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Dynamic Probability Assessment Of Hydrogen Leakage In Urban Hydrogen Refuelling Station

Jinduo Xing, Jiaqi Qian, Yanxue Wang

School of Mechanical-Electronic and Vehicle Engineering,
Beijing University of Civil Engineering and Architecture, Beijing 102600, China

Abstract

Hydrogen leakage of hydrogen refueling stations is a key risk node for safety operation in hydrogen refueling stations, which may lead to fires and explosions subsequently. Hydrogen leakage risk analysis is a necessary option to ensure the safety of hydrogen production hydrogen refueling stations during system operation. In this paper, a dynamic probability analysis method for modelling hydrogen leakage in hydrogen refueling stations by a dynamic Bayesian network (DBN) is proposed to address the potential uncertainty and dynamic nature of the risk of unit leakage within the hydrogen refueling station system. An example study of hydrogen leakage from a hydrogen refueling station is carried out to demonstrate the applicability and advantages of the method. The results show that the probability of hydrogen unit leakage can be significantly reduced within one month by equipment maintenance. In addition, the failure and repair rates of compressor diaphragm and hose ruptures were the largest contributors to hydrogen refueling station unit leakage. Finally, some recommendations are made for furthering reduce the risk of hydrogen leakage from hydrogen refueling stations.

Keywords: dynamic risk assessment, dynamic Bayesian network, sensitivity analysis, hydrogen refueling station, hydrogen energy

1. Introduction

Global energy is now entering a transition phase, and hydrogen energy, with its abundant sources and as an important clean energy source, is an important research direction for realizing the energy transition (Kang et al., 2024). Hydrogen refueling stations are gas stations where hydrogen from different sources is pressurized and stored in high pressure tanks within the station by compressors, and then refueled by dispensers for hydrogen fuel cell vehicles. However, hydrogen, as a light substance, has a wide limit range of 4.1% to 74.1% (volumetric concentration) and diffuses easily. Finally, it tends to accumulate in the upper part of the room. If not properly removed in time, it may gradually accumulate and reach the explosion limit, causing a fire or even an explosion (Muduli et al., 2024). Therefore, hydrogen refueling station operations are often carried out at high risk, and fire safety issues due to hydrogen leakage have been a focus of safety research. Nowadays, the research on hydrogen refueling stations mainly focuses on hydrogen energy, the relationship within the hydrogen industry chain, hydrogen-related technologies, and research related to clean energy(Wang et al., 2024). There are fewer studies on the safety and risks of hydrogen refueling stations.

To minimize the consequences of hydrogen leakage accidents due to compressor damage, the risk of the corresponding emergency and maintenance operations needs to be fulfilled at an acceptable level (Li et al., 2024). This paper focuses on the risk assessment of fire safety issues in a hydrogen refueling station system due to hydrogen leakage. Research was performed on the system to collect basic information, i.e., data information in the hydrogen station system, expertise from various studies and other tacit knowledge, to identify the safety barriers and causal factors within the system. These risk influencers were mapped as nodes of dynamic Bayesian network (DBN). A quantitative analytical model of these factors was constructed using DBN, including Dynamic Bayesian transform, conditional probability tables, and probability updates, and a final sensitivity analysis of the accident causal factors of this system was obtained through Fault Tree (FT), and DBN, as well as the impact of the degradation of the causal factors of this system over time. Besides, the impact of different levels of maintenance or repair on the safety of the system. This process needs to map the FT to a Bayesian network (BN), where the events of the FT correspond to the network nodes of the BN, and the logical relationships correspond to the state descriptions in the conditional probability table. Finally summarize and propose preventive measures. Based on the diagnostic inference of the DBN, the factors significantly affecting the hydrogen leakage accident are identified by calculating the posterior probabilities of the relative risk variables. The last step is the model validation, according to the three axioms, this paper validates the designed model by using the obtained critical factors as examples.

The paper is organized as follows: First, a hypothetical hydrogen leak scenario was formulated by FT. Second, the developed hydrogen leakage FT model was mapped to BN. Third, a DBN model was developed to capture the dynamic influences of hydrogen leakage accidents at hydrogen refueling stations. And, the prior probability, state transition probability are determined by references and Markov Chain. Finally, a sensitivity analysis was conducted to validate the proposed model.

2. Methodology

2.1. Dynamic Bayesian network

BN analysis methods are increasingly used in the construction of system reliability models, risk management and safety analysis based on probabilistic and uncertain knowledge (Cai et al., 2019). BN are directed acyclic graphs where nodes represent variables, arcs represent direct causal relationships between linked nodes, and conditional probability tables assigned to nodes specify the degree of influence between linked nodes. A conditional probability table is associated between each node, which is based on the likelihood of previous information and experience. The conditional probability table gives the distribution of variables in the combined state of each parent node(Gao et al., 2024). In contrast to static BN, the conditional probabilities of DBN need to be considered in addition to the conditional probabilities between different nodes within the same interval (Meng and An, 2021).

BN calculate posterior probabilities based on evidence as well as prior probabilities, the updating equation can be formulated as:

$$P(a|X) = \frac{P(X|a) \times P(a)}{P(X)} \tag{1}$$

where $P(a)$ is the prior probabilities, and $P(X \mid a)$ is the conditional probability of X given a. $P(a)$ is the probability of observation or evidence, and $P(a \mid X)$ is the conditional probability of a given X (Cui et al., 2024).

According to the chain rule, the joint probability distribution (JPD) of the network can be obtained by:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|Pa(X_i)) \tag{2}$$

where $Pa(X_i)$ is the parent set of any node X_i, and n is the number of nodes in the network.

Based on BN, DBN adds the concept of the time slice, which adds BN with dynamic characteristics. The transition relationship between time slices can be expressed as:

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{n} P(Z_{i,t}|Pa(Z_{i,t})) \tag{3}$$

where $Z_{i,t}$ is a the node at time t, and $\mathrm{Pa}(Z_{i,t})$ is the parent nodes of $Z_{i,t}$ from the same nodes in the time $t-1$ (Wen et al., 2024).

2.2. Time-dependent component modeling

The degraded nodes in DBN can be represented by a multi-state model. The key to model multi-state component is to determine their state transition process. Markov Chain can be used to analyze systems with redundancies, interdependencies, complex maintenance strategies and sequential failures. As the number of system components increases, the number of states and the complexity of the state transfer diagram grows rapidly. In the state transfer process, let $X(t)$ denote the state of the system at time t. The state $X(t)$ is a random variable for some future point in time t. $\{X(t); t \geq 0\}$ is known as a continuous-time stochastic process (Luu et al., 2024).

The main advantages of Markov Chain are:

- A well-established theoretical foundation that has been used and thoroughly validated in many fields.
- It is an effective tool for analysing small dynamically characterized systems which cannot be studied by using FT and static BN.

- Provides state transfer diagrams that contain important information, are easy to understand by non-specialists, and can give analysts a better understanding of how the system operates.

Thus, static BN are not time-independent, it may not be possible to analyze the dynamic properties of the system(Tang et al., 2024). In contrast, DBN can be incorporated into static BN by incorporating graphical structures based on Markov models. Explicitly modelling the changes in the system over time provides effective dynamic transfer parameters for the study of hydrogen leakage at hydrogen refueling stations. Markov Chain can provide a specific description of the applied methods for state transfer process (Damásio and Nicolau, 2024).

2.2.1. Modeling Transfer State Process

The key issues of imperfect repair and preventive maintenance are modelled by assuming that each parent node is a multi-state degraded system. Three assumptions are made:

- the system may undergo different degrees of degradation corresponding to different performance levels, from perfect state to complete failure;
- systems can fail randomly from any operational state;
- all transition rates are constant and exponentially distributed.

As shown in Fig. 1, each parent node of the DBN in the graph involves three states, namely, No, DS, and Yes. The state "No" refers to the no-failure or perfect functional state. The state "Yes" refers to a failed or failing state. The state DS is the degraded state. Each parent node is initially in its perfect functional state (No). Over time, it can enter a degraded state (DS) or a failed state (Yes).

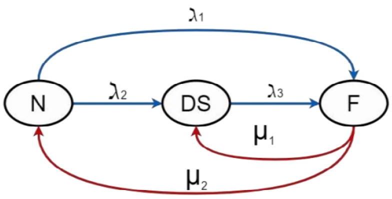

Fig. 1. State transition diagram for multi-state degraded components.

2.2.2. Determination of Transition Probability Table

If the inspection reveals that the node is in a degraded state, it does not meet the requirements and must be considered as a failure and needs to be repaired. It is repaired into a perfectly functional state, which is considered a perfect repair, or it can enter a degraded state, which is considered an imperfect repair. The failure and repair rates are given above the state transition arcs as shown in Fig. 1 assuming the current time is t and the time interval between two consecutive trials is Δt.

The determination of the table of transfer probabilities is an important step in DBN (Han et al., 2024). These probabilities can be viewed as the state values of the parent node moving over time (Guo and Ma, 2024). In DBN, we consider some nodes as polymorphic degenerate systems, and the corresponding probabilities can be determined. For example, Table 2, Table 3 and Table 4 give the transition relationships between continuous nodes with no repair, incomplete repair, incomplete repair, and preventive maintenance, respectively (Abdelhafidh et al., 2023). Given the failure rate λ and repair rate μ of each parent node, the failure rates $\lambda 1$, $\lambda 2$, $\lambda 3$, and repair rates $\mu 1$, $\mu 2$ between states can be obtained from the following hypothetical equations (Guo and Wu, 2023; Zhang et al., 2024).

$$\lambda 2 = \lambda 3 \tag{4}$$

$$\lambda 1 : \lambda 2 = 3:2 \tag{5}$$

$$\lambda 1 + \lambda 2 + \lambda 3 = \lambda \tag{6}$$

$$\mu 1 : \mu 2 = 3:7 \tag{7}$$

$$\mu 1 + \mu 2 = \mu . \tag{8}$$

The repair and failure rates of dynamic nodes are shown in Table 1.

Table 1. The repair and failure rates of dynamic nodes.

Dynamic nodes	Failure rates	Repair rates
X6	2.79E-05	7.60E-03
X11	4.97E-05	1.19E-02
X12	1.55E-05	8.40E-03

Table 2. Transition relations between sequential nodes without repair.

t	$t+\Delta t$ N	DS	F
N	$e^{-(\lambda_1+\lambda_2)\Delta t}$	$\frac{\lambda_2}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$	$\frac{\lambda_1}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$
DS	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
F	0	0	1

Table 3. Transition relationships between sequence nodes with perfect repair.

t	$t+\Delta t$ N	DS	F
N	$e^{-(\lambda_1+\lambda_2)\Delta t}$	$\frac{\lambda_2}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$	$\frac{\lambda_1}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$
DS	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
F	$1-e^{-(\mu_1+\mu_2)\Delta t}$	0	$e^{-(\mu_1+\mu_2)\Delta t}$

Table 4. Transition relationships between sequential nodes with imperfect repair.

t	$t+\Delta t$ N	DS	F
N	$e^{-(\lambda_1+\lambda_2)\Delta t}$	$\frac{\lambda_2}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$	$\frac{\lambda_1}{\lambda_1+\lambda_2}(1-e^{-(\lambda_1+\lambda_2)\Delta t})$
DS	0	$e^{-\lambda_3\Delta t}$	$1-e^{-\lambda_3\Delta t}$
F	$\frac{\mu_2}{\mu_1+\mu_2}(1-e^{-(\mu_1+\mu_2)\Delta t})$	$\frac{\mu_1}{\mu_1+\mu_2}(1-e^{-(\mu_1+\mu_2)\Delta t})$	$e^{-(\mu_1+\mu_2)\Delta t}$

3. Case Study

Before building the FT model, we need to analyze three basic factors that lead to hydrogen leakage: uncertainties in the environment, equipment in an unsafe condition, and unsafe maneuvers by personnel. As shown in Fig. 2, it is the hydrogen leakage FT of the hydrogen refueling station. The symbols of the root nodes as well as the prior probabilities are shown in Table 5.

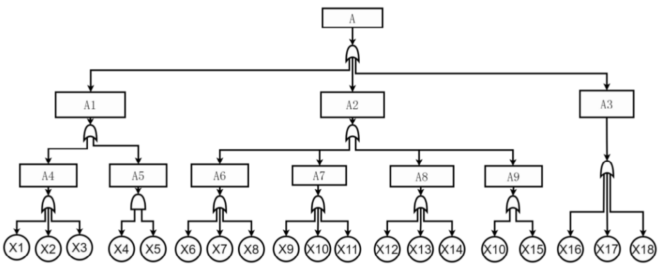

Fig. 2. FT of hydrogen leakage.

Table 5. Root nodes and prior probabilities.

Symbol	Event	Priori probability	Symbol	Event	Priori probability
A	Hydrogen leak	-	X5	Third-party impact	1.42E-03
A1	Uncertainties in the environment	-	X6	Hose rupture	2.19E-03
A2	Equipment in an unsafe condition	-	X7	Hose fitting rupture	5.40E-04
A3	Unsafe manoeuvres by personnel	-	X8	Control panel malfunction	6.73E-04
A4	Accidents in hydrogen refuelling stations	-	X9	Pipe joint seal failure	7.21E-04
A5	Overall hydrogen refuelling station accident	-	X10	Hydrogen embrittlement occurs	4.13E-04
A6	Dispenser/pillar failure	-	X11	Weld cracking	1.61E-03
A7	Leakage from pipeline network failure	-	X12	Compressor diaphragm damage	1.67E-03
A8	Compressor or accessory leaks	-	X13	Compressor seal failure	3.64E-03
A9	Leaking tanks or fittings	-	X14	Uneven flange preload	4.13E-03
X1	Irrational layout	2.77E-04	X15	Insufficient valve screw torque	6.73E-04
X2	Natural disaster	1.21E-04	X16	Lack of training or experience	9.05E-03
X3	Vehicle collision	8.70E-04	X17	Poor organizational system	1.56E-02
X4	Poor choice of location	1.09E-05	X18	Unreasonable provisions	1.84E-02

The relationship of logic gates in the FT can be represented by CPT in BN (Bai et al., 2023). Therefore, the BN model can be obtained by mapping relationships. Then, the FT model is mapped to the DBN. The basic event in FT is transformed into a parent node in DBN. The time-dependent model can be added with time arcs. The transformed dynamic Bayesian using GeNIe software is shown in Figure 3. The prior probabilities of the root nodes are obtained from references and relevant databases. A Markov chain can provide probabilistic information about the impact of decisions that may help the decision maker but does not provide recommended decisions (Hong et al., 2023). It can be used to model system performance, reliability, availability, dependability, and safety (Zhang et al., 2024). It is a tool for modelling the design of complex systems with respect to timing, sequencing, repair, redundancy, and fault tolerance, as well as determining system availability to identify the flow of the system and enumerate the failure rate (forward), the repair rate (backward) and the probability of failure of different components.

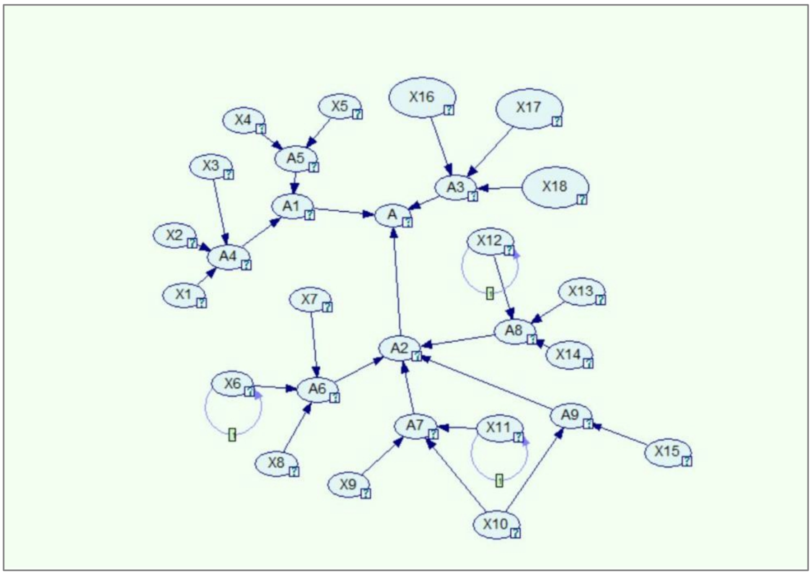

Figure 3 DBN of hydrogen leakage.

4. Sensitivity analysis

The sensitivity analysis aims to identifying the factors that are more sensitive to emergency failures. By setting the status of the hydrogen-producing leak node to Yes and if a hydrogen leak has occurred, diagnostic analysis is performed to obtain the critical causes that significantly influence the occurrence of the leaf node. When sensitivity analysis is performed, the reliability of the whole system can be further improved by increasing the reliability of these root nodes (Chen et al., 2023). On the other hand, sensitivity analysis can also be used to compare the impact of individual root nodes on the failure events.

Based on the developed dynamic model, it has become possible to predict the probability of hydrogen leakage failure in a hydrogen refueling station within one month (30 days) by causal dynamic Bayesian inference. The dynamic probability of hydrogen plant leakage failure with and without equipment repair is output, and the sensitivity analysis is performed after calculating the a priori probability of the dynamic node with the last imperfect repair (Liu et al., 2023). The leaf node A1 is set as the target event in the GeNIe software, and subsequently the BN can be obtained after performing the sensitivity analysis, as shown in the following figure. The orange nodes are the nodes that have a greater impact on the hydrogen leakage from the leaf node hydrogen station; the grey nodes are the nodes that have an insignificant impact; and the white nodes are the nodes that have a smaller impact.

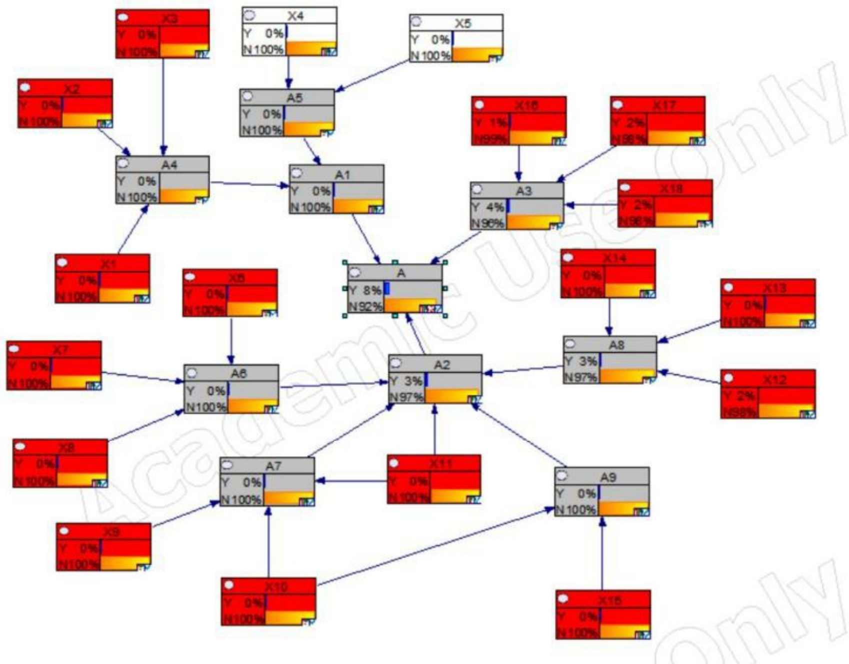

Figure 4 Sensitivity analysis.

Based on the above analysis, we can infer the following conclusions:

- The root nodes that had the greatest impact on the hydrogen leakage of the leaf node were unreasonable regulations, compressor diaphragm damage, poor organizational system, lack of training or experience, etc. It can be known that the influence of personnel factors and the failure of key equipment compressors and hoses had a greater impact on the leaf node.
- For the environmental uncertainty factors, the degree of influence of the root nodes is in the following order: third-party influence, vehicle collision, and unreasonable regulations. Among them, the impact of natural disasters and improper site selection is small, probably because only major natural disasters such as earthquakes and lightning strikes can have an impact on the leaf node, but the impact of these natural disasters on the leaf node is small. Impact on the leaf node, but the possibility of these times is too small, so the impact of the proportion of the response is reduced and can be ignored (Mohammadi et al., 2023).

- For equipment in an unsafe state have a greater impact on compressor diaphragm damage, uneven flange pre-tensioning, compressor seal failure, hose rupture.
- Comprehensive analysis can be found equipment sealing performance, valve or flange pre-tensioning, and personnel factors are the most important factors for hydrogen leakage in hydrogen refuelling stations.

Combined with the above conclusions, this paper takes the three root nodes that have the largest, smallest, and medium impact on hydrogen leakage for dynamic analysis, which are: compressor diaphragm damage, weld cracking, hose rupture.

4.1. Different maintenance effectiveness analysis

As shown in Fig. 5, on the 30th days, the probabilities of having no, perfect, and imperfect equipment repairs are 0.561, 0.071, and 0.073, respectively. Thus, the probability of leakage in the hydrogen refueling station system can be significantly reduced within one year by equipment repairs. The reason that imperfect equipment repair does not significantly increase the leakage probability compared to perfect repair is because the failure rate of components in the devices within the hydrogen station is much lower than their repair rate (Tien, 2023).

Similarly, the dynamic probability of these 3 outcomes can be realized by predictive analysis of a DBN (Sen et al., 2022). The probabilities of the consequences of the 3 accidents occurring on day 30 are shown. are the dynamic probabilities of A1 and A2 during the incomplete repair process. Fig. 6 shows that the dynamic probability of occurrence of A1 gradually decreases by 98.00%, while A2 gradually increases by 0.43% in one year. Therefore, regular inspection and repair of equipment can effectively reduce the probability of accidents.

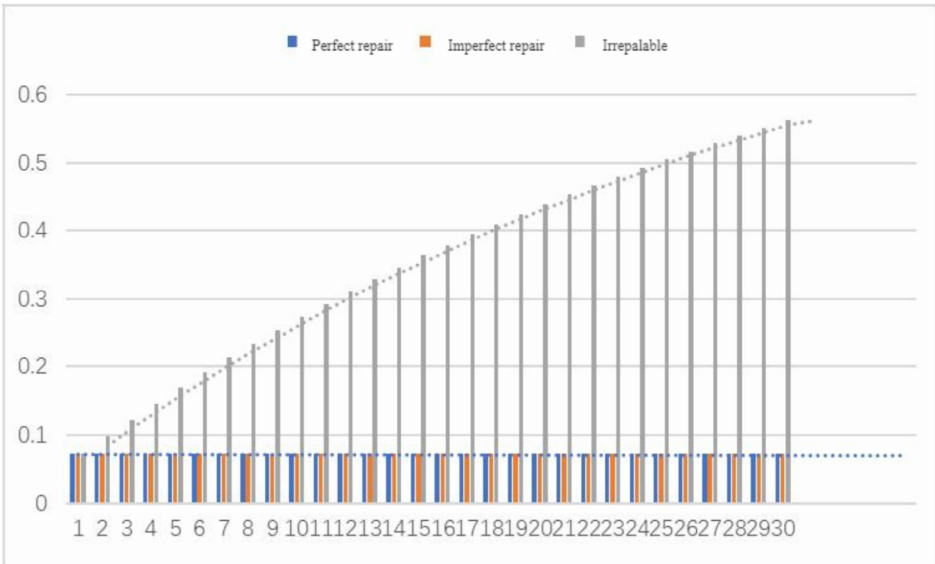

Fig. 5 Dynamic probability prediction of different levels of equipment maintenance within one month.

Fig. 6 Dynamic probability of A1 and A2 with imperfectly maintained equipment within one month.

5. Conclusions

Based on the above research and discussion, we draw the following conclusions:

- Dynamic risk analysis shows that the probability of hydrogen leakage within 30 days is reduced by equipment maintenance. The reason why imperfect equipment maintenance does not significantly increase compared to perfect maintenance is that the probability of hydrogen leakage due to equipment failure rate (λ) is much lower than its maintenance rate (μ).
- The root nodes X6, X11, X12, X16, X17, and X18 are the influencing factors for emergency failures. In addition, the reliability parameters of critical nodes, such as an increase in the failure rate or a decrease in the repair rate, increase the probability of an emergency failure.
- Through the sensitivity analysis of "uncertainties in the environment" and "unsafe state of equipment", it is found that the damage of compressor diaphragm is the main cause of hydrogen leakage.

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