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On the application of the window of opportunity and complex network to risk analysis of process plants operations during a pandemic

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ABSTRACT

To quantify the pandemic specific impact with respect to the risk related to the chemical industry, a novel risk analysis method is proposed. The method includes three parts. Firstly, the two types of “window of opportunity” (WO) theory is proposed to divide an accident life cycle into two parts. Then, a qualitative risk analysis is conducted based on WO theory to determine possible risk factors, evolution paths and consequences. The third part is a quantitative risk analysis based on a complex network model, integrating two types of WO. The Fuzzy set theory is introduced to calculate the failure probabilities of risk factors and the concept of risk entropy is used to represent the uncertainty. Then the Dijkstra algorithm is used to calculate the shortest path and the corresponding probability of the accident. The proposed method is applied to the SCR denitrition liquid ammonia storage and transportation system. The results show that it is a comprehensive method of quantitative risk analysis and it is applicable to risk analysis during the pandemic.

Author statement

Hao Sun, Writing - review & editing, Writing - original draft, Investigation, Formal analysis, Methodology, Conceptualization. Haiqing Wang, Supervision, review, editing Project administration, Funding acquisition. Ming Yang, Methodology, Formal analysis, Investigation, Writing - review & editing. Genserik Reniers, Writing - review & editing, Visualization.

1. Introduction

On January 8, 2020, a pandemic pathogen was confirmed as a new coronavirus; WHO named this new coronavirus "COVID-19" (Tu et al., 2020). On January 30, the WHO announced that the COVID-19 was listed as a “Public Health Emergency of International Concern” (PHEIC). As of May 3, 2020, the number of confirmed cases surpassed 3,349,000, continuing to rise (WHO, 2020). The outbreak has had a severe impact on a global scale, and many industries face enormous challenges due to the strict quarantine policies adopted by many countries. As one of the pandemic safety measures, many chemical plants have limited personnel at workplaces and shift significantly to remote working. Only employees in important production and management positions are required to reduce the number of people returning to work. Due to the shortage of human resources, the workers’ workload and pressure will increase substantially, resulting in plants facing higher risks than usual. These measures have caused severe disruptions to normal operations of chemical plants. This has created a more challenging environment for the process industry to manage the risks of major process accidents. For example, Tertiary Butyl Catechol (TBC), a chemical inhibitor, was found unavailable on the site and was not added to the tank for one and half months (Mathur, 2020).

The shortage of human resources caused by the pandemic will increase the staff workload. The on-site workers speed up operations to complete a large amount of work, thereby increasing the probability of operational errors; besides, inadequate or no supervision due to human resources shortage will increase the probability of operational errors turning into accidents. The impact of the pandemic on the accident stage is mainly reflected in the daily inspection and maintenance, as well as the emergency response time and efficiency. For example, the shortage of human resources will reduce the number of on-site inspections and

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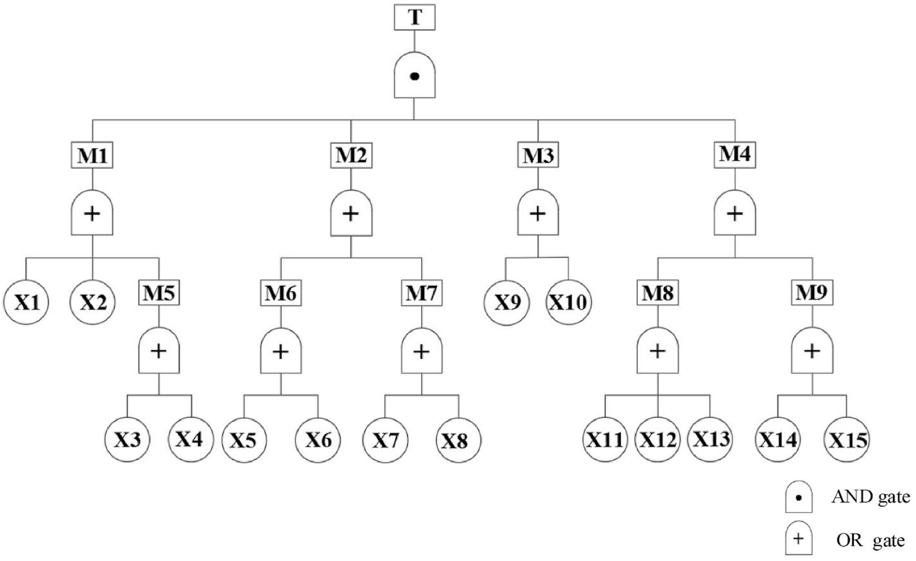


Fig. 1. The pandemic impact on human errors.

routine maintenance, significantly increasing the potential risks of the plant. Besides, when an accident occurs, operators' response speed and efficiency will also be affected to different degrees. The specific impact of the pandemic on the process industries is discussed in Section 2.

In order to analyze the risks in the system, many accident models have been proposed. Reason's (1990) Swiss cheese model significantly affects the understanding of an accident. He believes that the occurrence of an accident is the result of a combination of factors, including potential and direct factors. Leveson (2004) proposed a new accident model based on system theory concepts, called the system-theoretic accident model and process (STAMP). In her opinion, accidents in complex systems occur because the control system fails to deal with external disturbances or non-functional interactions between system components promptly, rather than merely due to the failure of independent components. These models cannot represent the overall view of system safety, nor can they be adapted to the modeling of multiple causal factors. They are mainly descriptive models, not predictive models (Rathnayaka et al., 2011). Rathnayaka et al. (2011) developed a process accident model, named SHIPP (System hazard identification, prediction and prevention). It combines the concepts of Bow-Tie to model causality. The probability of accidents can be updated using the Bayesian update mechanism. Bayesian network is a popular method for conducting quantitative risk analysis for process systems. Abimbola and Khan (2014) used the Bayesian network to evaluate the dynamic risk of the drilling system, and he used the value of the safety barrier failure probability changing with time to obtain the relationship between the accident occurrence probability and time. Zarei et al. (2019) used the fuzzy Bayesian network (FBN) to perform a quantitative risk assessment on a natural gas station. They compared the Bayesian network with FBN, and show the advantages of FBN. Yang et al. (2013) proposed a framework that used a precursor-based hierarchical Bayesian approach (HBA) for rare event frequency estimation and demonstrated it with the BP Deepwater Horizon accident in the Gulf of Mexico. Vianello et al. (2019) used an API risk-based inspection assessment approach to reduce maintenance costs and, increase the plant's reliability and availability. Li et al. (2019) proposed a risk-based accident model to analyze the problem of subsea pipeline leakage quantitatively and effectively predicted the probability of subsea pipeline leakage accidents. Milazzo et al. (2015) proposed a quantitative risk assessment approach to analyze the uncertainties related to the results of the analysis, which derive from assumption in the application of the standard models. Vianello et al. (2016) used the Inspection Manager software to overcome the complexity and time-consuming data collection in RBI.

The above studies focus on the probability of accidents and the risks of comprehensive accident causes. Those methods cannot represent the risk of a single path. However, due to the pandemic's unique and complex impact on the chemical industry, it is essential to identify and eliminate the most vulnerable risk factors in a limited time. In light of the above, it is necessary to design a method that can quickly find the most likely accident path and corresponding risk factors.

This paper aims to establish a risk-based model for hazardous material leakage accidents in the case of human resources shortage during a pandemic. The model is divided into two parts. The first part uses qualitative risk analysis to identify the potential risk factors and the possible accident consequences during a pandemic. In the second part, quantitative risk analysis is applied to determine the accident's evolution from causes to consequences, quickly identifying the most likely path, compute its corresponding probability, and finally discover the critical risk factors in the path. The research provides strong support for decision-making during the outbreak.

The remaining parts of this paper are organized as follows. The influence of pandemic in the industry is presented in Section 2. A brief description of the proposed method, including the window of opportunity, complex network, and risk entropy, is shown in Section 3. The qualitative risk analysis based on the window of opportunity and the quantitative risk analysis based on the complex network are presented in Section 4. Section 5 compares the proposed method with Bow-Tie and Bayesian networks for accident modeling. Finally, conclusions are drawn in Section 6.

2. The influence of pandemic in the chemical process safety

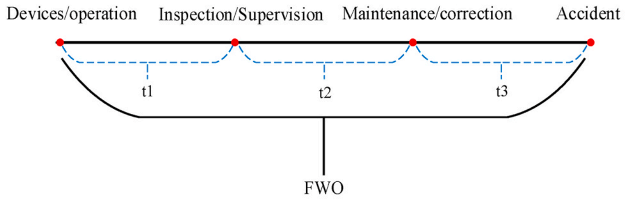
In the face of any pandemic's rapid spread, and especially in case of the COVID-19 pandemic some governments decided to suspend public transport and impose a temporarily lockdown to reduce the population flow. Even so, it could be observed in many countries that the pandemic still spread dramatically and adversely affected people's lives and economy. The delay of the loch-to-work situation caused by this outbreak has had a significant impact on the chemical industry. The impact of the outbreak on the chemical industry is divided into two parts: i) the impact on human errors, and ii) the impact on accident stages.

2.1. *The impact on human factors*

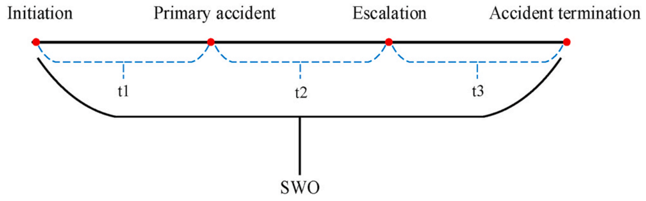
The outbreak in China began in early 2020. After the Spring Festival,

Table 1
Descriptions of risk factors for human errors.

Symbol	Risk factors	Symbol	Risk factors
X_1	Inadequate knowledge	X_9	No supervision
X_2	Inadequate technique	X_{10}	Inadequate supervision
X_3	Inadequate human resources	X_{11}	Unclear task assignment
X_4	Inadequate training	X_{12}	Increased absenteeism of workers
X_5	Inadequate communication	X_{13}	High work stress
X_6	Communication failure	X_{14}	Night work
X_7	Temperature discomfort	X_{15}	Unscheduled working hours
X_8	Prolonged wearing of masks leads to oxygen deprivation	–	–



(a)The first type of window of opportunity (FWO).



(b)The second type of window of opportunity (FWO).

Fig. 2. The window of opportunity (WO) in process industries.

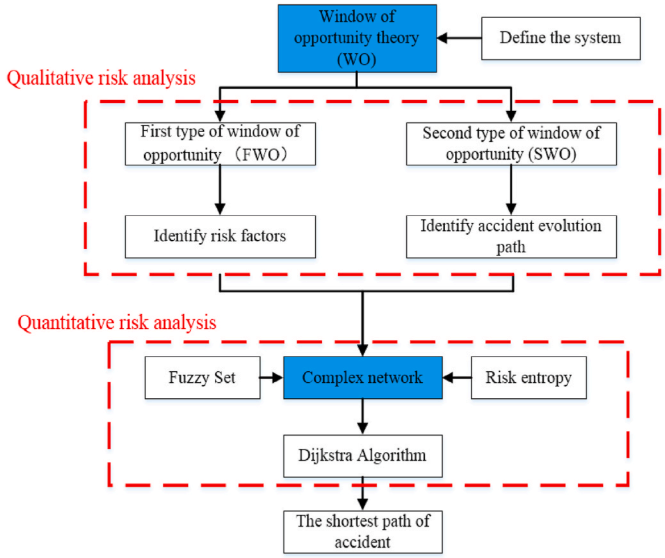


Fig. 3. The proposed methodology for assessing the accident shortest path and its probability under the influence of COVID-19.

employees were about to return to work. Due to the pandemic's impact, some non-local employees were not allowed to return to work, or 14 days of quarantine observation before resuming work (Hao et al., 2020; Kumar et al., 2020). This led to a shortage of workers in the plant. Besides, in order to implement the pandemic prevention and control requirements, some employees were seconded to other departments, which made the shortage of some positions more serious. During the pandemic, some international routes and ports were shut down (Fu et al., 2020), which caused a large amount of hazardous materials to be stored in the plant. As the storage tanks are full for a long time and lack staff, this has caused delays in daily inspections, supervision, and other work.

The Human Factors Analysis and Classification System (HFACS) classifies the causes of accidents into four categories: unsafe acts, the preconditions for unsafe acts, unsafe supervision, and organization influence (Shappell and Wiegmann, 2000). With its systematic methodology and taxonomic nature, the HFACS reduces the incompleteness caused by experts' limited knowledge and missing information during the identification and classification of human and organizational factors (Fu et al., 2020). According to the unique impact of the pandemic, the causes of human error are classified into four categories in this present work, namely, operational error (M1), the preconditions for unsafe acts (M2), unsafe supervision (M3), and organizational influence (M4). Fig. 1 demonstrates the logical relationship between the factors caused by the pandemic.

For operational errors, due to the impact of staff shortage and secondment, the tasks assigned to the staff during the pandemic may not be familiar to them. Insufficient or no training for the staff may reduce the technical ability, safety awareness, and effectiveness of the staff's supervision. For the preconditions for unsafe acts, in response to the call for pandemic prevention and control, the staff must wear masks and keep a proper distance, which increases the difficulty of communication and dramatically reduces the effectiveness of information transmission. Besides, due to the long-term wearing of masks and high work pressure, employees are likely to make a mistake. This also increases the probability of human errors. For organizational influence, due to the shortage of personnel and the increase in the absenteeism rate of the personnel, the daily production, and management of the plant can only rely on a few employees. In this case, there will be unclear task assignments, unreasonable scheduling, night work, and over time, which increases the staff's burden and increases the probability of human error. The impact of the pandemic on workers will be throughout the entire production process. Table 1 demonstrates the risk factors of human errors. The specific analysis of the human errors is shown in Section 4.2.

2.2. *The impact on accident stages*

The concept of window of opportunity (WO) is mostly used in the medical field to indicate the best time to treat a disease (Ismail et al., 2017; Langer et al., 2011; Sweeney, 1997; Andersen, 2003). WO represents the best time to invest in a business and the best time to catch up with competitors (Kwak and Yoon, 2020; Yap and Truffer, 2019). In this research, the time from the accident precursor stage to the time before the accident termination is defined as the WO representing the best time for the system to prevent and control accidents. The life cycle of an accident can be divided into two stages, each stage corresponding to a WO. The first stage is the accident precursor stage, corresponding to the first type of WO (FWO). The second stage is the accident evolution stage, corresponding to the second type of WO (SWO). The pandemic's impact is different at each stage, but one thing in common is that it shortens the window of opportunity. During the accident precursor period before the accident initiation stage (i.e., FWO), the operators' main task is daily inspections to identify and eliminate risk factors in time. The FWO can be divided into three segments, as shown in Fig. 2 (a). Under normal circumstances, routine inspection and maintenance will promptly and effectively discover and eliminate risk factors, thus reducing the probability of accidents and extending the time of FWO. However, due to the shortage of human resources during the pandemic, the number and frequency of daily inspections are relatively low. Besides, with the increased workload and pressure of workers, the effectiveness of inspection and maintenance will be reduced, resulting in a reduced

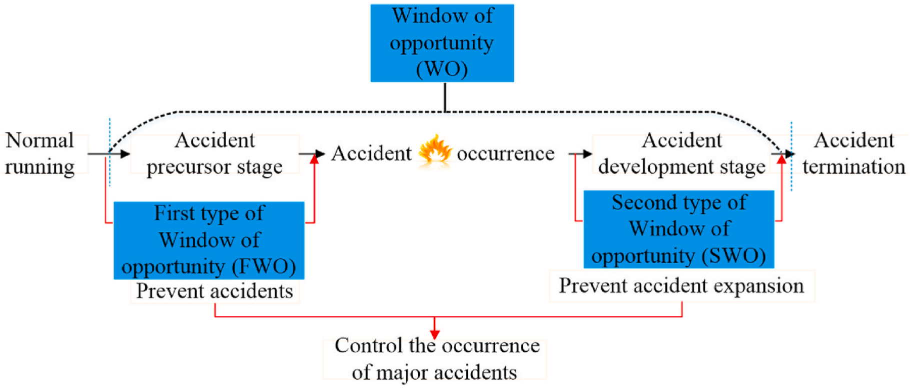


Fig. 4. The relationship between two types of WO and accident development.

probability of finding and eliminating risk factors. This means that the number of risk factors present in the plant during the pandemic is higher than usual significantly shortening the FWO. For the accident evolution stage (SWO), the operators' main task is to take emergency measures to prevent the escalation of the accident. The SWO can be divided into three segments, as shown in Fig. 2 (b). Whether and what measures were taken in each time period would lead to the accident develop in different directions. Due to the shortage of human resources and emergency supplies, the response speed of workers, the speed of taking measures and the effectiveness will be affected during the pandemic. Therefore, the development path of the accident cannot be effectively cut off in time, which will shorten the SWO and lead to the rapid escalation of the accident into a catastrophe.

3. The proposed methodology

In the last section, we analyzed the special impact of the pandemic on chemical process safety. The methodology is developed in this section to deal with those special risk factors, which include identifying the potential risk factors, accident scenarios, and assessing the accident shortest path and its probability under the influence of a pandemic. The proposed methodology is comprised of several steps, as demonstrated in Fig. 3. Each step of the methodology is discussed in detail in the following section.

3.1. Window of opportunity theory

In recent decades, a large number of catastrophic accidents have occurred in the process industry. The most common example of these accidents is personnel poisoning, fire, and vapor cloud explosion (VCE). Leakages are often the causes of these accidents. Therefore, this paper focuses on investigating leakage-induced accident risks in the process industry under the pandemic situation. Dangerous gas leakage accidents can be divided into several stages on the time axis, and each stage will exhibit different dynamic characteristics. The time from the accident precursor stage to the time before the accident termination is called the window of opportunity (WO) , as shown in Fig. 4. Whether and what measures are taken in each period would lead to the accident develop in different directions.

There are two types of WO: the first type of WO (FWO) refers to the stage of the accident precursor stage. Potential risk factors exist in this stage, but they are not eliminated in a timely and effective manner. As time goes on, they eventually lead to accidents. Notably, during the pandemic situation, the impact of human resources shortage shortened the FWO. It may increase the probability of human errors. Therefore, studying the FWO is beneficial to deal with the special effects of the pandemic. The purpose of studying the FWO is to discover and eliminate the risk factors before the accident occurs and extend the FWO, to prevent the occurrence of accident fundamentally. The second type of WO (SWO) refers to the time from the accident occurrence to the time before the accident terminates. During this period, the initial accident may lead to a disastrous accident. Due to the pandemic's impact, the speed of emergency response will be reduced when an accident occurs. This increases the probability that the initial accident evolves into a catastrophe. SWO aims to analyze the cause of barrier failure and to take adequate measures to control the development path of accidents and reduce their consequences. The relationship between the WO and the accident life cycle is shown in Fig. 4.

3.2. Complex network and risk entropy

Complex networks are between regular networks and random networks connected by logical operators. Initial events may evolve into result events through different network paths (Meng et al., 2019). The subtle relationship between the nodes is a guarantee that the entire system will normally complete the assigned tasks. The complex network abstracts the basic events and intermediate events as discrete points and abstracts the relationship between events as a directed edge with weights. The directed edge represents the relationship between events, and the weight represents the degree of connection. It is described by a directed acyclic sparse matrix connection graph $G=(N, E, W)$, where $N = (1, 2, \ldots n)$ is the set of nodes; $E = (e_1, e_2, \ldots e_n)$ is the set of edges; $W = (w_1, w_2, \ldots w_n)$ is the set of weights of the edges.

This paper introduce the Dijkstra algorithm to calculate the shortest path of an accident under the impact of pandemic. The implementation of the algorithm is based on greedy thinking. The basic idea is to traverse all nodes from one vertex until finding the shortest path to the endpoint. The algorithm adds the edge weights contained in each path, and the path with the smallest total edge weight is the shortest path from the start point to the end. In a complex network, the nodes' edge weights are represented by probabilities, the shortest path is:

$$
\begin{aligned}
& Max \prod P_{i,j} \cdot x_{i,j} \\
& s.t. x_{i,j} = \begin{cases} 1, n_{i,j} = 1 \\ 0, n_{i,j} = 0 \end{cases}
\end{aligned}
\tag{1}
$$

In the formula, i and j are any two nodes in a complex network ; when $x_{ij} = 1$, it means that there is risk transmission path between nodes i and j; when $x_{ij} = 0$ means that there is no direct connection between i and j; P_{ij} represents the probability of risk transfer from node i to node j. The maximum value is the optimal solution, that is, the path with the highest probability of accident.

Since the algorithm adds all the edge weights to find the shortest path, and the probability cannot be added, so the risk entropy with additivity is introduced to express the edge weights between nodes. Entropy is a state function introduced by Clausius in 1867 to complete the quantification of the second law of thermodynamics, which has evolved into a measure of system disorder or uncertainty (Clausius,

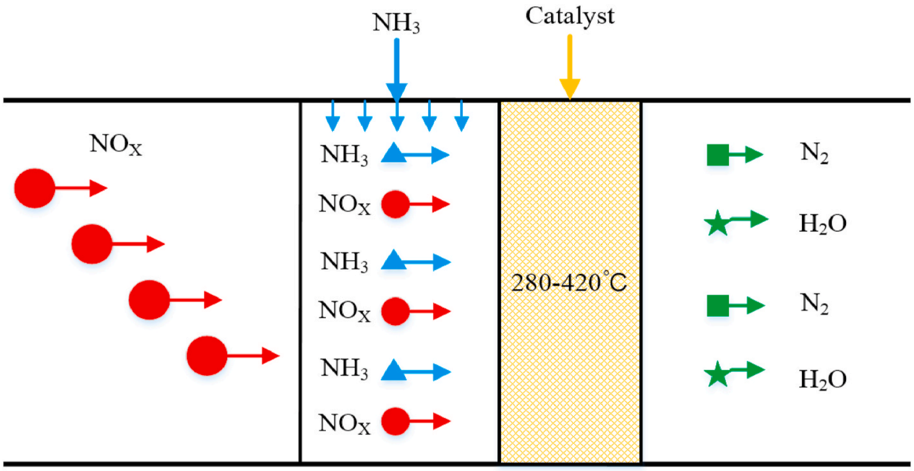


Fig. 5. Reaction principle diagram of SCR denitration.

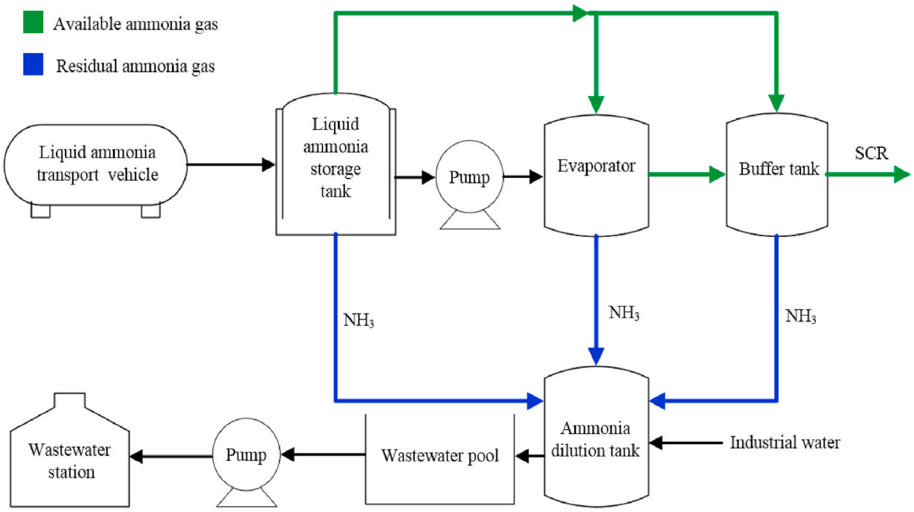


Fig. 6. The process of SCR denitrition liquid ammonia storage and transportation system.

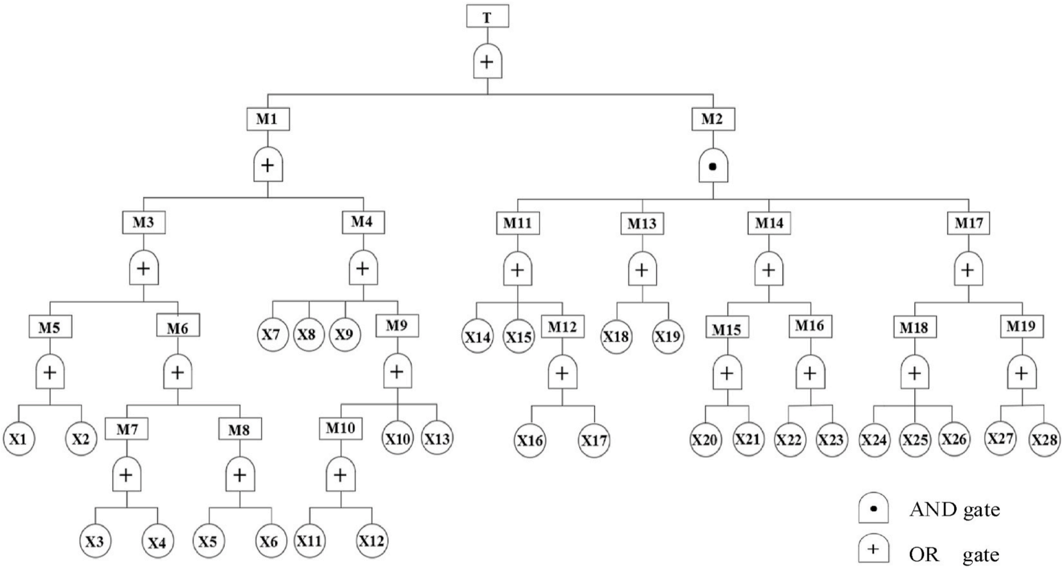


Fig. 7. Fault tree analysis of liquid ammonia storage and transportation system.

Table 2
Initial nodes and intermediate nodes for ammonia leakage accident.

Symbol	Basic event	Symbol	Basic event
X1	Unreasonable design	X42	Smoking
X2	Poor acceptance quality	X43	Lightning stroke
X3	Internal corrosion	X44	Static electricity
X4	External corrosion	X45	Strike sparks
X5	Overpressure	X46	On-site information failure
X6	Overfilling	X47	Off-site information failure
X7	Valve failure	X48	Poor human resources
X8	Flange seal failure	X49	Poor rescue resources
X9	Gasket failure	X50	Inadequate training
X10	Pipe joint weld rupture	X51	Emergency exits closed
X11	Internal corrosion of pipeline	X52	Inadequate experience
X12	External corrosion of pipeline	M1	Equipment factors
X13	External force damage	M2	Human factors
X14	Inadequate knowledge	M3	Tank leakage
X15	Inadequate technique	M4	Piping system leakage
X16	Inadequate human resources	M5	Tank original defect
X17	Inadequate training	M6	Tank rupture
X18	No supervision	M7	Corrosion
X19	Inadequate supervision	M8	Fatigue of tank
X20	Inadequate communication	M9	Pipeline rupture
X21	Communication failure	M10	Pipeline corrosion
X22	Temperature discomfort	M11	Operation error
X23	Prolonged wearing of masks leads to oxygen deprivation	M12	Inadequate training
X24	Unclear task assignment	M13	Supervision failure
X25	Increased absenteeism of workers	M14	Preconditions for unsafe acts
X26	High work stress	M15	Information transfer failure
X27	Night work	M16	Poor working environment
X28	Unscheduled working hours	M17	Unreasonable work design
X29	Unreasonable detector arrangement	M18	Improper schedules
X30	Detector failure	M19	long-time working
X31	Out of detection range	M20	Gas detection failure
X32	Long delay in inspection	M21	Isolation barrier failure
X33	Poor safety awareness	M22	Automatic gas detection failure
X34	Detection alarm failure	M23	Manual gas detection failure
X35	Signal failure	M24	ESD failure
X36	Shutdown valve failure	M25	Manual shutdown failure
X37	Insufficient daily maintenance of the shutdown system	M26	Operation error
X38	Manual valve failure	M27	Information transfer failure
X39	Lack of training	M28	Emergency rescue failure
X40	Operating procedures are not standardized	M29	Emergency evacuation failure
X41	Insufficient daily maintenance		

1867). Shannon (1948) used information entropy to describe the uncertainty of an information source. Drawing on the definition of self-information in information theory, this paper uses self-information to represent the edge weights between nodes, called risk entropy. For the event x_i with probability $P(x_i)$, its self-information is $I(x_i)$ (Shannon, 1948):

$$I(x_i) = -\ln P(x_i) \tag{2}$$

The calculation of an accident shortest path can be converted into the optimal solution problem. Since the higher the probability of an event, the smaller the self-information; therefore, the shortest path of an accident is the path with the lowest risk entropy. The objective function is transformed into a risk entropy function, as shown in the following equation:

$$\begin{aligned} &Min \sum -\ln\left(P_{i,j}\cdot x_{i,j}\right) \\ &s.t.\, x_{i,j} = \begin{cases} 1, n_{i,j} = 1 \\ 0, n_{i,j} = 0 \end{cases} \end{aligned} \tag{3}$$

4. Case study

4.1. SCR denitration liquid ammonia storage and transportation system

The flue gas generated by coal combustion in thermal power plants contains enormous nitrogen oxides. To prevent environmental pollution, the flue gas should be denitrified. SCR technology refers to the process of reducing agent under the action of catalyst to convert nitrogen oxides in flue gas into nitrogen and water. Ammonia gas is usually selected as a reducing agent, and the reaction temperature is 280–420 °C, the specific reaction process is shown in Fig. 5.

Ammonia as a reducing agent is used in the denitration process. Fig. 6 represents the process flow diagram for the ammonia storage and transportation system in the SCR denitration process. The liquid ammonia from the transport vehicle is discharged into the liquid ammonia storage tank, and the evaporated gas is discharged into the evaporator and buffer tank. The liquid ammonia is pumped to the evaporator for evaporation. Then the evaporated ammonia gas is discharged into the buffer tank, which stabilizes the supply of ammonia gas. Finally, the ammonia gas enters the SCR denitrification system. The residual NH_3 in the storage tank, evaporator, and buffer tank is absorbed by the industrial water in the ammonia dilution tank. Then it is discharged into the wastewater tank. Finally, it is pumped to the industrial wastewater station.

4.2. Qualitative risk analysis based on WO theory

(1) Hazard identification

The research of FWO aims to identify potential risk factors to prevent accidents. In this period, the Fault tree model is used to find potential risk factors according to the process flow in Fig. 7.

Due to the special impact of the pandemic on the WO and human errors, the probability of equipment failure being detected and eliminated is reduced, while the probability of human errors has increased. This makes accidents' probability higher than normal. Equipment and human factors are the main causes of leakage accident. The equipment factors of liquid ammonia storage and transportation system can be divided into two parts, namely storage equipment and pipeline equipment. In the pandemic situation, human factors are mainly composed of four parts, which are operation errors, poor information transmission, unreasonable work design and poor working environment. There are 28 basic events and 19 intermediate events in the fault tree, which means that there are 28 risk factors that may cause an accident in the FWO under the impact of a pandemic. If these risk factors can be eliminated in a timely and effective manner during FWO, the leakage accident can be avoided. The identified risk factors are shown in Fig. 7 and Table 2.

(2) Accident sequence

When an accident occurs, the safety barrier's effectiveness determines the accident propagation scenarios, and each scenario can be represented by an accident evolution path. Due to the impact of the epidemic, the frequency and efficiency of safety barrier inspection and maintenance are reduced, leading to an increased possibility of safety barrier failure. Besides, the shortage of human resources reduces the speed of emergency response. The research of SWO aims to identify the potential accident evolution path. In this period, the Event Tree model can be used to find out the possible failure reasons of the safety barriers and the potential development path of the accident. Ammonia is not

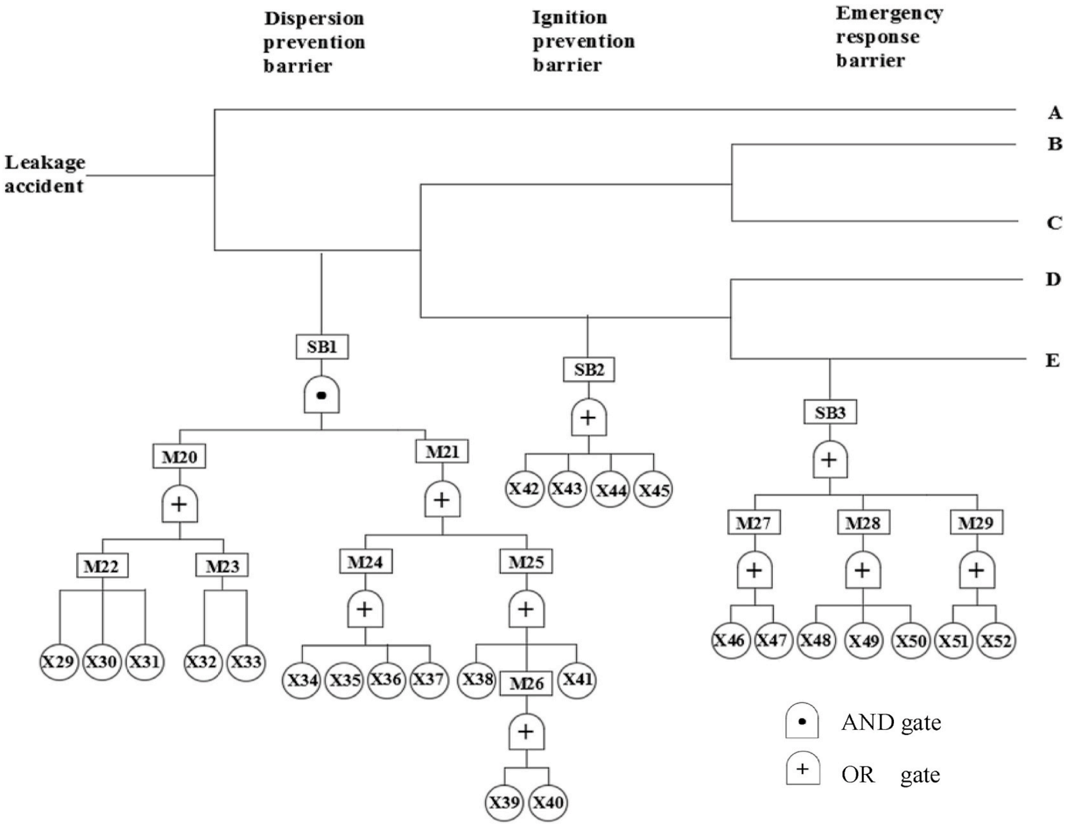


Fig. 8. Event tree analysis of liquid ammonia storage and transportation system.

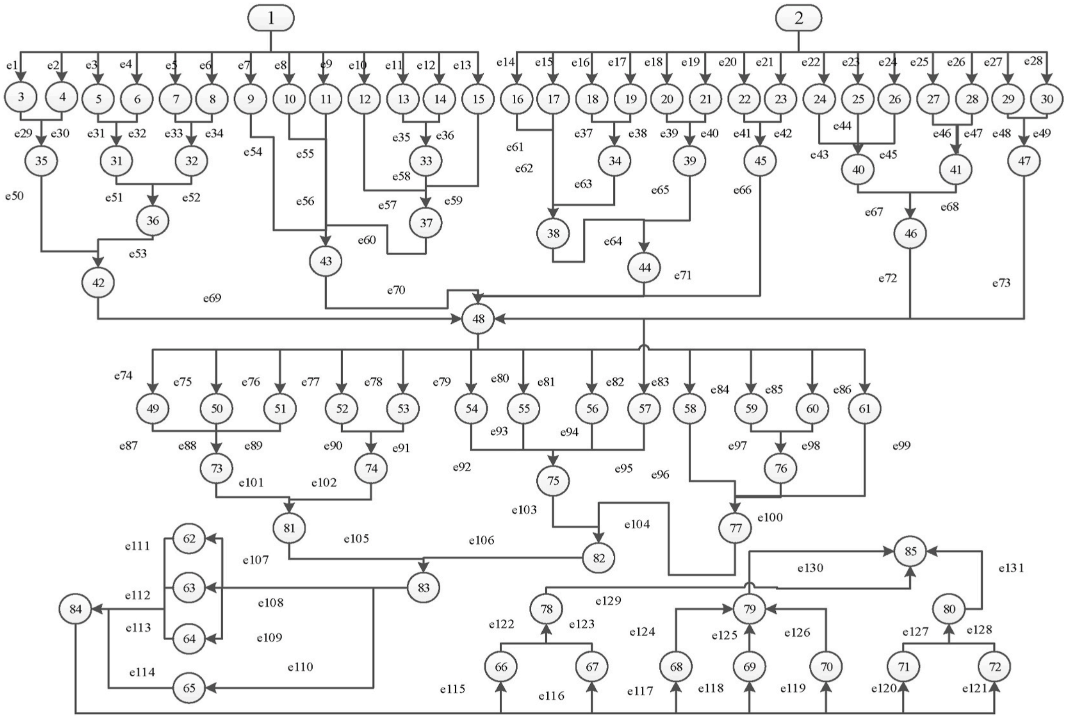


Fig. 9. Complex network model for liquid ammonia storage and transportation system during the pandemic.

easily ignited, and the explosion limit of ammonia is 15.7%–27.4%. However, when ammonia gas accumulates in large quantities, there will still be explosion accidents in the presence of ignition sources (Inanloo and Tansel, 2015; Tan et al., 2020). The types of safety barriers in this article are mainly divided into three categories, namely the dispersion prevention barrier, the ignition prevention barrier, and the emergency response barrier. The effectiveness of the safety barrier is affected by multiple risk factors. In Fig. 8A and B, C, D, E means safe, near miss,

Table 3
Descriptions of risk factors in the complex network.

Number	Risk factor	Number	Risk factor
1	Equipment factor	44	Operation error
2	Human factor	45	Information transfer failure
3	Unreasonable design	46	Unreasonable work design
4	Poor acceptance quality	47	Poor working environment
5	Internal corrosion	48	Leakage accident
6	External corrosion	49	Unreasonable detector arrangement
7	Overpressure	50	Detector failure
8	Overfilling	51	Out of detection range
9	Valve failure	52	Long delay in inspection
10	Flange seal failure	53	Poor safety awareness
11	Gasket failure	54	Detection alarm failure
12	Pipe joint weld rupture	55	Signal failure
13	Internal corrosion of pipeline	56	Shutdown valve failure
14	External corrosion of pipeline	57	Insufficient daily maintenance of the shutdown system
15	External force damage	58	Manual valve failure
16	Inadequate knowledge	59	Lack of training
17	Inadequate technique	60	Operating procedures are not standardized
18	Inadequate human resources	61	Insufficient daily maintenance
19	Inadequate training	62	Smoking
20	No supervision	63	Lightning stroke
21	Inadequate supervision	64	Static electricity
22	Inadequate communication	65	Strike sparks
23	Communication failure	66	On-site information failure
24	Unclear task assignment	67	Off-site information failure
25	Increased absenteeism of workers	68	Poor human resources
26	High work stress	69	Poor rescue resources
27	Night work	70	Inadequate training
28	Unscheduled working hours	71	Emergency exits closed
29	Temperature discomfort	72	Inadequate experience
30	Prolonged wearing of masks leads to oxygen deprivation	73	Automatic gas detection failure
31	corrosion	74	Manual gas detection failure
32	Fatigue of tank	75	ESD failure
33	Pipeline corrosion	76	Operation error
34	Inadequate training	77	Manual shutdown failure
35	Tank original defect	78	Information transfer failure
36	Tank rupture	79	Emergency rescue failure
37	Pipeline rupture	80	Emergency evacuation failure
38	Inadequate skill	81	Gas detection failure
39	Supervision failure	82	Isolation barrier failure
40	Improper schedules	83	Dispersion barrier failure
41	long-time working	84	Ignition barrier failure
42	Tank leakage	85	Emergency response barrier failure
43	Piping system leakage		

poisoning accident, explosion accident, and catastrophe, respectively. The details are shown in Fig. 8 and Table 2.

4.3. *Quantitative risk analysis based on WO theory*

The study of WO can effectively identify the cause, evolution path, and consequences of the accident under the impact of a pandemic. In order to quantitatively analyze the accident risk, the complex network is introduced to integrate the two types of WO (FWO and SWO) to calculate the shortest path and the probability of the accident. The fuzzy set theory can be used to present subjective, vague, linguistic and imprecise data and information effectively, in which fuzzy numbers scored by invited experts will characterize the probability values of primary events, and subsequently fuzzy number in linguistic term can be transformed into fuzzy failure (prior) probability of factors (Chang et al., 2019; Zarei et al., 2019). In the present work, expert elicitation is introduced to calculate the failure probabilities of the events. The specific calculation procedure can be seen in Zarei et al. (2019). Table Appendix A demonstrates expert judgments, aggregation of fuzzy numbers, fuzzy possibility, and the probability of root events in Figs. 7 and 8.

4.3.1. *Complex network modeling*

The complex network model (Fig. 9) was developed based on the identified risk factors (Fig. 7) and their relationships (Fig. 8). In order to simplify the modeling process of a complex network, node types are divided into two categories: equipment factors and human factors. There are 85 nodes and 131 edges in the complex network model, and the risk factors associated with each node are shown in Table 3.

The complex network's edge weights are expressed by probabilities. In this paper, when a node i has only one parent node j, the edge weight W_{ji} between the two is the failure probability of the node i. The Fuzzy set theory is used to calculate the specific failure probability of factors (Lavasani et al., 2011). When a node has more than one parent node, the node represents an intermediate event. At this point, the edge weights between the node and its parent nodes are obtained according to the relationship between the AND gate and the OR gate in Figs. 7 and 8. In the complex network, the edge direction is used to indicate the risk transitivity, and the edge weight is used to indicate the risk value. According to Eq. (2), all edge weight values of risk factors are converted into risk entropy, as shown in Table 4.

4.3.2. *Accident shortest path calculation*

The purpose of accident scenario calculation is to search for the shortest path from the initial event to the resulting event. The shortest path of a dangerous gas leakage accident is equivalent to the path with the lowest risk entropy. Based on the Dijkstra algorithm and Equation (3), MATLAB software is used to calculate the shortest path of the accident caused by various risk factors. The results are shown in Table 5.

The shortest paths of leakage and escalation accidents caused by different risk factors are listed in Table 5. The nodes in each path are the principal risk factors in the accident evolution. According to Table 5, an ammonia leakage accident caused by human errors is the shortest, followed by equipment factors. It can be seen that the probability of human factors increase due to the impact of the pandemic has increased, thereby increasing the probability of leakage accidents. The shortest leakage accident path is 2 → 26→40 → 46→48, and its probability is 1.49E-02, indicating that after a few steps, the initial event can cause a leakage accident. When ammonia leakage occurs, the dispersion prevention barrier will eventually fail due to the automatic detector failure, long delayed inspection and manual detection failure, resulting in a large amount of ammonia leakage and dispersion. As ammonia gas is highly corrosive and toxic, workers will have obvious uncomfortable reactions when inhaled, such as cough, dizziness and dyspnea. This has seriously affected the speed and efficiency of personnel emergency response. Ammonia is not easily ignited. However, due to the failure to take effective measures to control the leakage of ammonia gas, a large amount of ammonia gas accumulates, and explosion accidents will occur under the conditions of the existence of ignition sources, which further caused damage to personnel and the plant. The shortest escalation accident path is 2 → 26→40 → 46→48 → 52→74 → 81→83 → 64→84 → 68→79 → 85, and its probability is 1.06E-08.

It can be seen from Table 5 that different initial events cause leakage accidents, and to avoid the occurrence of leakage accidents, corresponding measures can be taken in the FWO, such as strengthening routine inspection, reduce work stress and have a reasonable work schedule. When the leakage accident occurs, the shortest development path of the accident is almost the same. A long delay in inspection, static electricity, and inadequate human resources are the leading causes of the failure of dispersion prevention barriers, ignition prevention barriers, and emergency response barriers, respectively. When the leakage accident occurs, to avoid the escalation of the accident, corresponding measures can be taken in SWO to cut off the expansion path of the

Table 4
wt of edges in the complex network.

Edge	Direction	Probability	Risk entropy	Edge	Direction	Probability	Risk entropy
e_1	1 → 3	4.760×10^{-4}	7.651	e_{67}	40 → 46	0.996	0.004
e_2	1 → 4	9.820×10^{-4}	6.926	e_{68}	41 → 46	0.996	0.004
e_3	1 → 5	9.050×10^{-4}	7.008	e_{69}	42 → 48	0.850	0.163
e_4	1 → 6	2.800×10^{-3}	5.892	e_{70}	43 → 48	0.850	0.163
e_5	1 → 7	3.200×10^{-3}	5.736	e_{71}	44 → 48	0.850	0.163
e_6	1 → 8	2.000×10^{-3}	6.224	e_{72}	46 → 48	0.850	0.163
e_7	1 → 9	1.740×10^{-3}	4.053	e_{73}	47 → 48	0.850	0.163
e_8	1 → 10	5.000×10^{-3}	5.298	e_{74}	48 → 49	2.300×10^{-3}	6.057
e_9	1 → 11	5.000×10^{-3}	5.298	e_{75}	48 → 50	6.000×10^{-3}	5.112
e_{10}	1 → 12	6.300×10^{-3}	5.072	e_{76}	48 → 51	3.400×10^{-3}	5.684
e_{11}	1 → 13	2.000×10^{-3}	6.227	e_{77}	48 → 52	1.810×10^{-2}	4.010
e_{12}	1 → 14	2.000×10^{-3}	6.224	e_{78}	48 → 53	1.410×10^{-2}	4.258
e_{13}	1 → 15	1.100×10^{-3}	6.806	e_{79}	48 → 54	9.821×10^{-4}	6.926
e_{14}	2 → 16	7.200×10^{-3}	4.939	e_{80}	48 → 55	6.188×10^{-4}	7.388
e_{15}	2 → 17	7.200×10^{-3}	4.939	e_{81}	48 → 56	7.500×10^{-3}	4.894
e_{16}	2 → 18	1.810×10^{-2}	4.010	e_{82}	48 → 57	5.000×10^{-3}	5.298
e_{17}	2 → 19	7.500×10^{-3}	4.894	e_{83}	48 → 58	4.600×10^{-3}	5.389
e_{18}	2 → 20	2.000×10^{-3}	6.224	e_{84}	48 → 59	3.200×10^{-3}	5.736
e_{19}	2 → 21	3.700×10^{-3}	5.587	e_{85}	48 → 60	2.300×10^{-3}	6.057
e_{20}	2 → 22	6.000×10^{-3}	5.114	e_{86}	48 → 61	7.500×10^{-3}	4.894
e_{21}	2 → 23	6.600×10^{-3}	5.024	e_{87}	49 → 73	0.988	0.012
e_{22}	2 → 24	3.200×10^{-3}	5.736	e_{88}	50 → 73	0.988	0.012
e_{23}	2 → 25	8.200×10^{-3}	4.808	e_{89}	51 → 73	0.988	0.012
e_{24}	2 → 26	1.810×10^{-2}	4.010	e_{90}	52 → 74	0.968	0.033
e_{25}	2 → 27	1.410×10^{-2}	4.258	e_{91}	53 → 74	0.968	0.033
e_{26}	2 → 28	5.000×10^{-3}	5.298	e_{92}	54 → 75	0.986	0.014
e_{27}	2 → 29	5.000×10^{-3}	5.298	e_{93}	55 → 75	0.986	0.014
e_{28}	2 → 30	1.300×10^{-3}	6.676	e_{94}	56 → 75	0.986	0.014
e_{29}	3 → 35	0.999	0.001	e_{95}	57 → 75	0.986	0.014
e_{30}	4 → 35	0.999	0.001	e_{96}	58 → 77	0.983	0.017
e_{31}	5 → 31	0.996	0.004	e_{97}	59 → 76	0.995	0.005
e_{32}	6 → 31	0.996	0.004	e_{98}	60 → 76	0.995	0.005
e_{33}	7 → 32	0.995	0.005	e_{99}	61 → 77	0.983	0.017
e_{34}	8 → 32	0.995	0.005	e_{100}	76 → 77	0.983	0.017
e_{35}	13 → 33	0.996	0.004	e_{101}	73 → 81	0.957	0.044
e_{36}	14 → 33	0.996	0.004	e_{102}	74 → 81	0.957	0.044
e_{37}	18 → 34	0.975	0.025	e_{103}	75 → 82	0.969	0.032
e_{38}	19 → 34	0.975	0.025	e_{104}	77 → 82	0.969	0.032
e_{39}	20 → 39	0.994	0.006	e_{105}	81 → 83	0.927	0.076
e_{40}	21 → 39	0.994	0.006	e_{106}	82 → 83	0.927	0.076
e_{41}	22 → 45	0.987	0.013	e_{107}	83 → 62	0.0015	6.527
e_{42}	23 → 45	0.987	0.013	e_{108}	83 → 63	1.369×10^{-4}	8.897
e_{43}	24 → 40	0.971	0.029	e_{109}	83 → 64	2.800×10^{-3}	5.892
e_{44}	25 → 40	0.971	0.029	e_{110}	83 → 65	9.753×10^{-4}	6.933
e_{45}	26 → 40	0.971	0.029	e_{111}	62 → 84	0.995	0.005
e_{46}	27 → 41	0.981	0.019	e_{112}	63 → 84	0.995	0.005
e_{47}	28 → 41	0.981	0.019	e_{113}	64 → 84	0.995	0.005
e_{48}	29 → 47	0.994	0.006	e_{114}	65 → 84	0.995	0.005
e_{49}	30 → 47	0.994	0.006	e_{115}	84 → 66	5.000×10^{-3}	5.298
e_{50}	35 → 42	0.990	0.010	e_{116}	84 → 67	5.000×10^{-3}	5.298
e_{51}	31 → 36	0.991	0.009	e_{117}	84 → 68	1.810×10^{-2}	4.010
e_{52}	32 → 36	0.991	0.009	e_{118}	84 → 69	8.500×10^{-3}	4.764
e_{53}	36 → 42	0.990	0.010	e_{119}	84 → 70	5.000×10^{-3}	5.298
e_{54}	9 → 43	0.962	0.039	e_{120}	84 → 71	8.200×10^{-3}	4.804
e_{55}	10 → 43	0.962	0.039	e_{121}	84 → 72	5.700×10^{-3}	5.161
e_{56}	11 → 43	0.962	0.039	e_{122}	66 → 78	0.990	0.010
e_{57}	12 → 37	0.989	0.011	e_{123}	67 → 78	0.990	0.010
e_{58}	33 → 37	0.989	0.011	e_{124}	68 → 79	0.969	0.032
e_{59}	15 → 37	0.989	0.011	e_{125}	69 → 79	0.969	0.032
e_{60}	37 → 43	0.962	0.039	e_{126}	70 → 79	0.969	0.032
e_{61}	16 → 38	0.961	0.040	e_{127}	71 → 80	0.986	0.014
e_{62}	17 → 38	0.961	0.040	e_{128}	72 → 80	0.986	0.014
e_{63}	34 → 38	0.961	0.040	e_{129}	78 → 85	0.946	0.056
e_{64}	38 → 44	0.955	0.046	e_{130}	79 → 85	0.946	0.056
e_{65}	39 → 44	0.955	0.046	e_{131}	80 → 85	0.946	0.056
e_{66}	45 → 48	0.850	0.163	–	–	–	–

Table 5
The shortest path of different accidents during the pandemic.

Initial event	The shortest path	Risk entropy	Probability
1	1 → 9→43 → 48	4.255	1.42×10^{-2}
1	1 → 9→43 → 48→52 → 74→81 → 83→64 → 84→68 → 79→85	18.413	1.01×10^{-8}
2	2 → 26→40 → 46→48	4.206	1.49×10^{-2}
2	2 → 26→40 → 46→48 → 52→74 → 81→83 → 64→84 → 68→79 → 85	18.364	1.06×10^{-8}

accident, to avoid the occurrence of the escalation of the accident.

The shortest path of an explosion accident caused by human factors and equipment factors are shown in Fig. 10. The blue line in the figure represents the shortest accident path caused by equipment factors; the green line represents the shortest accident path caused by human factors, and the red line represents the common path of the accident caused by both. There are some identical risk factors in the shortest path of different accidents.

The risk factors of each path are interlinked. Targeted measures can be taken to cut off the development path of the accident and make the accident develop in a relatively favorable direction. For equipment factors, targeted inspection should be carried out as much as possible in the case of human resources shortage. Especially for components with high failure frequency (such as valve failure in this case), the effectiveness of inspection and maintenance should be increased. This can not only effectively reduce the number of risk factors and the failure probability, but also extend the time of FWO to carry out more inspections and repairs. Besides, it can compensate for some of the impact of the human resources shortage. For human errors, reasonable work arrangement and communication can not only reduce the workers' pressure but also reduce the impact caused by the poor working environment. Targeted development of emergency plans during the pandemic can reduce the decision time and the probability of decision failure. It can also improve the effectiveness of emergency response, and control the direction of accidents in a limited time to reduce accident consequences.

5. Discussions

5.1. *Comparison with Bow-Tie and Bayesian networks for accident modeling*

Bow-Tie (BT) and Bayesian network (BN) model are widely used as risk analysis techniques in the field of chemical process safety (Ferdous et al., 2012; Khakzad et al., 2013; Abimbola and Khan, 2014; Zarei et al.,

Table 6
The difference between the proposed method and BT and BN.

Methods	Aspects		
	Model structure	Inputs	Outputs
BT model	Sequential	Failure data expert judgements	Possible accident consequences and their probability
BN model	Non-sequential	Failure data expert judgements and abnormal state	Possible accident consequences and their probability
The proposed method	Non-sequential	Failure data expert judgements	1)Possible accident consequences and their probability 2)Critical and shortest accident route

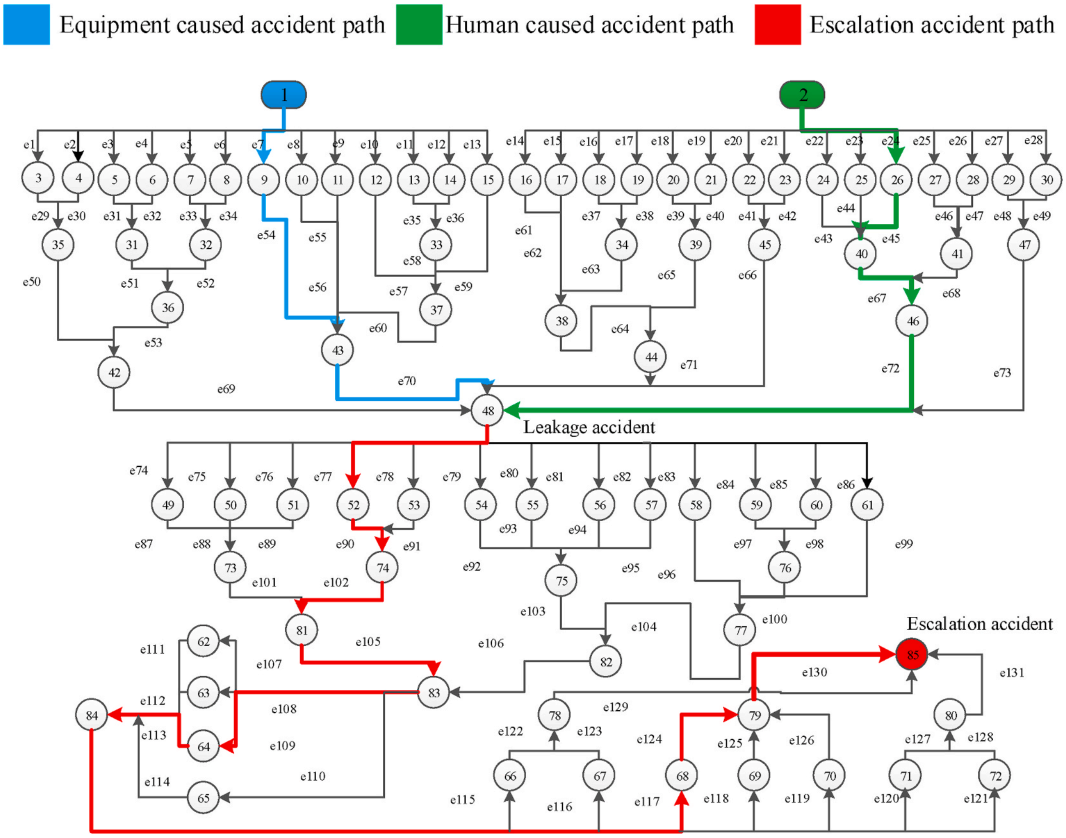


Fig. 10. The shortest paths of different initial events during the pandemic.

2019). BT is used to represent the relationship between the cause of an accident, the path of the accident, the consequences of the accident and the measures to prevent the accident. It is a risk analysis method that is easy to use and operate, and it is highly visual. BT can graphically represent the entire life cycle of an accident, and help workers establish effective measures to prevent accidents. However, most of the modern complex industrial systems suffer from multiple failure modes and exhibit dynamic failure behaviour. Therefore, conventional tool is unable to deal with dynamic failure behaviour of complex systems (Kabir, 2017). BT, as a conventional risk analysis method, uses generic failure data. This makes it to be non-case-specific and introduce uncertainty into the results (Li et al., 2016). Besides, it cannot represent the risk of a single path.

BN is a probabilistic inference technique for reasoning in uncertain situations, which can relax the limitation of conventional methods and consider conditional dependence and common failures in the process of accident modeling (Yuan et al., 2015). However, BN focus on solving the overall risk of accidents, and cannot represent the risk of a single path. During the pandemic, due to the shortage of human resources, it is essential to identify and eliminate the most vulnerable risk factors in limited time. This can increase WO's time so as to make more rounds of inspection and maintenance. Compared with the BN method, this method fully displays the risk factors on the network graph systematically and intuitively on the basis of considering the uncertainty. The detailed difference between the proposed method and BT and BN is shown in Table 6.

The proposed methodology leverages the strength of BT and BN, which mapped from Fault Tree and Event Tree, and considers the data uncertainty. It can solve the probability of the path between any nodes, and quickly identify the shortest path of accidents, and most the vulnerable risk factors, to provide more targeted decision support for accident prevention and control during a pandemic.

5.2. *The impact of pandemic with respect to process industry*

The pandemic's impact on the process industry is mainly reflected in two aspects: human errors and accident stages. Human errors should be analyzed from four aspects: organization, unsafe supervision, preconditions for unsafe acts, and unsafe acts. Due to the shortage of human resources, there will be secondments during the epidemic, workers' ambiguity about new tasks, and insufficient training will increase the probability of human errors. Besides, organizations will take various measures to deal with the impact of the pandemic. The manager may make wrong decisions or policies because of lack of experience in the pandemic. For the influence of unsafe supervision, the lack of human resources will reduce or even eliminate normal supervision efficiency, thereby increasing the risk of accidents. For the preconditions of unsafe acts, the shortage of human resources caused by the pandemic increases the workers' stress and workload. The on-site workers speed up operations to complete many tasks, thereby increasing the probability of operational errors.

The impact of the pandemic on the accident stage is mainly reflected in the daily inspection and maintenance as well as the emergency response time and efficiency. In the FWO, the shortage of human resources will reduce the number of on-site inspections and routine maintenance. Due to the lack of normal inspection and maintenance, the possibility of accidents in the process industry is greatly increased. Due to the impact of the pandemic, personnel's emergency efficiency and response time will be greatly affected in the event of an accident, thus shortening SWO. This means that when the initial accident occurs, the probability of accident escalation increases greatly, increasing the risk of the process industry.

According to the shortest path calculation results, the main reason for the leakage accident in the process industry is the valve failure caused by insufficient maintenance, and the delayed inspection finally leads to the leakage accident. When the automatic gas detector fails, the shortage of human resources leads to manual detection failure, which leads to the failure of the dispersion prevention barrier. Due to the pandemic's impact, no fire prevention measures were taken after the leakage accident, which eventually led to the explosion accident. Emergency rescue is not carried out in a timely and effective manner because of the pandemic's impact and personnel poisoning, which causes severe casualties, property losses, and environmental damage.

6. Conclusions

The special influence of a pandemic on chemical process safety is analyzed, and is divided into two parts: the impact on human errors and the accident stages. For human errors, operational errors, information transmission failure, unreasonable working hours, and poor working environment are the main causes of human errors. For accident stages, the number of workers is reduced during the pandemic, thereby increasing the number of risk factors and the probability of failures, shortening the window of opportunity and increasing the possibility of accidents.

The WO concept is proposed to analyze the special risk factors during a pandemic, and to divide the accident life cycle into two parts. It reveals the possible risk factors, accident scenarios and accident consequences of chemical process safety under the impact of a pandemic.

Based on a qualitative risk analysis, the complex network is introduced to integrate the WO. The complexity of accident process is displayed intuitively on the network model. The Dijkstra algorithm is used to find the shortest path of an accident and to identify the shortest path caused by different risk factors. Since the probabilities cannot be added, the use of the Dijkstra algorithm is limited. In order to overcome this shortcoming, the concept of risk entropy is proposed to convert probability into risk entropy to represent edge weights. Human error caused by high working pressure as the initial event leads to the shortest path of escalation accident.

The advantages and disadvantages of the BT and BN models are analyzed. The results show that BT and BN have their own strengths, but they cannot calculate the risk of a single path. The proposed method combines the advantages of BT and BN to make the modeling process and results more scientific. It can more effectively reduce the probability of accidents during the pandemic within a limited time. Taking targeted measures can cut off the development of the accident and make the accident develop in a relatively favorable direction. It has certain engineering significance for reducing the probability of accidents and controlling the consequences of accidents during any pandemic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Expert judgment, fuzzy possibilities (FPs) and fuzzy probabilities (FPr) of root events in fault tree and event tree.

Symbol	E[a] 1	E 2	E 3	E 4	Aggregation of Fuzzy Numbers				FPs[b]	FPr[c]
X1	VL	L	L	M	0.11	0.22	0.26	0.40	0.25	0.0005
X2	L	M	L	L	0.15	0.31	0.31	0.47	0.31	0.0010
X3	VL	L	L	H	0.17	0.28	0.31	0.44	0.30	0.0010
X4	L	M	M	M	0.24	0.42	0.42	0.60	0.42	0.0028
X5	M	L	M	M	0.25	0.44	0.44	0.63	0.44	0.0032
X6	M	L	L	M	0.21	0.38	0.38	0.56	0.38	0.0020
X7	H	M	H	H	0.53	0.69	0.69	0.85	0.69	0.0174
X8	M	H	L	M	0.32	0.50	0.50	0.68	0.50	0.0050
X9	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X10	L	H	M	H	0.37	0.53	0.53	0.69	0.53	0.0063
X11	L	H	VL	M	0.24	0.36	0.39	0.53	0.38	0.0020
X12	M	L	L	M	0.21	0.38	0.38	0.56	0.38	0.0020
X13	VL	M	VL	H	0.20	0.28	0.33	0.47	0.32	0.0011
X14	M	H	L	H	0.39	0.55	0.55	0.72	0.55	0.0072
X15	M	H	L	M	0.32	0.50	0.50	0.68	0.50	0.0072
X16	H	H	H	M	0.54	0.70	0.70	0.86	0.70	0.0181
X17	M	H	M	M	0.37	0.56	0.56	0.75	0.56	0.0075
X18	M	L	L	M	0.21	0.38	0.39	0.56	0.38	0.0020
X19	M	H	VL	M	0.30	0.44	0.47	0.63	0.46	0.0037
X20	H	H	L	L	0.38	0.53	0.53	0.68	0.53	0.0060
X21	M	L	VH	M	0.37	0.54	0.56	0.70	0.54	0.0066
X22	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X23	L	H	L	VL	0.20	0.32	0.34	0.48	0.33	0.0013
X24	M	M	L	M	0.25	0.44	0.44	0.63	0.44	0.0032
X25	H	L	M	H	0.41	0.57	0.57	0.73	0.57	0.0082
X26	H	H	H	M	0.54	0.70	0.70	0.86	0.70	0.0181
X27	M	H	VH	M	0.49	0.65	0.69	0.82	0.66	0.0141
X28	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X29	M	M	VL	M	0.23	0.38	0.41	0.58	0.40	0.0023
X30	L	H	VH	L	0.38	0.52	0.55	0.66	0.53	0.0060
X31	M	M	M	L	0.26	0.45	0.45	0.64	0.45	0.0034
X32	H	H	H	M	0.54	0.70	0.70	0.86	0.70	0.0181
X33	M	H	VH	M	0.49	0.65	0.70	0.82	0.66	0.0141
X34	L	M	L	L	0.15	0.31	0.31	0.47	0.31	0.0010
X35	L	M	VL	L	0.12	0.25	0.27	0.42	0.27	0.0007
X36	M	M	H	M	0.37	0.56	0.56	0.75	0.55	0.0075
X37	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X38	M	L	VH	L	0.33	0.48	0.51	0.64	0.49	0.0046
X39	M	M	L	M	0.25	0.44	0.44	0.63	0.44	0.0032
X40	M	M	VL	M	0.23	0.38	0.41	0.58	0.40	0.0023
X41	M	M	H	M	0.37	0.56	0.56	0.75	0.56	0.0075
X42	M	VL	M	L	0.19	0.33	0.35	0.52	0.35	0.0015
X43	L	L	VL	VL	0.06	0.14	0.18	0.31	0.17	0.0001
X44	L	L	H	M	0.26	0.42	0.42	0.58	0.42	0.0028
X45	VL	L	M	M	0.16	0.28	0.31	0.47	0.31	0.0010
X46	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X47	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X48	H	H	H	M	0.54	0.70	0.70	0.86	0.70	0.0181
X49	H	H	L	M	0.42	0.58	0.58	0.74	0.58	0.0085
X50	M	M	M	M	0.30	0.50	0.50	0.70	0.50	0.0050
X51	VH	L	M	M	0.41	0.57	0.60	0.72	0.57	0.0082
X52	H	M	L	M	0.35	0.52	0.52	0.69	0.52	0.0057

[a] Expert judgment (E).

[b] Fuzzy possibilities (FPs).

[c] Fuzzy probabilities (FPr).

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