Bayesian network-based risk analysis methodology: a case of atmospheric and vacuum distillation unit

Junyan Zhang[1,2], Baoping Cai[1,2*], Kabwe Mulenga[2], Yiliu Liu[3], Min Xie[2]

[1]College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, Shandong, 266580, China

[2]Department of Systems Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong

[3]Department of Production and Quality Engineering, Norwegian University of Science and Technology, Trondheim, Norway

Abstract

Chemical and petrochemical accidents, such as fires and explosions, do not happen frequently but have considerable consequences. These accidents compromise not only human safety but also cause significant economic losses and environmental contamination. The increasing complexity of chemical infrastructures increases the requirements of risk prevention. Thus, risk analysis for petrochemical systems is essential in helping analysts find the weakest process in the entire system and be used to strengthen the process and improve safety. Risk analysis has been previously studied; however, traditional methods have limitations. This study proposes a methodology that is based on Bayesian networks by giving a model for system risk analysis. The event is classified into three categories; cause, incident, and accident, according to criticality and thus, the model is analyzed as a three-layered structure. The application of the methodology is demonstrated by analyzing a vacuum distillation and an atmospheric unit. An exact reasoning method is used to infer the causality and probability within the events. After inferring the relationship between causes and accidents, mutual information and variance of beliefs are calculated to find the most sensitive event in an accident.

*Corresponding author:
E-mail address: caibaoping@upc.edu.cn (B. Cai); zhangjunyan0225@gmail.com (J. Zhang)

Subsequently, means of strengthening operations to prevent accidents are suggested. This study may help companies decrease the cost of risk reduction.

Keywords: Risk analysis; Bayesian networks; Chemical plant; Three-layer hierarchical model

1. Introduction

Petrochemical process industries utilize complex piping and other equipment necessary for processing (Zhang et al., 2017). An interlock is an essential component in petrochemical processes, it controls various systems and provides better efficiency and reliability. Thousands of interlocks involved in the control system make the process a complex one. In this case, the occurrence of one event triggers another and in turn, lead to a series of events and thus making sure that the entire system is stable with no fault happening is vital. The occurrence of any fault in such a complex control system may lead to a series of incidents, even accidents. Accidents occurring in chemical plants have low frequency but significant consequences. Historical data show that several accidents with severe consequences have occurred in this industry. Hisken et al. (2016) reported an accident that occurred in December 2005 in Buncefield Complex, at the Hertfordshire Oil Storage Terminal, in Hertfordshire, England, where a massive fire and a series of explosions led to 43 injuries and substantial property losses. The primary cause of the fire was leakage of 250,000 L of fuel, and then an explosion in a vapor cloud of evaporated petrol. Li et al. (2016) documented one of the most significant accidents reported in history, which happened at the British Petroleum's refinery in Texas City, Texas, the USA on 23 Mar 2005. A spillage of raffinate led to the evaporation, and a nearby vehicle engine ignited the vapor cloud, resulting in an explosion. The company lost approximately $1.5 billion in monetary terms, and 15 fatalities and 180 injuries were recorded. A fire and explosion caused by the expanded high-pressure methane gas occurred at the Macondo Well, the Gulf of Mexico in the United States on 20 April 2010, which led to 11 workers missing and 17 injuries (Feng et al., 2016). This explosion then resulted in a severe oil spillage in the ocean, which lasted for 87 days. This spillage was excessively harmful to the environment and wildlife, which made it the most massive accidental marine oil spill in the history of the petroleum industry.

The severity of these accidents shows that a risk analysis process for petrochemical systems is essential to potentially help identify the weakest link in the system and thus strengthen the process and improve safety. Several methods have been developed for risk analysis. Cai et al. (2012) used the Markov method with the multiple-error shock model to evaluate triple and dual modular redundancy systems within subsea blowout preventer control systems. Ramírez-Marengo et al. (2015) utilized a stochastic approach that included a Monte Carlo simulation to assess risks of vapor cloud explosions using Analytic Solver Platform. Fu et al. (2016) proposed a quantitative risk assessment model for the potential leakage risk of liquefied natural gas (LNG)-fueled vessels; their methods use event tree analysis and computational fluid dynamics simulation. Martins et al. (2016) presented a complete quantitative risk analysis for unexpected events that can happen during LNG processing. Fuentes-Bargues et al. (2016) used hazard and operability (HAZOP) analysis and risk evaluation to analyze the risk in industrial plants. However, this HAZOP method is not able to provide quantitative analysis like probability or likelihood dimension to give a risk assessment.

Bayesian network (BN) is an important probabilistic graphical model, which can efficiently deal with various uncertainty problems based on probabilistic information representation and inference. In recent years, researchers have been using Bayesian networks (BNs) for quantitative risk analyses to calculate risk models due to the flexibility of the networks. Cai et al. (2013a) proposed a methodology that uses BNs for the quantitative risk assessment of operations in offshore oil and gas industries by translating a flowchart into five steps. Yeo et al. (2016) provided a dynamic safety analysis model for LNG carrier offloading; their model investigates different risk factors during the process using a BN. Bhandari et al. (2015) introduced a dynamic safety analysis that uses a BN for deep-water managed pressure and underbalanced drilling operations. Cai et al. (2013b) presented a quantitative risk assessment model that uses BNs for an offshore blowout; their model focuses on human factors, which were described as human factor barrier failures. This research was extended by Cai et al. (2015) by combining root cause analysis and reliability evaluation phases that are based on BNs and dynamic BNs, respectively, to present a real-time reliability evaluation methodology. Several mature, accurate, and approximate inference algorithms have been developed for BNs. Approximate inference algorithms can be used when the number of components is increasing.

This research presents a BN-based risk analysis methodology, which we apply to a critical system in petrol chemical processing: an atmospheric and vacuum distillation unit. This component is necessary for petroleum refinery plants and has universal applications. An atmospheric and vacuum distillation unit has an elaborate system comprising many separate structures and control nodes. Equipment and material failures like cracks in the storage vessels, or human errors like operational errors or external perturbation, can have a significant influence on work safety. Therefore, system control and accident reduction methods need to be developed to identify the weakest processes in the system and improve safety. We use BNs for risk analysis in this work.

The remaining parts of this paper are organized as follows; section 2 presents the proposed methodology, based on a BN as a model for system risk analysis. The event is classified into three categories; cause, incident, and accident, by criticality, and the model is analyzed as three-layered. Section 3 discusses the application of the proposed method to the risk analysis of atmospheric and vacuum distillation units. After inferring the relationship between the causes and the accident in the system, the most plausible cause is detected. Then, suggestions for accident prevention are given. Section 4 concludes the work based on the findings. This research can help companies in the petrochemical industry reduce the cost of risk analysis.

2. Methodology

2.1 BN overview

A BN is a probabilistic graphical model, which is a statistical model that represents a set of random events denoted by nodes in a graph. The conditional dependencies of these events are represented by edges via a directed acyclic graph. Each node is associated with a probability function as input that selects a particular set of values for the parent variables of the node and gives the probability or probability distribution of the variable represented by the node. Fig. 1 shows a typical BN example.

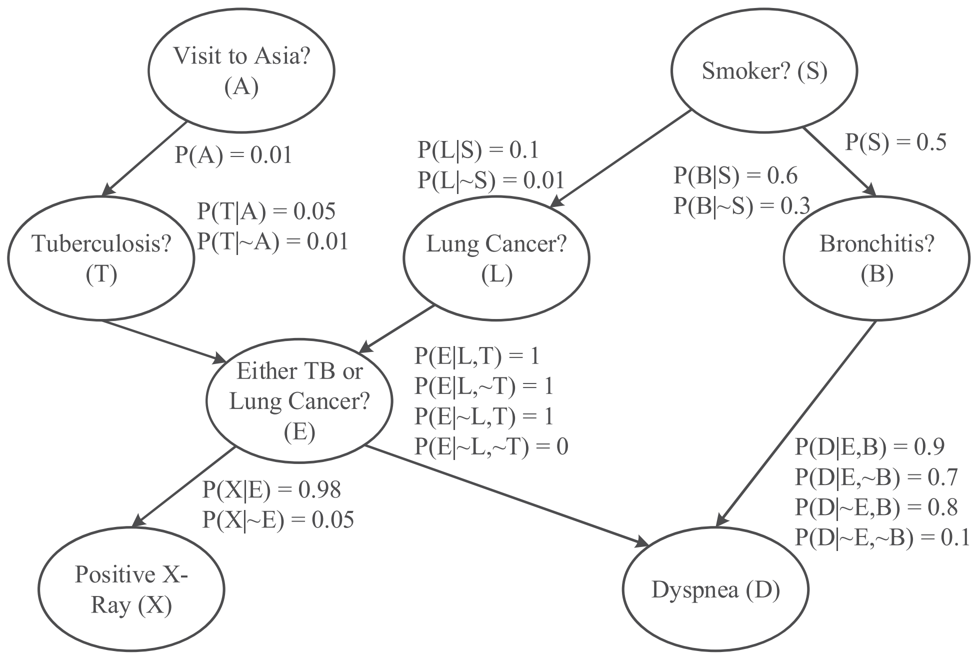

Fig. 1. A typical example of BNs

Several basic statistical formulas and theories for quantitative BNs are presented based on conditional independence and the chain rule and by calculating the product of conditional probability tables (CPT), the joint probability of a set of variables $U = \{A_1, A_2,..., A_n\}$ can be given as

$$P(U) = \prod_{i=1}^{n} P(A_i|P_a(A_i)), \quad (1)$$

where $Pa(A_i)$ is the parent node of A_i in the BNs and $P(U)$ represents the probabilities (Jensen and Nielsen, 2007).

BNs could provide the analyst the capability to perform forward (predictive) and backward (diagnostic) analyses (Cai et al. 2016; 2017; 2018). In diagnostic analysis, a series of evidence E is examined, and the posterior probability distribution can be calculated using various inference algorithms that are based on *Bayes' theorem* as follows (Darwiche, 2009):

$$P(U|E) = \frac{P(E|U)P(U)}{P(E)} = \frac{P(E,U)}{\sum_U P(E,U)}. \quad (2)$$

The important degree of the basic event to the system failure can be assessed using Shannon's mutual information (entropy reduction), which is a widely used measurement model for ranking information sources, as shown by Pearl (1988). The uncertainty of a system is assumed to be represented by an entropy function given as

$$H(T) = -\sum_t P(t) log P(t), \quad (3)$$

where $P(t)$ is the probability distribution of the random variable T.

Mutual information is the total uncertainty-reducing potential of X, given the original uncertainty in T before consulting X. The mutual information of T and X is given by

$$I(T,X) = -\sum_x \sum_t P(t,x) log \frac{P(t,x)}{P(t)P(x)}, \tag{4}$$

where $P(t, x)$ is the joint probability distribution function of T and X, and $P(t)$ and $P(x)$ represent the marginal probability distribution functions of T and X, respectively.

2.2 BN-based risk analysis methodology

Many error or non-error causes may happen in chemical plants because they are complex systems with imperfect reliability, and these causes can develop into incidents. An incident is an abnormal event that is not supposed to happen in daily operation. If no response is undertaken when an incident occurs or if self-healing cannot be performed, then an incident may turn into an accident, which is unfavorable.

Cause, incident, and accident illustrate a sequence of increasing level of criticality. The three events are defined as follows. (1) Causes are actions that may cause an abnormal event. (2) Incidents are unusual events that may result in an accident, although they have no severe criticality in and of themselves. (3) Accidents are the events that have severe consequences and threaten to compromise human safety and cause economic loss.

Although several causes or their combinations may cause an accident, humans prefer the nonoccurrence of the accident. From previous data, we can give an analysis of the probability of each cause to lead to an accident, if any. Then, from the quantitative analysis, the cause, which has the most significant influence on accidents, can be found. After identifying the most influential causes, we can gain insights into eliminating such accidents.

To find the probability relationship between cause and accident, a hierarchical BN model comprising three layers (cause, incident, and accident) is established in this section. The steps are as follows.

Step 1: Analyzing the system

A system consists of several components and equipment, which have varying reliabilities. Events of different severity levels may happen in the components. The first step is finding the components and possible events in it.

Step 2: Establishing the structural model

This process is qualitative. Fig. 2 shows the main idea of this paper: the proposed three-layered hierarchical model that classifies the events into cause, incident, and accident. The different states of an event are variables shown by BN nodes. The arrows show their dependencies and cause-effect relationships.

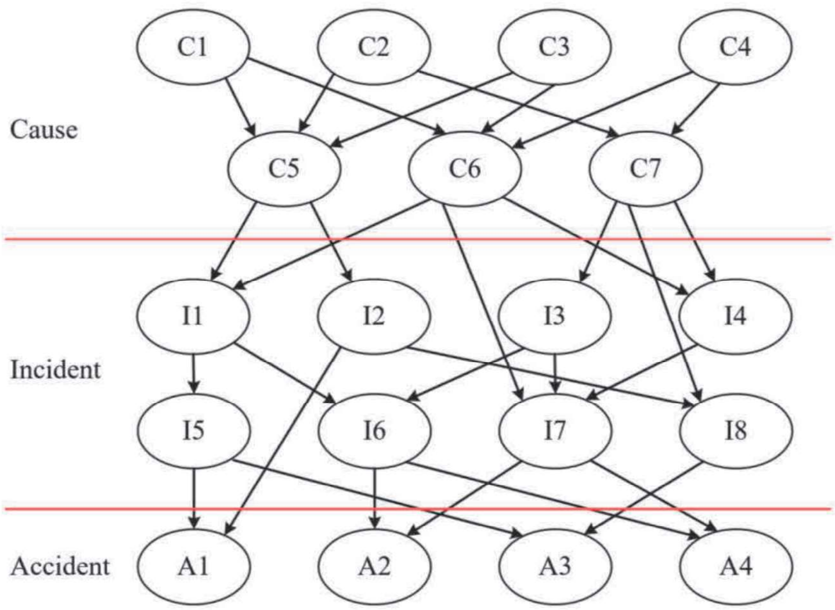

Fig. 2. Three-layered hierarchical model of BNs

Step 3: Establishing the parameter model

This process is quantitative. By analyzing the prior probability of the parent event and establishing CPT (distribution), the quantitative relationships among the related events are represented.

Step 4: Performing inference analysis

By placing the entire established structure and parameter models into Netica, which is a supporting software that is introduced in the succeeding section, the inferential relationship is analyzed, the results are obtained, and the most influential factor is found.

Step 5: Validating the model

Validation can make the model persuasive and is thus a necessary process. To validate the proposed BN model, this study uses a three-axiom-based validation method. The three axioms, which were studied by Jones et al. (2010), are as follows.

(1) A slight increase/decrease in the prior subjective probabilities of each parent node should result in a relative increase/decrease of the posterior probabilities of the child node.

(2) Given the variation in the subjective probability distributions of each parent node, the magnitude of influence on the child node values should remain consistent.

(3) The total influence magnitudes of the combination of the probability variations from x attributes on the values should always be higher than those from the set of x-y ($y \in x$) attributes.

3. Risk analysis of atmospheric and vacuum distillation unit

3.1 Petrochemical plant and equipment

We apply the proposed model in Section 2 to an atmospheric and vacuum distillation unit, which is a typical equipment used in the petroleum refining process. Oil refineries use different boiling points of several products to separate them and remove the unwanted product. This process also provides preparations for further processing which utilizes chemical reactions to convert to the desired product. This process yields qualified petroleum products, such as liquefied petroleum gas, jet fuel, fuel oils, and other relevant energy sources. The oil refinery process is divided into primary and secondary processes. During the primary process, distillation separates the crude oil into gasoline, diesel, wax oil, and residual oil, which have different boiling ranges. The secondary process then transfers the heavy products from crude oil distillation into light fractions. Then, refinery light fractions or composite is performed with gas to produce high-octane-rating oil. Refineries depend on distillation units to separate crude oil into fractions. Atmospheric and vacuum distillation units, as necessary units in petroleum refinery plants, have universal applications in the industry. Also, these units are the most common equipment in chemical plants. This study illustrates the proposed method using this unit due to its relative importance in plants.

Atmospheric distillation unit is used to separate petroleum fractions under atmospheric pressure by using temperature. Due to their different boiling point, low boiling fractions vaporize before high boiling fractions. Therefore, the vapor contains more low boiling fractions, and the mixed liquid contains more high boiling fractions. The fractions are separated, and a vacuum distillation unit is used to separate heavy oil fractions come from atmospheric bottoms, into gas oils and asphalt under reduced pressure. Fig. 3 shows the external view of the unit. Fig. 4 shows the typical flow chart of an atmospheric and vacuum distillation unit. The complex system, which contains many adjunctive systems and control nodes, is shown by the flowchart.

Fig. 3. External view of atmospheric and vacuum distillation unit

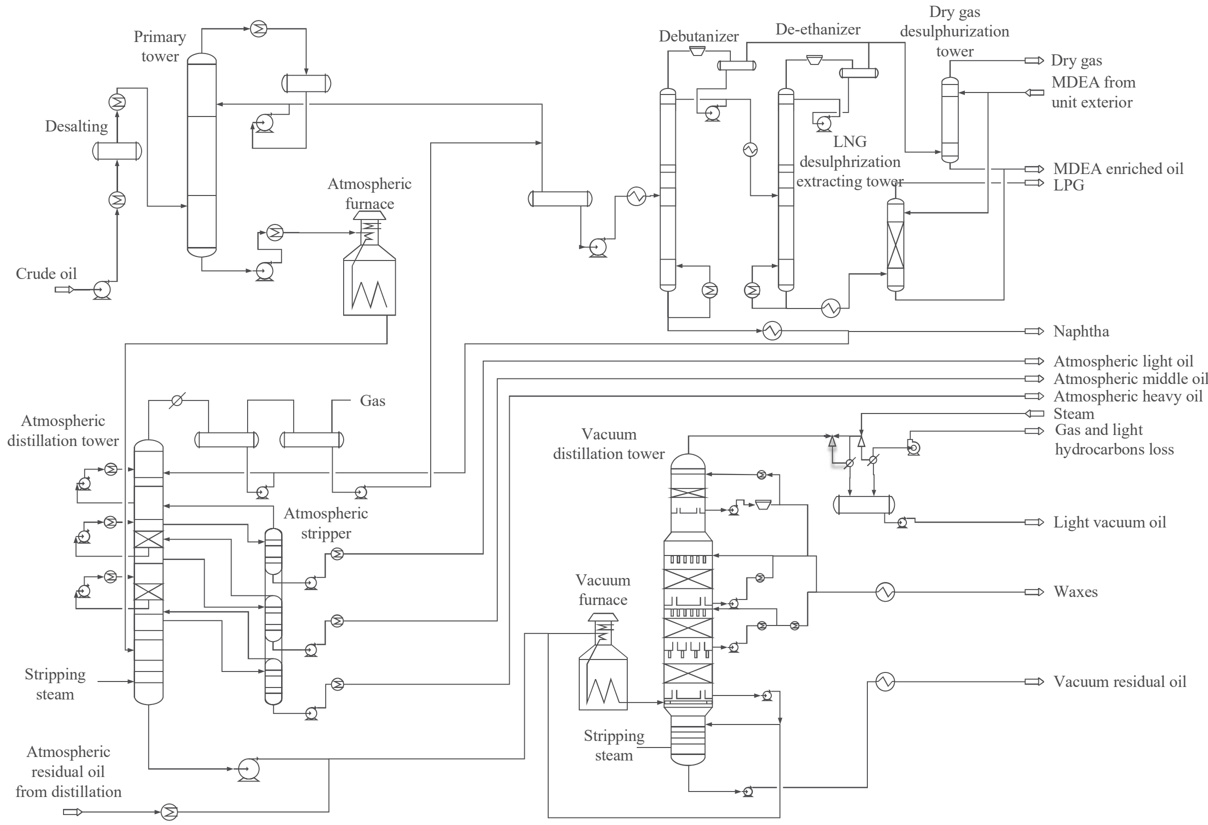

Fig. 4. Flowchart of atmospheric and vacuum distillation unit

3.2 Application of the BN-based methodology

A real petrochemical plant and its atmospheric and vacuum distillation units are analyzed using the proposed methodology. The events and cases are based on previous failure reports and operators' or experts' experience. This application should follow the five steps discussed in the succeeding paragraphs.

Step 1: Analyzing the system

Possible events in the plant and their relationships should be analyzed first. To explain the meaning of "relationships" in the hierarchical BNs model, a common event at the plant is used here as an example, excessively low ambient temperature. This event may lead the operator to prefer staying indoors, which may result in the negligence of closing an inlet valve (normally a gate valve) of a tank, then lead to excessive high operation levels, followed by spills, eventually a fire.

Several relationships of possible events are identified and illustrated as follows:

(1) One event happens, leading to another event.

For example, sometimes because of fluctuations in production, a busy situation may arise, or there may be an emergency situation, and the system needs to be shut down. In this case, an operator who is doing a shift change may neglect to pass necessary system command to the next crew. The shifted operator does not efficiently execute the command resulting in the command not being completed. Specifically, shift change may cause crew A to forget to pass the command "close the inlet valve of the tank" to crew B, and the inlet valve remaining open will lead to a high level in the tank and eventually resulting in tank overflow.

Another example is of low ambient temperatures that may cause the tank pressure control valve to freeze, leading to a loss of control, creating high pressure in the tank, and finally causing a relief valve to lift.

(2) Several causes concurrently happen, leading to one event.

When the ambient temperature is high, the water curtain system is supposed to be triggered to open to cool the equipment. However, if there is a failure of tank water curtain system, it cannot open normally.

The main product of petroleum tank sulphur corrosion is FeS, usually found at the bottom of the tank. At the bottom of the tank containing the petrochemical product, there is a low oxygen content, and some of the FeS partially oxidize leading to the production of free sulphur. This low auto-ignition point sulphur mixed with a loosen structured FeS creates a conducive environment for FeS spontaneous ignition. At the same time, when FeS oxidizes, the process (is exothermic) will release heat resulting in the tank and product to heat up. If the heating is not controlled in time, the rise in temperatures may result in self-ignition. This ignition may burn the rubber seal ring and eventually lead to a fire or explosion.

Another example is of medium volatilization, or heat exchanger, a leakage may cause water to run into the standby pump outlet pipeline. If the operator starts this standby pump without checking it and removing the water, vaporization can occur leading to pump exhaustion due to the difference of water and medium density. The phenomenon of describing when medium cannot be pumped out because system consists of both air and liquid is referred to as "airlock." The outlet pressure and flow may then drop much lower than the normal value. This abnormal value will trigger the interlock to turn off the gas feed causing the furnace to turn off.

(3) Several causes may independently be the reason for one event.

For example, an oil leakage, which can lead to a fire, may be caused by any of the following events:

a. High-temperature and high-pressure pumps sealing failure, leading to product leakage.
b. Usually, there is a little water gathering at the bottom of the oil tank. The operator needs to drain and cut off the water then separate it from the oil. When the operator does not identify the water level accuracy, he/she may drain and cut off the water with oil, which may lead to oil leakage.
c. Fracture of outlet pipe fittings such as pipes, elbows, half couplings, nipples, tees, etc., resulting from corrosion or aging.

Additionally, failure to pump the medium (pump outlet low flow) may be caused by the following events:

a. Insufficient opening level of the inlet valve.
b. Blocked inlet filter.
c. Gas remaining in the pump, because of the low density of the gas, the centrifugal force provided by impeller rotation is not enough to pump out the medium, which may lead to the low outlet flow.

Another example of several causes independently resulting in one event can be seen from the steam turbine, a steam turbine converts thermal energy to mechanical energy. The steam turbine exhaust pressure is one of the principal indicators to measure the work of steam turbine. The lower exhaust pressure, the better work. For example, a particular equipment's steam turbine uses 3.5MPa steam as primary steam supply and 1.0MPa steam as auxiliary steam supply, to ensure the turbine vacuum. After getting through the turbine, 3.5MPa steam enters a fixed-tube-sheet heat exchanger which uses seawater as heater tubing medium and cools as condensation water. If there is an abnormal high exhaust pressure of the steam turbine, it may be caused by the following events:

a. Insufficient 1.0MPa steam pressure.

b. Leakage point in the pipeline.

c. Blocked heat exchanger pipeline, which will cause condensation effectiveness of 3.5MPa steam get worse.

Table 1 describes other possible events with their name and meaning. Table 2 explains several abbreviations.

Table 1. Events for risk analysis of atmospheric and vacuum distillation unit

	Event	Description	State
1	AbHighP	Abnormal high-discharge pressure of compressor	Yes, No
2	AbPiP	Abnormal pipeline pressure	Yes, No
3	Aging	Equipment aging	Yes, No
4	AirLock	Pump airlock	Yes, No
5	AirMonitorFail	Air monitor failure	Yes, No
6	AirT	Air temperature	High, Nor., Low
7	BlockPi	Blocked heat exchanger pipeline	Yes, No
8	ClosingV	Closing lye tank valve	Yes, No
9	Corrosion	Corrosion	Yes, No
10	CVFreezing	Tank pressure control valve freezing	Yes, No
11	Damage	Equipment damage	Yes, No
12	DroponHighT	Liquid drops on high-temperature heat exchanger	Yes, No
13	EquipmentFail	Equipment failure	Yes, No
14	Fatigue	Fatigue operator	Yes, No
15	FeedSpeedFast	Feeding speed too fast	Yes, No
16	FilterB	Inlet filter blocking	Yes, No
17	Fire	Fire	Yes, No
18	GroupErr	Group error	Yes, No
19	HeaterT	Heater temperature	High, Nor., Low
20	HighPiT	High pipeline temperature	Yes, No
21	HighSourWT	High sour wastewater temperature	Yes, No
22	HighTaL	High tank level	Yes, No
23	HighTaP	High tank pressure	Yes, No
24	HumanErr	Human error	Yes, No
25	IndividualErr	Individual error	Yes, No
26	InPuDepletion	Incomplete pump depletion	Yes, No
27	InsExperience	Insufficient experience of operator	Yes, No
28	InsOpening	Insufficient opening	Yes, No
29	InsVOpening	Insufficient inlet valve opening	Yes, No
30	LossC	Loss of control	Yes, No
31	MixOilStain	Cooling water mixed with heavy oil stain	Yes, No
32	NoDecompression	No decompression for pump	Yes, No
33	OilJetting	Oil jetting	Yes, No
34	OilLeakage	Oil leakage	Yes, No

35	OrganizationErr	Organization error	Yes, No
36	PiFracture	Outlet pipeline elbow fracture	Yes, No
37	PiLeakage	Leakage point in pipeline	Yes, No
38	PiW	Water in pump outlet pipeline	Yes, No
39	PMonitorFail	Pressure monitor failure	Yes, No
40	PowerCut	Power cut	Yes, No
41	PuHighTandP	Pump with high-temperature and high-pressure medium	Yes, No
42	PuMediumFail	Pump medium failure	Yes, No
43	PuRemainGas	Remaining gas in pump	Yes, No
44	PuStarting	Pump required to start	Yes, No
45	SafetySFail	Safety and alarm system failure	Yes, No
46	SafetyVFail	Safety valve failure	Yes, No
47	ShiftChange	Shift change	Yes, No
48	Shutdown	Shutdown of unit	Yes, No
49	SpoIgnition	Spontaneous ignition	High, Nor., Low
50	SteamP	Steam pressure	Yes, No
51	TaCrack	Tank crack	High, Nor., Low
52	TaOverflow	Tank overflow	Yes, No
53	TaT	Tank temperature	Yes, No
54	TaWS	Open tank water curtain system	Yes, No
55	ToxicGas	Toxic gas release	Yes, No
56	Vaporization	Vaporization	Yes, No
57	Volatilization	Medium volatilization	Yes, No
58	WOil	Drain and cut off water with oil	Yes, No

Table 2. Abbreviations in model

Term	Abbr.
Abnormal	Ab
Blocking	B
Control	C
Error	Err
Failure	Fail
Insufficient	Ins
Level	L
Normal	Nor
Pipeline	Pi
Pressure	P
Pump	Pu
System	S
Tank	Ta
Temperature	T
Valve	V
Water	W

Step 2: Establishing the structural model

The identified possible events are then classified into three layers: cause, incident, and accident. On the basis of the identified relationships between the nodes, BNs are established for each layer.

(1) **Cause**: In a petrochemical plant, several common events can cause accidents, three of which are summarized as follows. The first cause is mistakes caused by human error. This cause is the most influential factor because humans refer to subjective operators of the entire unit. Human error can be further divided into organizational, group, and individual errors. Shift change, inadequate knowledge and skills, poor management, high work stress, misunderstandings, and poor attitude may result in abnormal events. The second cause is equipment failure. All equipment has its reliability that shows that the facility is not entirely reliable. Sometimes, long time exposure, rain, and time may result in corrosion and aging; device failure or fracture may also happen. When these events happen, the probability of incidents increases. Adequate actions should be implemented immediately to prevent the further development of severe consequences. The third cause is nature. For example, excessively low temperatures may cause medium freezing in the pump. Meanwhile, high ambient temperatures may cause tank temperature rising, and the flammable matter in the tank (e.g., FeS) has the probability to self-ignite. Also, earthquakes, snow, wind, and thunder are also likely to contribute to equipment failure. Fig. 5 shows the BNs for the cause layer.

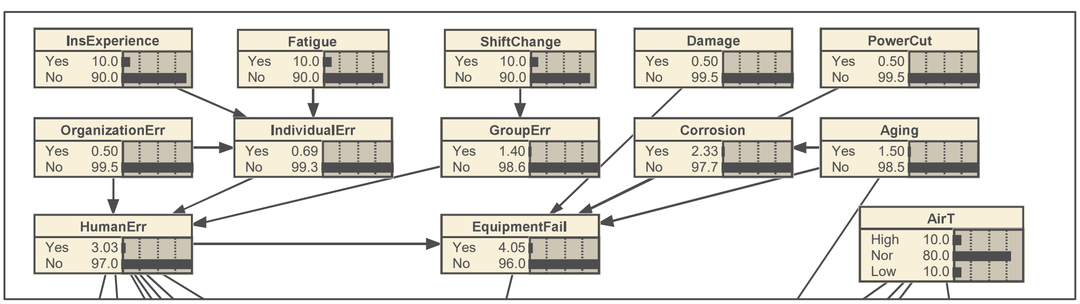

Fig. 5. BNs for cause layer

(2) **Incident**: Certain events happening in the plant can lead to more critical results than those causes previously described. Device abnormality can be considered an incident. Four parameters exist as the primary control parameters of the chemical process, namely, level, pressure, temperature, and flow. Individually, their abnormal values are incidents, such as a high level of a tank, which may

lead to spill, a high pressure of a pipeline or a vessel, a high temperature of the water tank, or low flow. Fig. 6 shows the BNs for the incident layer.

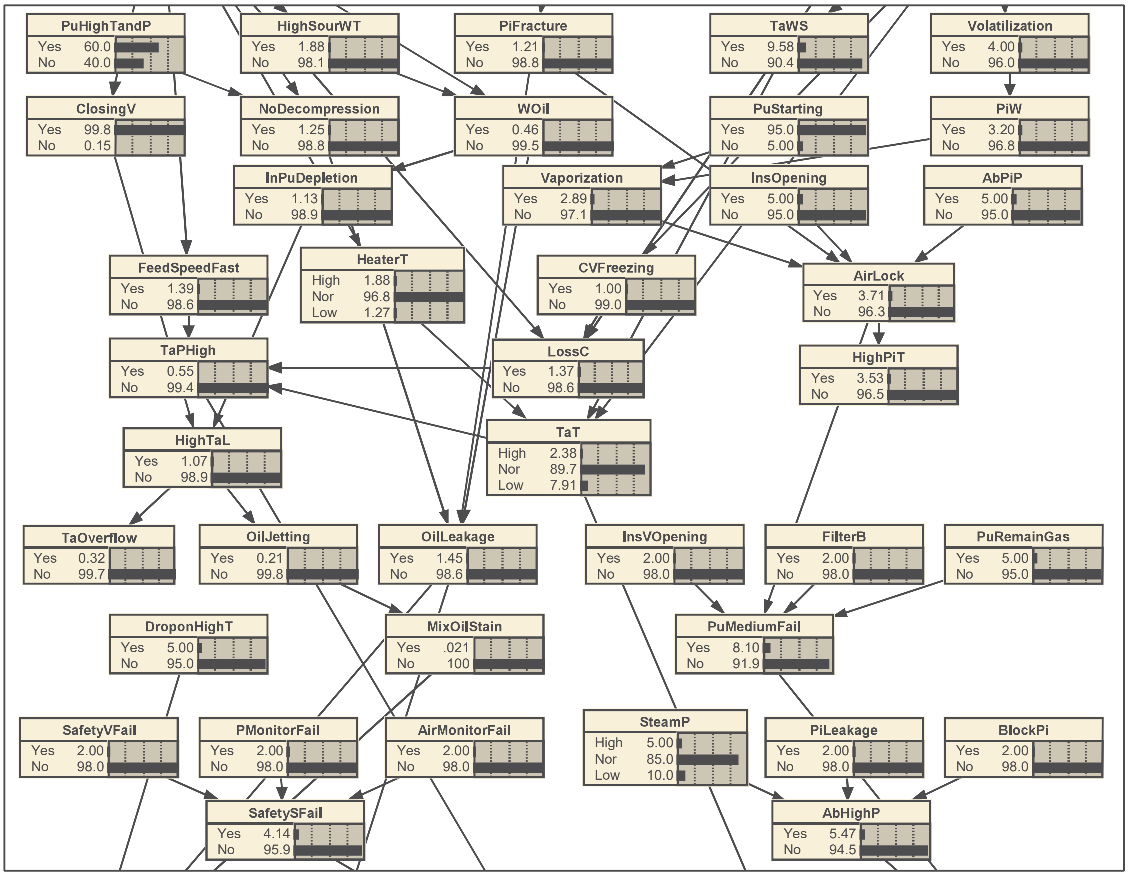

Fig. 6. BNs for incident layer

(3) **Accident**: The consequence of an accident is worse than that of others, especially in the chemical plant, although they do not occur frequently. Typical accidents are spills or leaks, fires, explosions, or vessel ruptures. All of them contribute to a substantial economic loss and can sometimes threaten human safety. Fig. 7 shows the BNs for the accident layer.

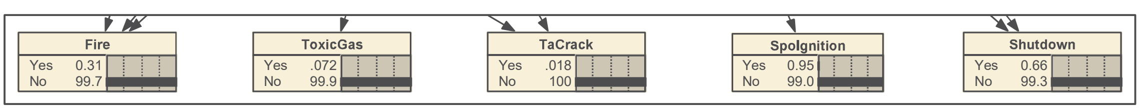

Fig. 7. BNs for accident layer

Step 3: Establishing the parameter model

The prior probability of the basic event and child nodes is input by using the supporting software, Netica.

For a basic event, for example, for the node "Fatigue," the probability of state "Yes" is 10.0%, which means the probability of an operator to become fatigued is 10.0%.

For a child event, n_p (the number of prior probability) of independent entries in the CPT grows exponentially with the number of parents. $n_p = m^n$, where m is the number of its states and n represents the number of parent nodes it has. For example, in Fig. 5, the node "EquipmentFail" has 2 states ("Yes" and "No"); therefore, $m = 2$. Moreover, this node has 4 parent nodes; thus, $n = 4$. Thus, for "EquipmentFail," $n_p = m^n = 2^4 = 16$. For the complicated probability, the worst-case scenario can be overcome in the two following ways.

(1) Noisy-OR

Four things can lead to taking the node "PuMediumFail" for example, "InsVOpening", "PuRemainGas", "FilterB", and "AirLock". They are parent nodes of "PuMediumFail". Table 3 shows the CPT of "PuMediumFail". When only one cause happened, which means only one state of four parent nodes is "Yes" and others are "No," the probability of "PuMediumFail" not happening is an independent failure probability (underlined in Table 3).

Table 3. CPT (%) of node "PuMediumFail"

InsVOpening	PuRemainGas	FilterB	AirLock	Yes	No
Yes	Yes	Yes	Yes	99.64	0.36
Yes	Yes	Yes	No	96.4	3.6
Yes	Yes	No	Yes	98.2	1.8
Yes	Yes	No	No	82	18
Yes	No	Yes	Yes	99.4	0.6
Yes	No	Yes	No	94	6
Yes	No	No	Yes	97	3
<u>Yes</u>	No	No	No	70	<u>30</u>
No	Yes	Yes	Yes	98.8	1.2
No	Yes	Yes	No	88	12
No	Yes	No	Yes	94	6
No	<u>Yes</u>	No	No	40	<u>60</u>
No	No	Yes	Yes	98	2
No	No	<u>Yes</u>	No	80	<u>20</u>
No	No	No	<u>Yes</u>	90	<u>10</u>
No	No	No	No	0	100

The expression formulas of the probabilities are as follows:

$$\mu\,(\neg PuMediumFail | VNoEnoL \& \neg PuRemainGas \& \neg FilterB \& \neg AirBinding) = 0.3$$

$$\mu\,(\neg PuMediumFail | \neg VNoEnoL \& PuRemainGas \& \neg FilterB \& \neg AirBinding) = 0.6$$

$$\mu\,(\neg PuMediumFail | \neg VNoEnoL \& \neg PuRemainGas \& FilterB \& \neg AirBinding) = 0.2$$

$$\mu\ (\neg PuMediumFail|\neg VNoEnoL\&\neg PuRemainGas\&\neg FilterB\&AirBinding) = \ 0.1$$

Then, other probabilities are calculated by these four independent failure probabilities. For example,

$$\mu\ (\neg PuMediumFail|VNoEnoL\&PuRemainGas\&FilterB\&\neg AirBinding) =$$

$$0.3\ \text{X}\ 0.6\ \text{X}\ 0.2\ \text{X}\ 0.1 = 0.0036.$$

Other probabilities follow the same rules.

(2) Experience

The relationship between parents and children is restricted in that conditional independencies exist between the nodes. For instance, if each node has no more than three parents, then a total number of possibility N < 8 n.

For example, for the node "LossC", three events lead to it: "CVFreezing", "HumanErr", and "Aging". Table 4 shows the CPT of "LossC". According to experience, when "CVFreezing" happens, "LossC" must happen. Therefore, when the state of "CVFreezing" is "Yes", the probability of state "Yes" of "LossC" is 100%. If "CVFreezing" does not happen but "HumanErr" and "Aging" occur, the probability of "LossC" is 15%. If one of "HumanErr" or "Aging" occurs, the probabilities of "LossC" happening are 10% and 5%, respectively. If nothing happens within "CVFreezing", "HumanErr", and "Aging", then the probability of "LossC" is 0.

Table 4. CPT (%) of node "LossC"

CVFreezing	HumanErr	Aging	Yes	No
Yes	Yes	Yes	100	0
Yes	Yes	No	100	0
Yes	No	Yes	100	0
Yes	No	No	100	0
No	Yes	Yes	15	85
No	Yes	No	10	90
No	No	Yes	5	95
No	No	No	0	100

Step 4: Performing inference analysis

After giving the CPT of each node, Netica is used to calculate the probability of each node by integrating all the probabilities. Fig. 8 shows the entire structure. Tables 5, 6, and 7 present the calculated results of each layer.

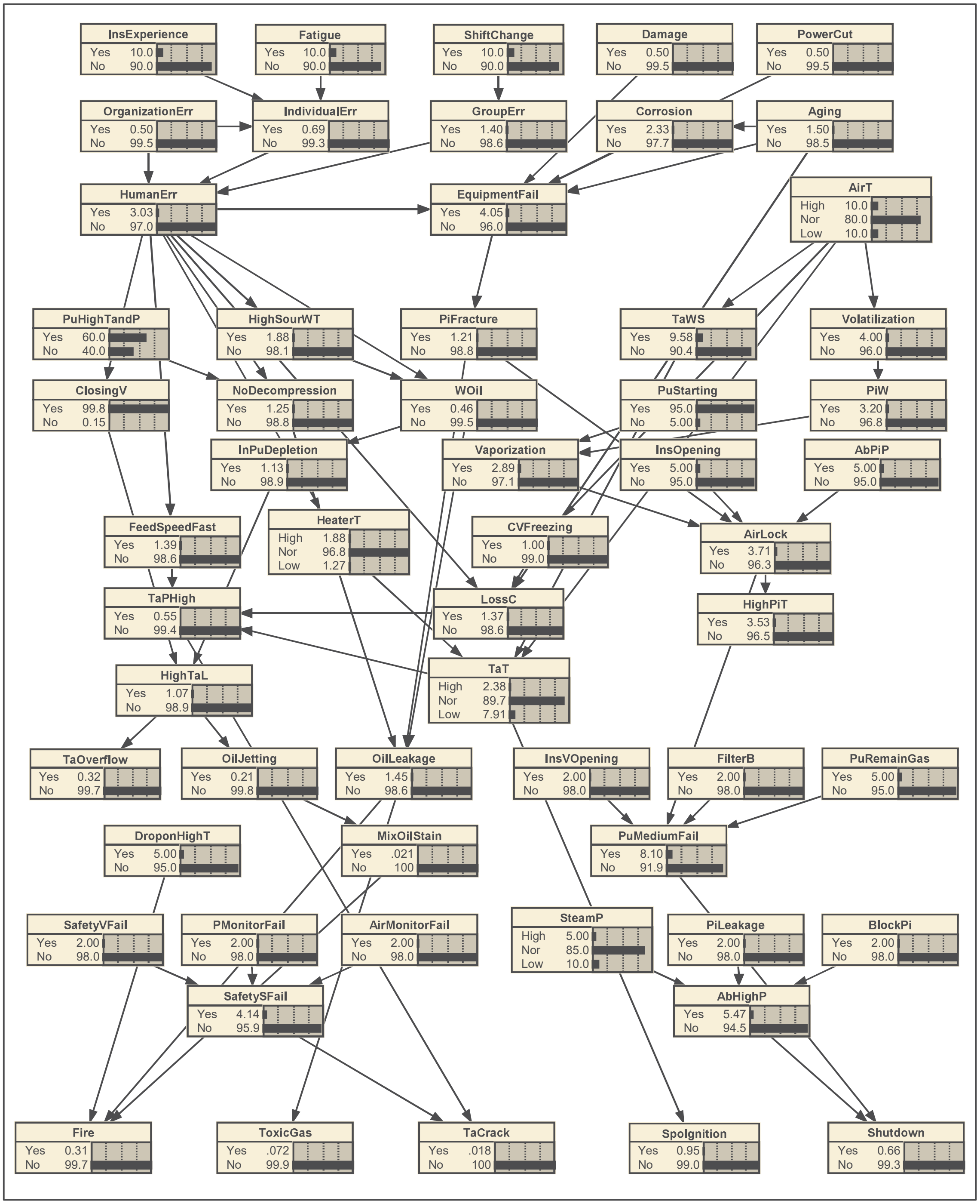

Fig. 8. BNs of the entire unit

Table 5. Probability of cause nodes at state "Yes"

Node	Probability of state "Yes" (%)	Basic node
Aging	10	Yes
AirT	-	Yes
Corrosion	2.33	No

Damage	0.5	Yes
EquipmentFail	4.05	No
Fatigue	10	Yes
GroupErr	1.4	No
HumanErr	3.03	No
IndividualErr	0.69	No
InsExperience	10	Yes
OrganizationErr	0.5	Yes
PowerCut	0.5	Yes
ShiftChange	10	Yes

Table 6. Probability of incident nodes at state "Yes"

Node	Probability of state "Yes" (%)	Basic node
AbHighP	5.47	No
AbPiP	5	Yes
AirLock	3.71	No
AirMonitorFail	2	Yes
BlockPi	2	Yes
ClosingV	99.8	No
CVFreezing	1	No
DroponHighT	5	Yes
FeedSpeedFast	1.39	No
FilterB	2	Yes
Heater	-	No
HighPiT	3.53	No
HighSourWT	1.88	No
HighTaL	1.07	No
HighTaP	0.55	No
LossC	1.37	No
MixOilStain	0.021	No
NoDecompression	1.25	No
InPuDepletion	1.13	No
InsOpening	5	Yes
InsVOpening	2	Yes
OilJetting	0.21	No
OilLeakage	1.45	No
PiFracture	1.21	No
PiLeakage	2	Yes
PiW	3.2	No
PMonitorFail	2	Yes
PuHighTandP	60	Yes
PuMediumFail	8.1	No
PuRemainGas	5	Yes

PuStarting	95	Yes
SafetySFail	4.14	No
SafetyVFail	2	Yes
SteamP	-	Yes
TaOverflow	0.32	No
TaT	-	No
TaWS	9.58	No
Vaporization	2.89	No
Volatilization	4	No
WOil	0.46	No

Table 7. Probability of accident nodes at state "Yes"

Node	Probability of state "Yes" (%)	Basic node
Fire	0.31	No
Shutdown	0.072	No
SpoIgnition	0.018	No
TaCrack	0.95	No
ToxicGas	0.66	No

Step 5: Validating the model

Validation is used to illustrate that the model is a reasonable representation of an actual system. The model is supposed to satisfy the three axioms described in Section 2.2. For example, by increasing the probability of state "Yes" of node "HumanErr" to 100%, the probability of state "Yes" of node "Fire" increases from 0.31% to 1.46%. Additionally, the probability of state "Yes" of node "TaCrack" increases from 0.018% to 0.31%. Therefore, if an error occurs because of human operation, then these accidents may happen. Increasing each influencing node satisfies the axioms, thus partially validating the model.

3.3 Results and Discussions

Other results from the model are presented in the following discussion.

3.3.1 Risk analysis when finding evidence

When an accident occurs, its most probable cause must be determined. In the model, the probabilities of state "Yes" of the nodes "Fire", "ToxicGas", and "TaCrack" are changed to 100%, which means they simulate the accidents happening. The probabilities of other nodes change accordingly. Fig. 9 shows the probabilities during a fire. Nodes with multiple changes in probabilities changed are circled in red. Table 8 shows the probabilities of several nodes. Underlined numbers represent prior probabilities.

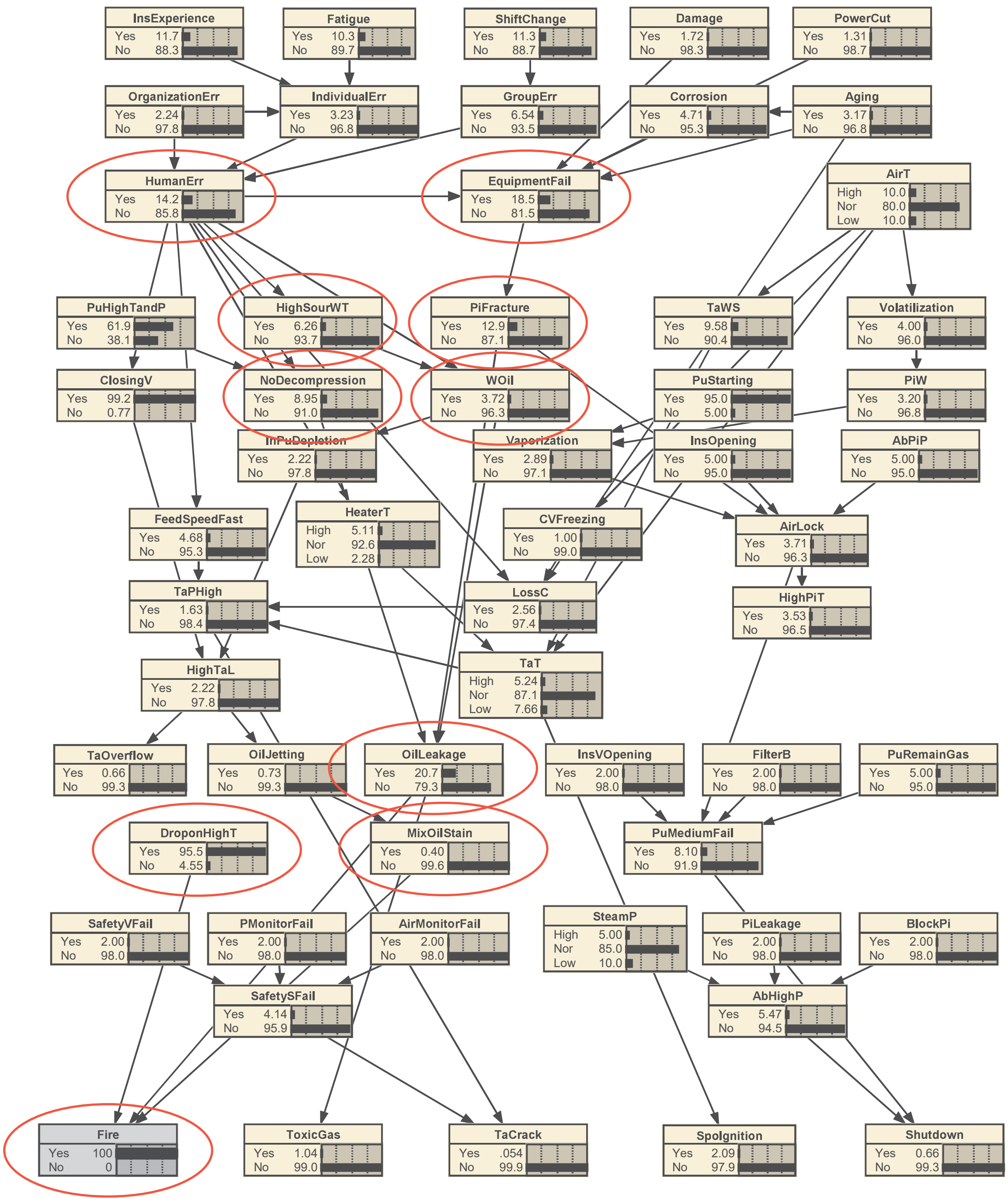

Fig. 9. Probabilities of events when finding "Fire"

Table 8. Probabilities when finding an evidence

Evidence		Probability (%)			
		Origin	Fire	ToxicGas	TaCrack
Parent node	InsExperience	10	11.7	18.5	17.3
	Fatigue	10	10.3	11.7	11.5
	ShiftChange	10	11.3	16.8	15.9
	Damage	0.5	1.72	6.75	0.5
	PowerCut	0.5	1.31	4.66	0.5
	Aging	1.5	3.17	10.1	10.2
Child node	HumanErr	3.03	14.2	59.7	51.9
	IndividualErr	0.69	3.23	13.6	11.8
	GroupErr	1.4	6.54	27.6	24
	OrganizationErr	0.5	2.24	9.38	8.15
	EquipmentFail	4.05	18.5	77.6	46
	Corrosion	2.33	4.71	14.5	10.1
Accident	Fire	0.31	100	4.47	0.92
	ToxicGas	0.072	1.04	100	0.79
	TaCrack	0.018	0.054	0.2	100
	SpoIgnition	0.95	2.09	6.77	7.25
	Shutdown	0.66	0.66	0.66	0.62

Fig. 10 shows the probabilities changing of several basic nodes when finding different evidence. For example, when “Fire” happens, “InsExperience”’s probability increases the most. Thus, it is the most likely cause of the fire. When “ToxicGas” occurs, “InsExperience”’s probability significantly increases. “ShiftChange” also increases considerably and hence, can be a possible and primary reason of “ToxicGas”. Similarly, when “TaCrack” happens, “InsExperience”, “ShiftChange,” and “Aging” can be considered first as the possible reasons.

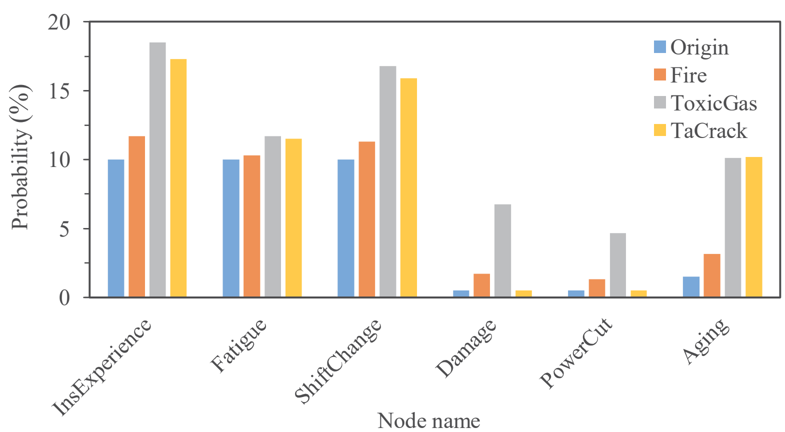

Fig. 10. Compared probabilities of basic nodes when an evidence is found

Fig. 11 shows the probabilities changing of several child nodes when finding different evidence. When “Fire”, “ToxicGas”, or “TaCrack” happens, “HumanErr” and “EquipmentFail” are the most responsible. When "ToxicGas" happens, the probability of "EquipmentFail" increases the most. Group error also has a relatively high probability responsible for the happening of "ToxicGas" and "TaCrack".

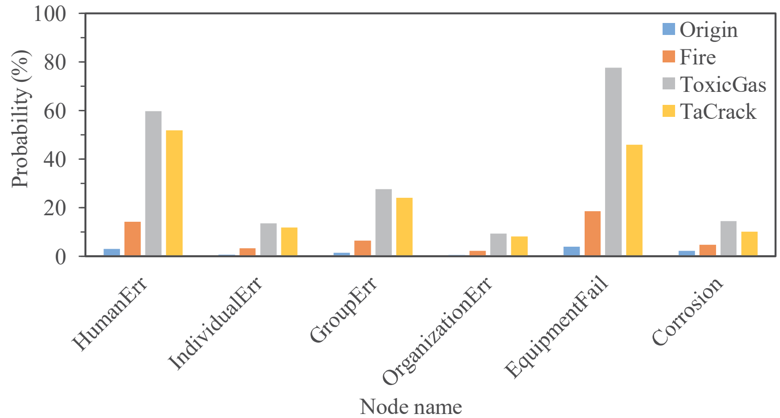

Fig. 11. Compared probabilities of several child nodes when an evidence is found

3.3.2 Mutual information and variance of beliefs (VB)

Mutual information and VB show the relevance between one node and other nodes. By calculating the mutual information and VB, related events can be found. The calculation can also help find the most probable cause for one accident.

We use Netica to calculate Mutual information and VB of "SpoIgnition" with some basic nodes. Table 9 presents the result. Fig. 12 shows compared results for mutual information of the basic nodes. Fig. 13 shows VB of each basic node. These two figures show that air temperature is the most related event, which means that high ambient temperature is the most probable cause of spontaneous ignition. Therefore, during high-temperature days, operators should remain alert of the weather. In addition, the equipment should be cooled using a drencher system promptly to prevent spontaneous ignition.

Table 9. Sensitivity of "SpoIgnition" at other nodes

Basic Node	Mutual Info	Percent	VB
AirT	0.00182	2.35	0.0000335
InsExperience	0.00015	0.199	0.0000023
ShiftChange	0.0001	0.131	0.0000015
Fatigue	0.00001	0.00896	0.0000001

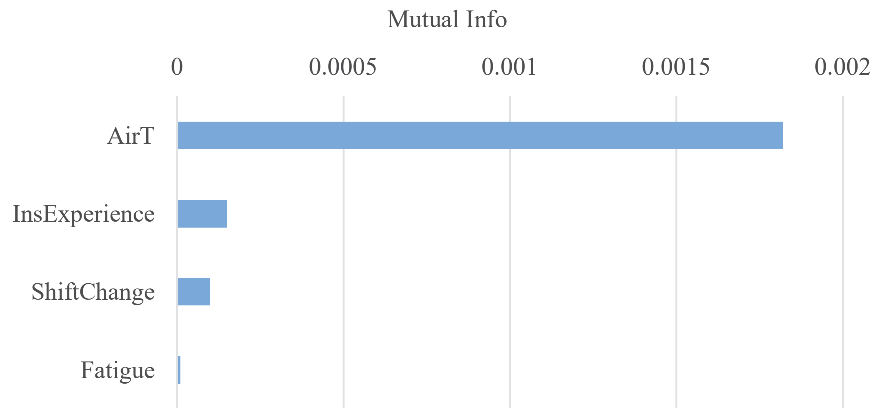

Fig. 12. Mutual information of “SpoIgnition” at other nodes

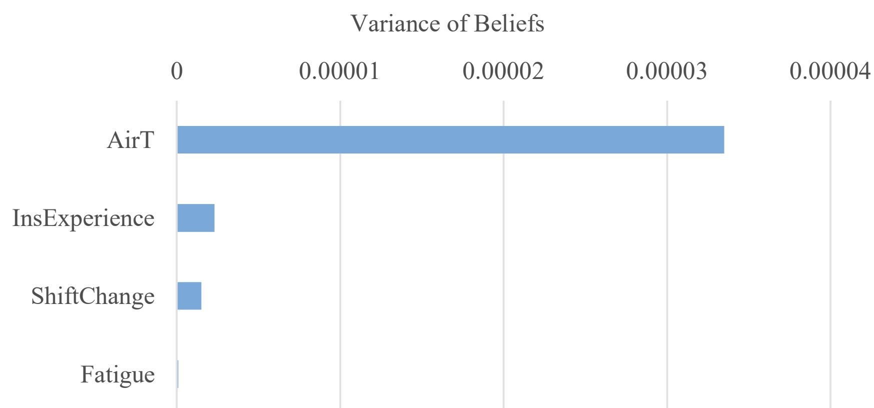

Fig. 13. VB of “SpoIgnition” at other nodes

We use Netica to calculate Mutual information and VB of “Shutdown” with some basic nodes. Table 10 presents the result. Fig. 14 shows compared results for mutual information of the basic nodes. Fig. 15 shows VB of each basic node. The results show that steam pressure is the most related event, which means that high steam pressure easily leads to an abnormally high discharge pressure of the compressor. This event is thus the most probable cause of “Shutdown”. Therefore, ensuring steam pressure stability is a relatively efficient way to prevent “Shutdown”.

Besides steam pressure, other events influence the occurrence of “Shutdown”. Fig. 14 shows that by mutual info, “PuRemainGas” (mutual info = 0.00103) has more influence on “Shutdown” than “InsVOpening” (mutual info = 0.00101). On the contrary, Fig. 15 shows that by VB, the value of “InsVOpening” (VB = 0.0000186) is larger than that of “PuRemainGas” (VB = 0.0000149). The results of the two parameters have only a small difference. Therefore, most of them are comparable, and the two parameters should be considered comprehensively.

Table 10. Sensitivity of "Shutdown" at other nodes

Basic Node	Mutual Info	Percentage	VBs
SteamP	0.00215	3.77	0.0000296
FilterB	0.00126	2.2	0.0000244
PuRemainGas	0.00103	1.8	0.0000149
InsVOpening	0.00101	1.78	0.0000186
AirT	0.00089	1.56	0.0000109
PiLeakage	0.00038	0.661	0.0000056
BlockPi	0.00038	0.661	0.0000056
PuStarting	0.00001	0.013	0.0000001

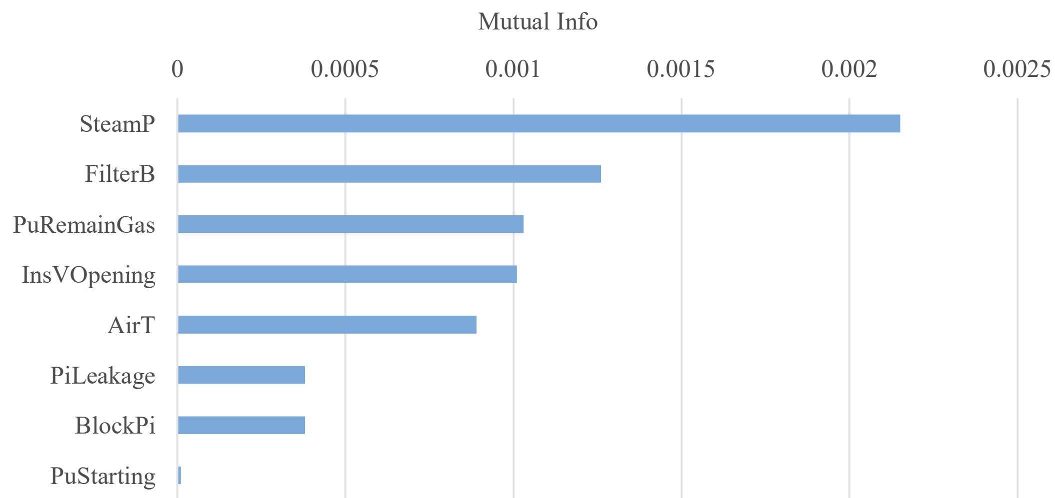

Fig. 14. Mutual information of "Shutdown" at other nodes

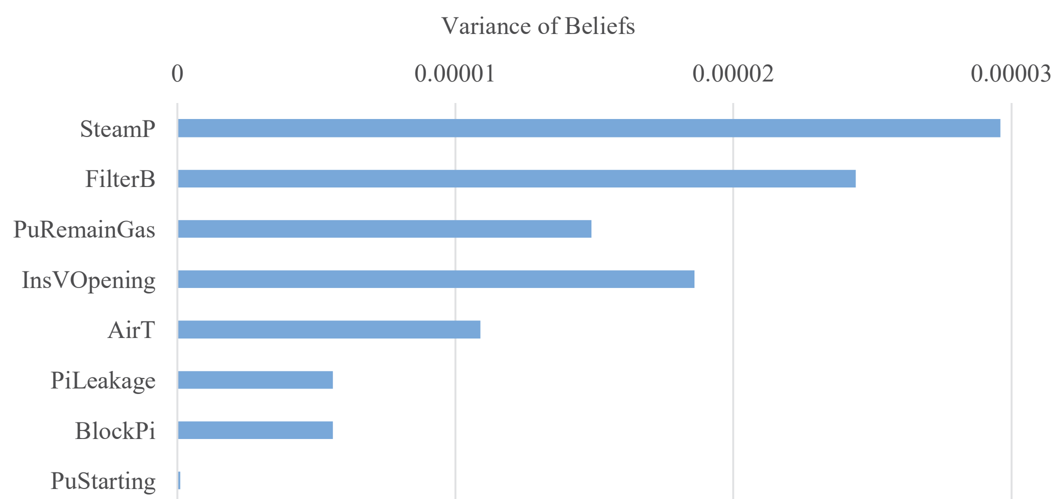

Fig. 15. VB of "Shutdown" at other nodes

3.3.3 Possible accident when an error occurs

Risk is best avoided by increasing reliability. However, mistakes are sometimes inevitable, and when an error occurs, people suffer adverse consequences. Simulation can show the situation in which people know that an error has happened and which accident is most likely to happen. In this case, operators can implement remedial measures to reduce risk. Table 11 gives the probability of several nodes when an error occurs. Underlined numbers represent the prior probabilities of identified causes.

Table 11. Probability when finding an error

Nodes		Probability (%)			
		Nature	HumanErr	OrganizationErr	EquipmentFail
Parent node	InsExperience	10	24.5	10	18.6
	Fatigue	10	12.9	10	11.7
	ShiftChange	10	21.7	10	16.9
	Damage	0.5	0.5	0.5	11.2
	PowerCut	0.5	0.5	0.5	7.6
	Aging	1.5	1.5	1.5	16.1
Child node	HumanErr	3.03	<u>100</u>	95.1	60.2
	IndividualErr	0.69	22.8	0.69	13.7
	GroupErr	1.4	46.2	1.4	27.8
	OrganizationErr	0.5	15.7	<u>100</u>	9.45
	EquipmentFail	4.05	80.3	76.5	<u>100</u>
	Corrosion	2.33	2.33	2.33	23.1
Accident	Fire	0.31	1.46	1.4	1.42
	ToxicGas	0.072	1.42	1.35	1.39
	TaCrack	0.018	0.31	0.3	0.21
	SpoIgnition	0.95	10.9	10.4	6.82
	Shutdown	0.66	0.66	0.66	0.66

Figs. 16 and 17 compare and present the probabilities of these nodes to change with the causes. The different column colors in the bar chart represent various identified causes (“HumanErr,” “OrganizationErr,” and “EquipmentFail”). The node names are on the horizontal coordinate, whereas the probabilities are on the vertical coordinate. In Fig. 16, the sixth column shows the occurrence of a human error (The probability of state “Yes” of “HumanErr” is 100%.). The probability of operators to become fatigued (state “Yes” of “Fatigue”) is 12.9%.

Fig. 16 shows the probability changing of certain basic nodes when an error happens. When “HumanErr” happens, “InsExperience” and “ShiftChange” increase the most, this means that they are the most likely reasons to result in human error. When "EquipmentFail" happens, "Damage" and "Aging" increase the most; "PowerCut" also increases. These observations indicate these three events can be possible reasons for equipment failure.

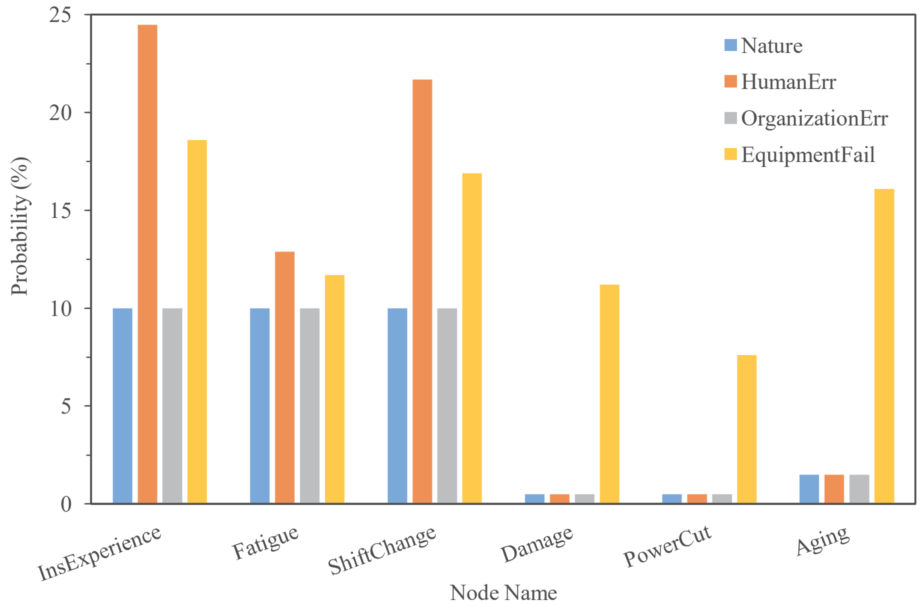

Fig. 16. Compared probabilities of basic nodes when an error is found

Fig. 17 shows the probabilities changing of certain child nodes when an error transpires. When "HumanErr" happens, "EquipmentFail" increases correspondingly. Human error may lead to equipment failure, according to the relationship shown in Fig. 8.

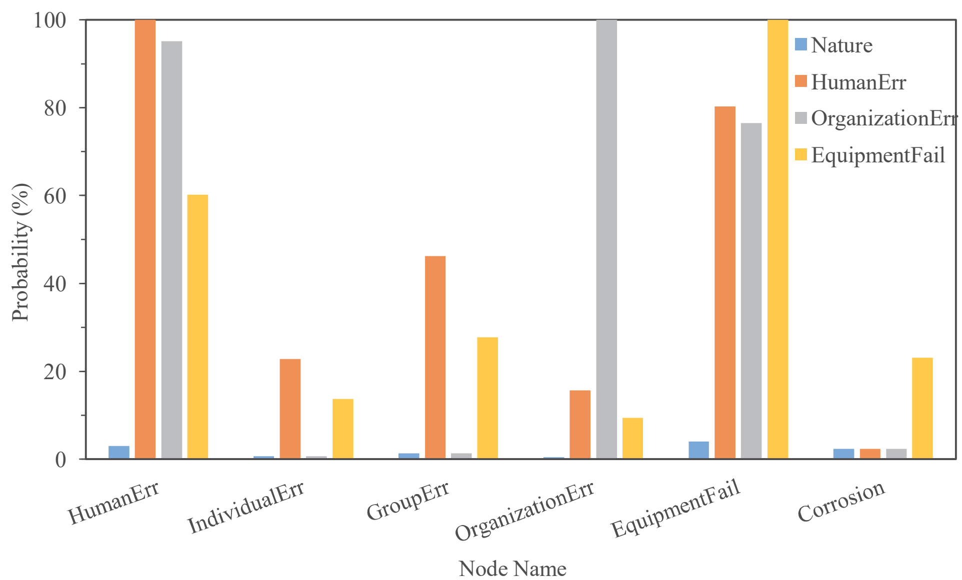

Fig. 17. Compared probabilities of certain child nodes when an error is found

Table 11 shows that when “HumanErr” occurs, the probability of “Fire” increases from 0.31% to 1.46%. “SpoIgnition”, which increases from 0.95% to 10.9%, shows the most noticeable change. Therefore, when a human error happens, the temperature should be given special attention to prevent fire and spontaneous ignition.

4. Conclusions

When a petrochemical accident materializes, it is more likely to have devastating consequences than other industries’ accidents. A risk analysis model for petrochemical systems should, therefore, be developed to help strengthen the relevant processes and improve safety. This work proposes a BN-based risk analysis methodology, whose core features a three-layered hierarchical model. Then, the methodology is applied to a case study for validation. The conducted analyses lead to the following conclusions.

(1) The case study application indicates the feasibility of the proposed methodology.

(2) When evidence is found, the probability of other events changes accordingly. Insufficient experience is the most responsible for fires and toxic gas releases. For non-basic nodes, human error and equipment failure influence accidents the most.

(3) Mutual information and VB analysis show that air temperature is the most related event within our consideration to spontaneous ignition and steam pressure is the most related event within our consideration to shut-down. These parameters sometimes show slightly different results but have similar trends. This research suggests that the two parameters should be considered comprehensively.

(4) When an error occurs, implementing timely and appropriate remedial measures can reduce risk to a certain extent. For example, when a human error happens, the probabilities of fire and spontaneous ignition increase substantially. Therefore, the temperature should be specially monitored to avoid accidents.

Based on the conducted risk analysis, the following recommendations are given;

(1) The reliability of workers should be increased, and the probability of human error should be reduced to prevent accidents because human error is the most influential event in the unit.

(2) On the basis of the five steps in the proposed methodology, plant managers can conduct risk analysis combined with a practical evaluation of the on-site situation, establish structural and

parameter models, divide the model into three layers according to criticality, provide a probability for each event, and then calculate. The results can determine the weakest point and the most influential event, thus reducing risk efficiently.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 51309240), the Specialized Research Fund for the Doctoral Program of Higher Education (No. 20130133120007), and the Fundamental Research Funds for the Central Universities (No. 17CX05022).

Reference

Bhandari, J., Abbassi, R., Garaniya, V., Khan, F., 2015. Risk analysis of deepwater drilling operations using Bayesian network. J. Loss Prevent. Proc. 38, 11-23.

Cai, B., Huang, L., Xie, M. 2017. Bayesian networks in fault diagnosis. IEEE Transactions on Industrial Informatics, 13 (5), 2227-2240

Cai, B., Liu, H., Xie, M. 2016. A real-time fault diagnosis methodology of complex systems using object-oriented Bayesian networks. Mechanical Systems & Signal Processing, 80, 31-44.

Cai, B., Liu, Y., Liu, Z., Tian, X., Li, H., Ren, C., 2012. Reliability analysis of subsea blowout preventer control systems subjected to multiple error shocks. J. Loss Prevent. Proc. 25, 1044-1054.

Cai, B., Liu, Y., Liu, Z., Tian, X., Zhang, Y., Ji, R., 2013a. Application of Bayesian Networks in Quantitative Risk Assessment of Subsea Blowout Preventer Operations. Risk Anal. 33, 7, 1293-1311.

Cai, B., Liu, Y., Ma, Y., Liu, Z., Zhou, Y., Sun, J., 2015. Real-time reliability evaluation methodology based on dynamic Bayesian networks: A case study of a subsea pipe ram BOP system. ISA T. 58, 595-604.

Cai, B., Liu, Y., Zhang, Y., Fan, Q., Liu, Z., Tian, X., 2013b. A dynamic Bayesian networks modeling of human factors on offshore blowouts. J. Loss Prevent. Proc. 26, 639-649.

Cai, B., Xie, M., Liu, Y., Liu, Y., Feng, Q. 2017. Availability-based engineering resilience metric and its corresponding evaluation methodology. Reliability Engineering & System Safety. 172, 216-224.

Darwiche, A., 2009. Modeling and Reasoning with Bayesian Networks. Cambridge University Press, New York.

Feng, J., Fu, J., Chen, P., Luo, J., Liu, Z., Wei, H., 2016. An advanced Driller's Method simulator for deepwater well control. J. Loss Prevent. Proc. 39, 131-140.

Fuentes-Bargues, J. L., González-Gaya, C., González-Cruz, M. C., Cabrelles-Ramírez, V., 2016. Risk assessment of a compound feed process based on HAZOP analysis and linguistic terms. J. Loss Prevent. Proc. 44, 44-52.

Fu, S., Yan, X., Zhang, D., Li, C., Zio, E., 2016. Framework for the quantitative assessment of the risk of leakage from LNG-fueled vessels by an event tree-CFD. J. Loss Prevent. Proc. 43, 42-52.

Hisken H., Enstad G.A., Narasimhamurthy V.D., 2016. Suppression of vortex shedding and its mitigation effect in gas explosions: an experimental study. J. Loss Prevent. Proc. 43, 242-254.

Li, W., Zhang, L., Liang, W., 2016. Job hazard dynamic assessment for non-routine tasks in gas transmission station. J. Loss Prevent. Proc. 44, 459-464.

Liu, X., Li, J., Li, X., 2017. Study of dynamic risk management system for flammable and explosive dangerous chemicals storage area. J. Loss Prevent. Proc. Xxx, 1-6.

Jensen, F.V., Nielsen, T.D., 2007. Bayesian Networks and Decision Graphs, Second ed. Information Science and Statistics. Springer.

Jones, B., Jenkinson, I., Yang, Z., Wang, J., 2010. The Use of Bayesian Network Modelling for Maintenance Planning in a Manufacturing Industry. Reliab. Eng. Syst. Safe. 95, 267-277.

Martins, M.R., Pestana, M.A., Souza, G.F.M., Schleder, A.M., 2016. Quantitative risk analysis of loading and offloading liquefied natural gas (LNG) on a floating storage and regasification unit (FSRU). J. Loss Prevent. Proc. 43, 629-653.

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan Kaufmann Publishers, San Francisco.

Ramírez-Marengo, C., Diaz-Ovalle, C., Vázquez-Román, R. Mannan, M.S., 2015. A stochastic approach for risk analysis in vapor cloud explosion. J. Loss Prevent. Proc. 35, 249-256.

Yeo, C., Bhandari, J., Abbassi, R., Garaniya, V., Chai, S., Shomali, B., 2016. Dynamic risk analysis of offloading process in floating liquefied natural gas (FLNG) platform using Bayesian Network. J. Loss Prevent. Proc. 41, 259-269.

Zhang, J., Cai, B., Liu, Y., Xie, M., 2017. Risk analysis of atmospheric and vacuum distillation unit using Bayesian networks. Conference: 2016 11th International Conference on Reliability, Maintainability and Safety (ICRMS).