words, when gas cylinders are in unstable states during storage or use, the likelihood of leakage or rupture significantly increases, greatly enhancing the probability of fire occurrence. Based on the above analysis results, special attention should be paid to gas cylinder management in the subsequent development of prevention and control strategies. Specifically, the following measures can be taken to effectively reduce fire risks: 1) Improve the regular inspection mechanism for cylinder valves to ensure their safety and reliability; 2) Increase the frequency of daily inspections to timely identify and handle potential hazards; 3) Strengthen standardized management of cylinder storage environments, such as using fixing devices to prevent cylinder tipping or rolling, thereby minimizing the risks of leakage and rupture. Through these multi-dimensional improvement measures, it is expected to curb fire occurrences from the source and provide solid guarantees for the improvement of overall safety levels.

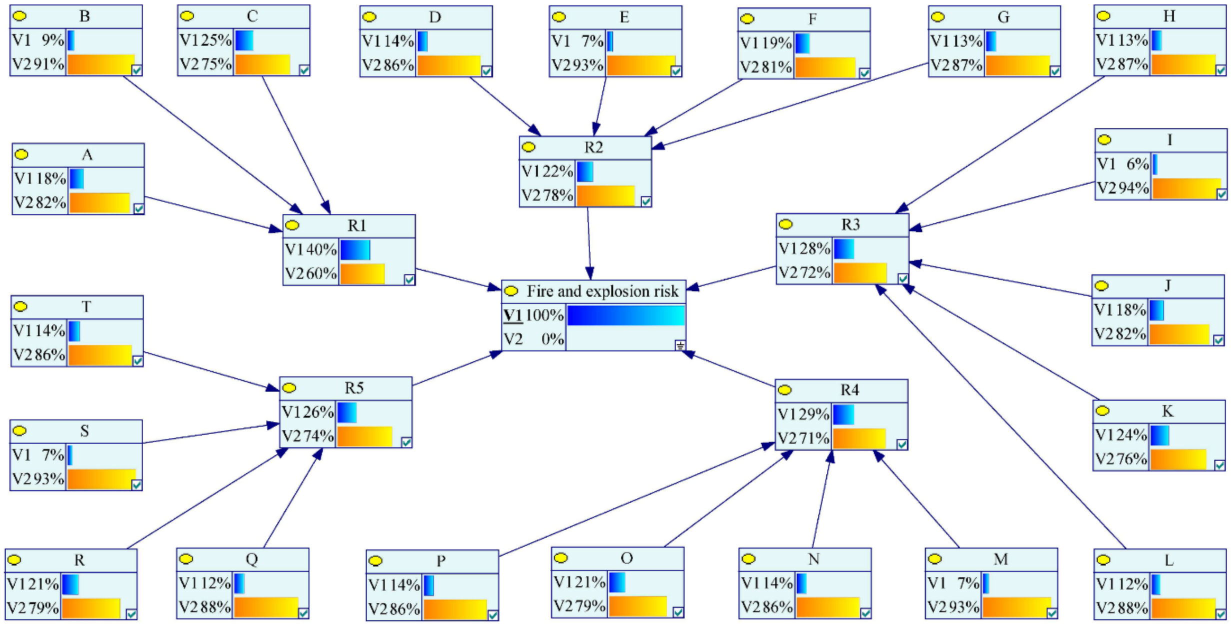

Figure 4. reverse inference

4. Conclusions

This study innovatively realizes dynamic and intelligent comprehensive risk assessment for mechanical processing through constructing a Bayesian network model. Compared with traditional static assessment methods, the breakthroughs of this study mainly lie in three aspects: First, a dynamic assessment system with a causal reasoning mechanism is established. Forward reasoning accurately predicts the fire occurrence probabilities of key risk nodes (such as first-level nodes A (failure to inspect oxygen and acetylene cylinders during storage), B (cylinder damage leading to leakage or rupture), and second-level nodes R1 (improper storage of hazardous gas cylinders), R4 (non-standard processing operations), R5 (improper storage of flammable and explosive materials), etc.). Reverse reasoning can quickly trace the causes of accidents, shifting risk prevention and control from passive response to active intervention. Second, sensitivity analysis is used to quantify the weights of key risk factors. It is clarified that A (failure to inspect oxygen and acetylene cylinders during storage) has the highest impact weight of 0.325 on R1 (improper storage of hazardous gas cylinders), E (hose aging and damage leading to leakage) and F (damage to acetylene cylinder flash arresters) have the highest impact weights of 0.291 on R2 (non-standard cylinder electric welding operations), and R2 (non-standard cylinder electric welding operations) has the most significant contribution of 0.239 to "fire and explosion risks", providing a scientific quantitative basis for risk classification and control. Third, empirical research reveals that the probability of fire caused by R1 (improper storage of hazardous gas cylinders) in specific areas is 0.16, which fills the gap in the industry's quantitative assessment of gas storage risks. The research results not only provide actionable risk prevention and control guidelines for mechanical processing workshops but also promote the transformation of industrial safety assessment from experience-driven to data-driven. In the future, by expanding the model dimensions to include more environmental variables and combining real-time monitoring data from the Internet of Things, a dynamic assessment system with prediction and early warning functions can be constructed, laying a theoretical foundation for establishing a fire risk assessment standard system in the mechanical manufacturing industry and significantly improving the scientificity and reliability of industrial safety management.

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