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An Integrated Quantitative Bayesian Network in Risk Management for Complex Systems

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Abstract

The development of complex systems such as industrial process plants is accompanied by a continuous improvement of industrial safety. This remains an important element such as production, in a world where accidents continue to cause a high number of fatalities and severe economic and material losses. In addition, these losses cannot avoid significant damages to the environment that have a negative effect on the present and future of society. A better way to deal with these complex systems is to use risk management, which is a necessary priority for our society and our companies today. It is essential to develop or integrate quantitative approaches in risk assessments to evaluate the safety of complex processes. The present work proposes a comprehensive risk assessment approach based on a bow tie diagram mapped to a Bayesian network, with the combination of a risk matrix. In this way, we firstly define the worst-case scenario by hazard analysis and then use a bow tie diagram to understand the flow of cause/effect relation between system components. This allows us to model the accidental scenario and then construct a Bayesian network. Secondly, a transformation operator is used to calculate the occurrence frequency of unwanted failures, which leads to the activation of various layers of protection within the system. Finally, a risk matrix is used to evaluate the residual risk with the help of a probability-severity ranking criterion. This proposed methodology has been applied to a gas treatment plant system based on risk management.

Keywords: risk management; risk assessment; Bayesian network; complex systems; process safety

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1. Introduction

Oil and gas industries are complex and involve the latest technological innovation. This technological development is accompanied by a continuous improvement of safety, which remains one of the main concerns in this field. Nowadays, the necessity of safety measures should be emphasized due to the possibility of catastrophic accidents that result from chemical materials at different process and storages conditions, such as high/low pressure and temperature. Accidents continue to cause significant damage and a high number of casualties [1-4]. For the purpose of managing the safety process, a risk management goal was defined as continuously analyzing and assessing potential dangerous events and proposing more up-to-date ways to control risks, while reducing every possible unwanted effect on the population, materials, or environment [5]. Risk management is integrated into three main axes: risk analysis, risk evaluation, and risk reduction/control. For this purpose, it is essential to develop quantitative or semi-quantitative approaches to evaluate the safety integrity level. Recently, many quantitative and qualitative approaches have been proposed and created for safety assessment. Many methods are presented as a review for chemical process safety [6], including qualitative analysis such as hazard and operability analysis (HAZOP), failure mode and effects analysis (FMEA), and what-if analysis. Moreover, quantitative analysis methods include fault tree analysis (FTA) and event tree analysis (ETA), and semi-quantitative analysis methods include a layer of protection analysis (LOPA). Each method has its advantages and disadvantages. For a better picture of systems safety, it is best to combine the two approaches; in our field, we refer to this as quantitative risk assessment (QRA) [5].

QRA is one of the most used and efficient methods for risk assessment that make it possible to predict accident scenarios in complex systems [7]. Among the efficient tools used in QRA are bow tie (BT) diagrams, which have also shown flexibility

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and effectiveness for enhancing personnel knowledge to better understand the risks and take appropriate action to prevent accidents [8,9]. These diagrams are used treat cause-consequence events between components in a complex system [10]. BT analysis can be implemented to analyze any type of risk, regardless of whether it is an environmental, safety, or commercial risk. Today, it is used worldwide in different industrial sectors to improve safety overall [11-13]. BT is mapped to a Bayesian network (BN) or Bayesian belief networks (BBNs), while taking into account the advantages of probability updating and uncertainty in risk assessment. It is a powerful tool to manage and integrate the objective or subjective probability data in risk assessment and reliability analysis [14,15]. BN has become more popular in reliability, availability, safety, and risk assessment for complex systems [16-22] . A review is presented in [23] that studied a recent brief statistical of BN applicability in the chemical and process industry. BN is applied as a dynamic safety analysis for complex process. For example, Zarei et al. [24] applied dynamic risk assessment of natural gas stations using BN. The same authors assessed the dynamic risk analysis of a storage tank by BN, and they modeled consequence impacts on the environment by PHAST software [25]. Another application is to assess domino effects by dynamic Bayesian networks in chemical infrastructures [26]. BN is a proper tool for handling uncertainty in risk assessments by using fuzzy logic or evidence theory [27-30].

This paper presents a case study in industrial gas plants specifically in a gas separator system. HAZOP is used for risk analysis and defining the causes, the worst-case scenarios, and the preventive or protective barriers implemented in the system. After that, the BT diagram is used to model the cause-effect that leads to unwanted events, while BN is used to consider conditional dependencies and probability updating. Lastly, the results from the BN analysis are compared with the acceptance criteria to assess the residual risks, and some measures will be recommended to improve the safety level in the industrial plant system.

2. Materials and Methods

2.1. The Proposed Methodology

The methodology of the proposed work is shown in Figure 1. It consists of a risk analysis, risk assessment, and risk evaluation. In the risk analysis, a HAZOP technique is applied to identify risks and possible unwanted events. In the risk assessment, a BT diagram is constructed by identifying cause-consequence relationships. After that, a mapping algorithm is used to convert the BT diagram to BN by assessing the occurrence probability or failure frequency of the top event (causes) and assessing all possible consequences. In the risk evaluation, the risk matrix is introduced to define the risk tolerability (unacceptable, tolerable, or acceptable). In the end, a sensitivity analysis with a recommendation is presented to improve the process safety level.

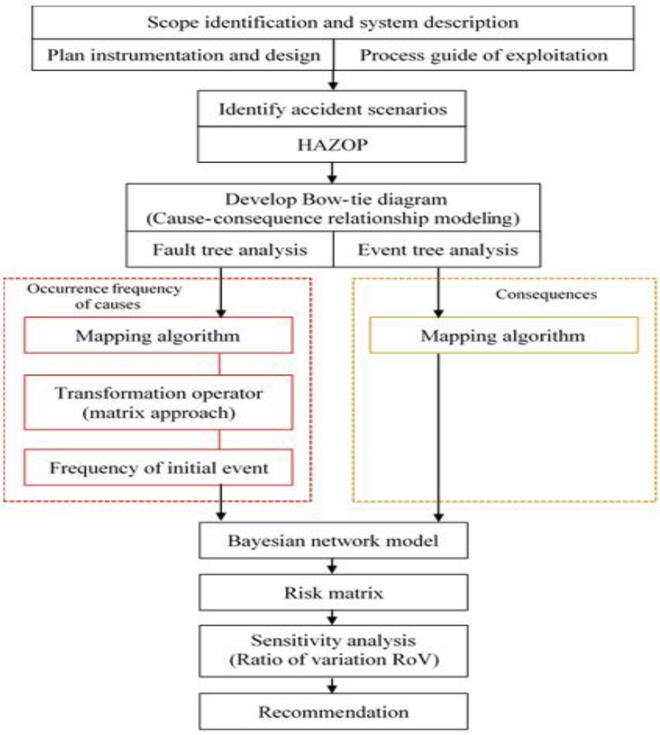

Figure 1. The diagram of the proposed approach

2.2. Bayesian Networks (BN)

A Bayesian belief network or a Bayesian network (BN) is a graphical model; it can be used as an alternative to FTA and ETA to illustrate the relationships between a system failure or an accident and its contributing factors (causes), as well as one or more results (consequences) in an industrial system [5]. BN analysis is more general than an FTA and ETA since the causes and consequences do not have to be binary events and may be qualitative or quantitative, and the combination between both ways depends on what is analyzed.

The network consists of nodes and directed arcs. Each node describes a component, state or condition, and each arc represents a direct influence between nodes.

A BN indicates the joint probability distribution $P(X)$ of variables $U = \{X_1, X_2 \ldots X_n\}$, included in the network as [31]:

$$P(U) = \prod_{i=1}^{n} P(X_i / Pa(X_i)) \tag{1}$$

where $Pa(X_i)$ is the parent set of a variable X_i; according to this, the probability of X_i is calculated as:

$$P(Xi) = \sum_{Xi} P(U) \tag{2}$$

A BN takes advantage of Bayes theorem to update the prior probability of events given new observations, called evidence E, thus rendering the updated or posterior probabilities:

$$P(U / E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_{U} P(U,E)} \tag{3}$$

Here, an algorithm proposed by Khakzad et al. that maps a BT diagram to a BN is used [32]. It is necessary to note that one must calculate the occurrence frequency of the top event in FTA [33,34] (initiating event in a BT and BN) and not its probability of failure, as seen in numerous publications [19,23-25,27,32]. In addition, the use of asymptotic values instead of instantaneous ones, as is often the case, could help get closer results to the reality at the end of the system life cycle. To compute the frequency of initiating events in a BN, an efficient transformation operator based on a matrix approach proposed by [35] and generalized by [36] is used here.

The unavailability of each parent node can be calculated using the exponential distribution:

$$U(t) = \frac{\lambda}{\lambda + \mu} - \frac{\lambda}{\lambda + \mu} e^{(-\lambda + \mu)t} \tag{4}$$

$$U(\infty) = \frac{\lambda}{\lambda + \mu} \tag{5}$$

2.3. Risk Matrix

The risk matrix used in this study is 4×4 dimensions, as shown in Figure 2. The failure frequency and the consequence of gravity can be categorized into four levels, as shown in Tables 1 and 2. The risks are organized into three categories: unacceptable, tolerable ALARP, and acceptable. They indicate a consecutively unacceptable level and the need for a global risk analysis followed by a maintenance inspection with corrections; this must be done as soon as possible. The tolerable level indicates that the system can function normally but with a significant increase in maintenance and control. The acceptable level shows that no special measure needs to be placed.

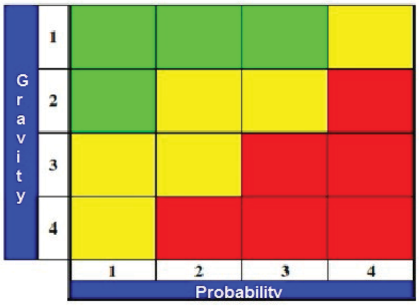

Figure 2. 4×4 risk matrix

Table 1. A ranking criterion of failure frequency

Level	Description	Frequency
P4	Very probable occurred frequently	> 1 / year
P3	Probable occurred frequently (or could occur), could occur during the lifetime of the installation	10^{-2} to 10^{-1} / year
P2	A few probable already (or could be) encountered in a similar organization	10^{-4} to 10^{-2} / year
P1	Unlikely never met or heard but physically possible (or extremely rare)	< 10^{-4} / year

Table 2. A ranking criterion of consequence gravity

Gravity	Personal	Environment	Public	Production/goods
G4	Several deaths	Long-term population out of bounds	Deaths	Important damage & total shut down
G3	Permed inability or one death	Uncontrolled internal population or pollution out of bounds	Significant injuries	Localized damage and partial stop of the unit
G2	Significant injuries	Controlled internal population	Minor injuries	Minor damage and short stoppage of production
G1	Minor injuries	Minor	No impact	No damage no stoppage of production

2.4. Sensitivity Analysis

The most efficient characteristics of the BN are focused on event likelihood updating (posterior) of each event given the occurrence of the initiating event. They show the accident features better than prior probabilities and thus are less uncertain. The ratio of variation (RoV) in Equation (6) can involve a dependable proportion of significance in any system failure and sensitivity analysis [24].

$$RoV(Xi) = \frac{\pi(Xi) - \theta(Xi)}{\theta(Xi)} \tag{6}$$

Where $\pi(Xi)$ and $\theta(Xi)$ denote, respectively, the posterior and prior probabilities of X_i.

3. Case Study

Figure 3 presents a debutanizer section in a gas refinery MPP4 gas plant (Hassi R'mel) in Algeria. The system has been designed to separate between LPG and condensate under high temperature and low pressure. The overhead C102 product is fully condensed in the E108 condenser. The overhead product is collected in the reflux accumulator D108 as a liquid LPG with a temperature of 35°C and pressure of 14.5 Bar. Part of this liquid is conveyed by pumps P105A/B to the upper plate as reflux of the column C102, and the other is transferred to T002 (storage sphere). A pressure indicator controller (PIC) controls the pressure in the D108. This sends an alarm signal to the control room when the pressure exceeds a certain limit. Furthermore, a relief valve opens to the flare in case of an emergency.

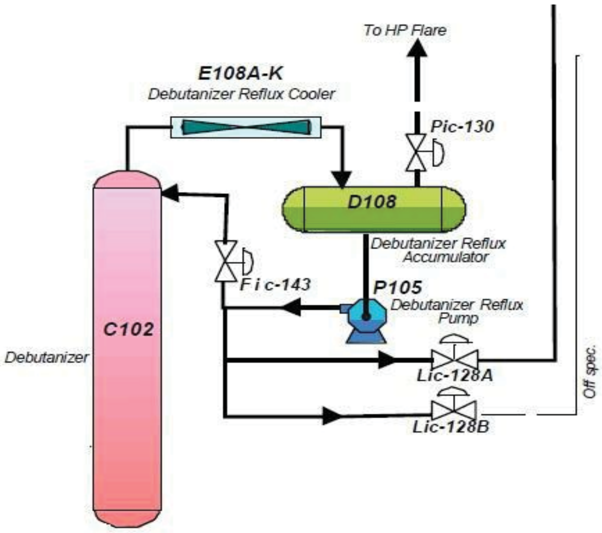

Figure 3. Debutanizer section

A HAZOP study was conducted to identify the most hazardous scenarios. The results revealed many potential scenarios. Table 3 shows catastrophic potentials scenarios that could lead to many different damages to the system environment. Two scenarios are selected to be studied as the highest risk scenario:

- First scenario: Explosion and process shutdown caused by the failure of the flow regulation system FIC (143).
- Second scenario: Pumps cavitation with partial process shutdown caused by the failure of a pressure regulation system PICB (130).

In order to avoid these scenarios, many prevention barriers are installed:

- Alarm and human operator: PAH130, LAL128, and LZAL129.
- Pressure regulation system PIC130A.
- Pressure safety valve PSV110.
- Safety instrumented system (SIS) LZL129: Emergency shutdown of the pumps P105A/B.

Table 3. HAZOP for system study

N°	Guide word	Element	Deviation	Causes	Consequences	Protective barriers
1	High	Pressure	High pressure	- Failure of the flow regulation system FIC (FIC143V valve stuck close).	- The pressure increase in D108. - Rupture the reflux accumulator D108, fire, explosion, flash fire, pool fire, vapor cloud explosion (VCE).	- High-pressure alarm PAH130. -Human operator. - Pressure regulation system PIC130A. -Pressure safety valve PSV110.
2	Low	Level	Low level	- Failure of the pressure regulation system PICB (LIC128VA/B valves stuck open).	-The level of GPL decrease in D108. - Pumps cavitation with the risk of pump breakage. - Pool fire.	- Low-level alarm LAL128 (60%). - Low-level alarm LZAL129 (15%). - SIS (LZL129) ESD of the pumps P105A/B. - Human operator.

3.1. Bayesian Network Model

A BT model was constructed for accident scenarios related to a case study (Figures 4 and 5). This model has provided a robust tool in QRA and has helped in the determination of relationships between initial events and the final event while showing every possible consequence. However, BT is mapped into a BN to overstep the limitations of BT by using an algorithm developed by Khakzad et al [32].

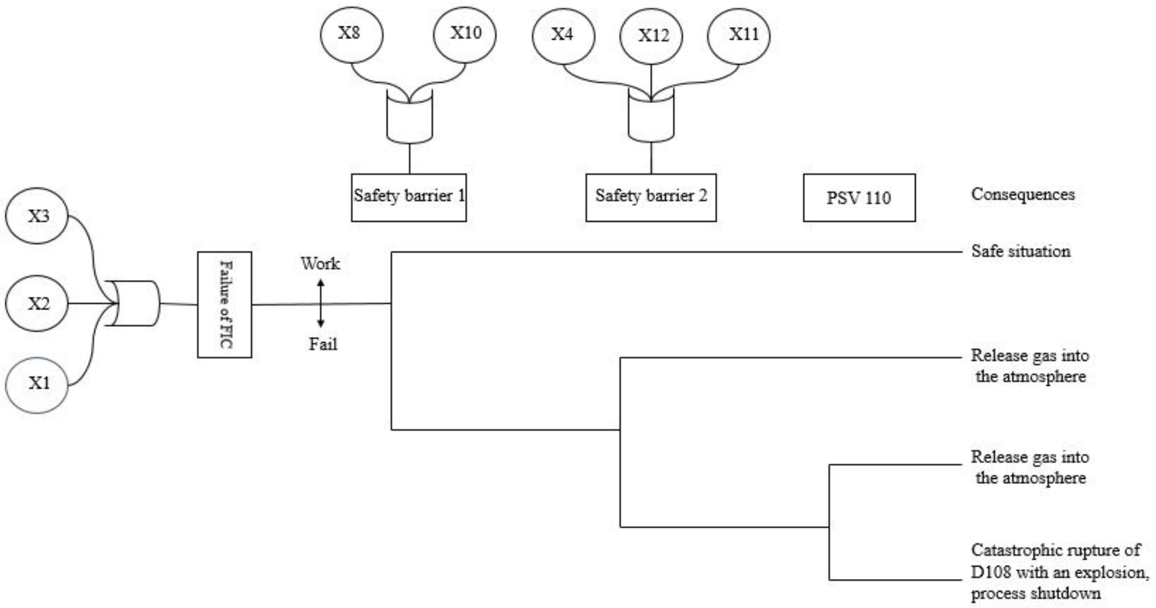

Figure 4. BT model of the first scenario

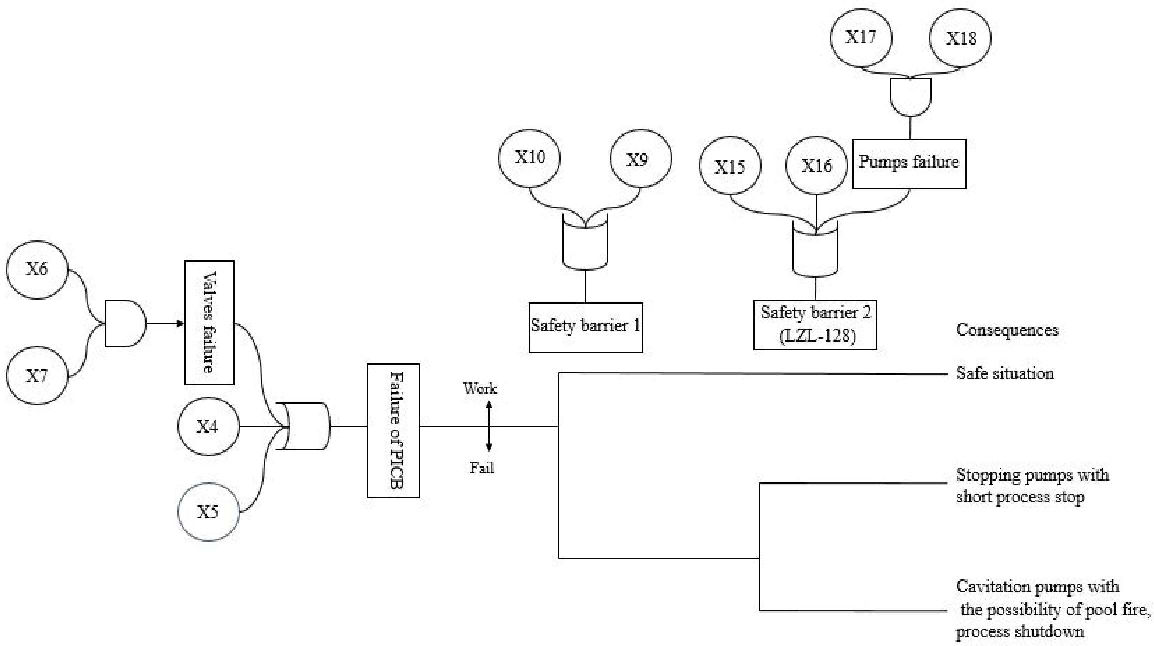

Figure 5. BT model of the second scenario

In the present work, the BN was simulated using GeNIe 2.2 software. First, the initiating events (causes) should be identified with their probabilities and frequencies of failure in the BN model. Then, the various prevention layers, initiating events, and possible consequences should be modeled. Finally, the residual risk for every scenario with the risk matrix posed by the company should be checked. If the residual hazards level surpasses the acceptable zone, extra proportions of safety must be suggested to improve the safety of the process plant.

In this case, Figures 6 and 7 present a BN model for the first scenario (high pressure) and the second scenario (low level) successively. In order to run the quantification part, Table 4 presents equipment symbols with their failure, repair rates or failure probability. All data are obtained from the database of OREDA [37].

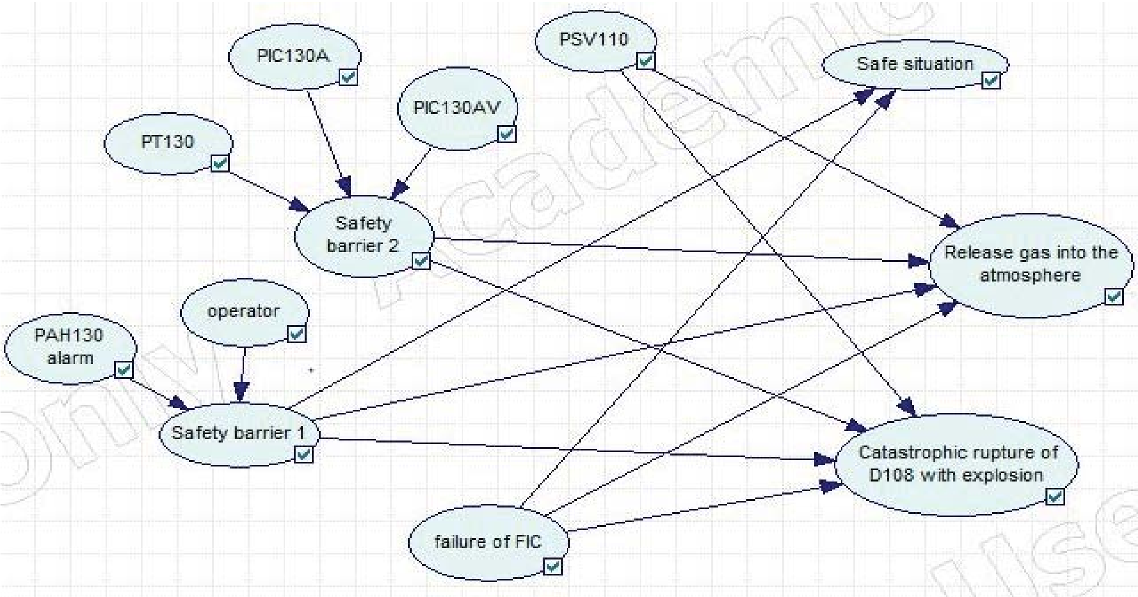

Figure 6. BN model of the first scenario

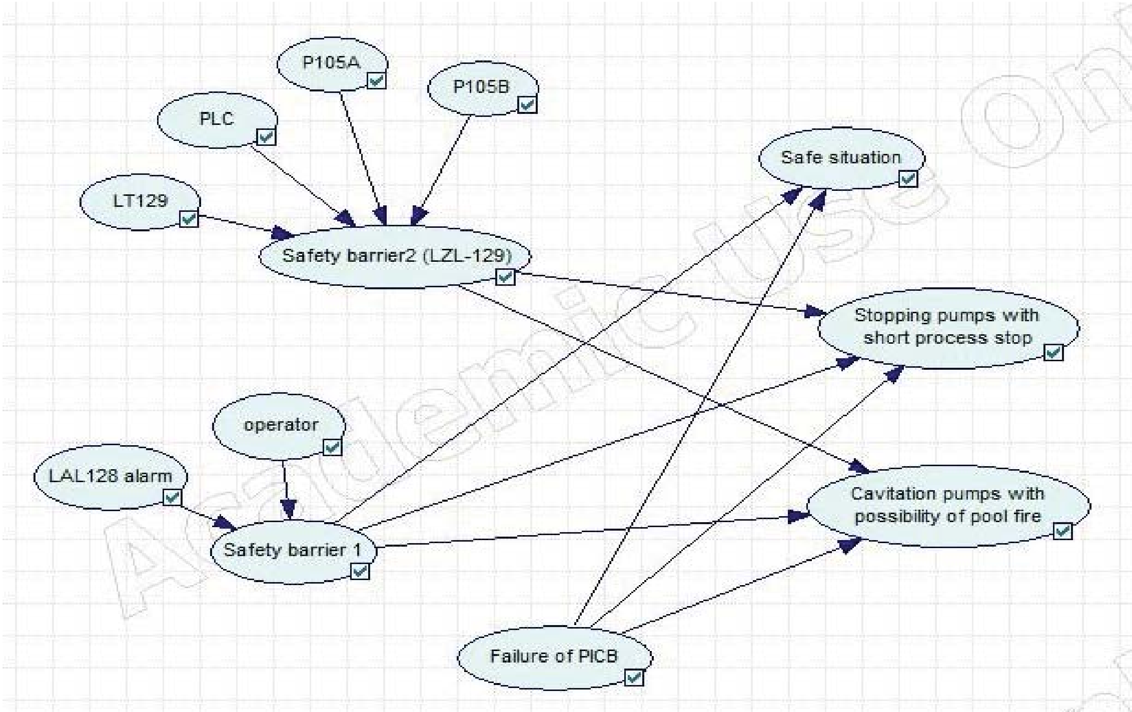

Figure 7. BN model of the second scenario

Table 4. Failure and repair rates

Symbols	Component	Failure rate (/h)	Repair rate (/h)	Failure probability
X1	FT143	1.26E-6	0.125	/
X2	FIC143	8.8E-6	0.2	/
X3	FIC143V	3.2E-5	0.1	/
X4	PT130	1.2E-6	0.125	/
X5	PIC130B	8.8E-6	0.2	/
X6	LIC128AV	3.2E-5	0.1	/
X7	LIC128BV	3.2E-5	0.1	/
X8	Alarm (PAH-130)	/	/	0.0183
X9	Alarm (LAL-128)	/	/	0.0183
X10	Operator	/	/	0.1
X11	PIC130AV	3.2E-5	0.1	/
X12	PIC130A	8.8E-6	0.2	/
X13	LTL128	1.4E-6	0.125	/
X14	LIC128	8.8E-6	0.2	/
X15	LTLL129	1.4E-6	0.125	/
X16	PLC129	4E-8	0.2	/
X17	P105A	3.6E-5	0.1	/
X18	P105B	3.6E-5	0.1	/
X19	PSV110	/	/	0.01

3.2. The Occurrence Frequency of the Initiating Events

Firstly, the occurrence probability of initiating events ''failure of FIC: $P(FIC=0)$'' and ''failure of PICB: $P(PICB=0)$'' should be determined by minimal cut sets in the BN model. After that, the transformation operator (matrix approach) is used to compute the initiating event frequency [36].

We consider:
$P(X=1)$: Component X is working.
$P(X=0)$: Component X is faulty.

3.2.1. The Occurrence Frequency of the First Scenario

The failure probability of FIC is:

$$P(FIC=0)=P(FT143=0)+P(FT143=1).P(FIC143=0)+P(FT143=1).P(FIC143=1).P(FIC143V=0) \tag{7}$$

The transformation matrix for ''failure of FIC'' is:

$$\begin{aligned}
\varphi(P(FIC=0)) &= \begin{bmatrix} P(FIC=0) & 0 \\ -W(FIC) & P(FIC=0) \end{bmatrix} \\
&= \begin{bmatrix} P(FT143=0) & 0 \\ -W(FT143) & P(FT143=0) \end{bmatrix} + \begin{bmatrix} P(FT143=1) & 0 \\ -W(FT143) & P(FT143=1) \end{bmatrix} \\
&\times \begin{bmatrix} P(FIC143=0) & 0 \\ -W(FIC143) & P(FIC143=0) \end{bmatrix} + \begin{bmatrix} P(FT143=1) & 0 \\ -W(FT143) & P(FT143=1) \end{bmatrix} \\
&\times \begin{bmatrix} P(FIC143=1) & 0 \\ -W(FIC143) & P(FIC143=1) \end{bmatrix} \times \begin{bmatrix} P(FIC143V=0) & 0 \\ -W(FIC143V) & P(FIC143V=0) \end{bmatrix}
\end{aligned} \tag{8}$$

$$\begin{aligned}
&W(FIC)=W(FT143).P(FIC143=1).P(FIC143V=1)+W(FIC143).P(FT143=1).P(FIC143V=1) \\
&+W(FIC143V).P(FT143=1).P(FIC143=1)=4.218E-5/h=0.36954/year
\end{aligned} \tag{9}$$

The occurrence frequency of FIC failure is 0.36954/year.

3.2.2. The Occurrence Frequency of the Second Scenario

The failure probability of PICB is:

$$\begin{aligned} &P(PICB=0)=P(PT130=1).P(PIC130B=1).P(LIC128AV=0).P(LIC128AV=0)\\ &+P(PIC130B=0)+P(PIC130B=1).P(PT130=0) \end{aligned} \quad (10)$$

The transformation matrix for ''failure of PICB'' is:

$$\begin{aligned} &\varphi(P(PICB=0))=\begin{bmatrix} P(PT130=1) & 0 \\ W(PT130) & P(PT130=1) \end{bmatrix}\times\begin{bmatrix} P(PIC130B=1) & 0 \\ W(PIC130B) & P(PIC130B=1) \end{bmatrix}\\ &\times\begin{bmatrix} P(LIC128AV=0) & 0 \\ -W(LIC128AV) & P(LIC128AV=0) \end{bmatrix}\times\begin{bmatrix} P(LIC128BV=0) & 0 \\ -W(LIC128BV) & P(LIC128BV=0) \end{bmatrix}\\ &+\begin{bmatrix} P(PIC130B=0) & 0 \\ -W(PIC130B) & P(PIC130B=0) \end{bmatrix}+\begin{bmatrix} P(PIC130B=1) & 0 \\ W(PIC130B) & P(PIC130B=1) \end{bmatrix}\times\begin{bmatrix} P(PT130=0) & 0 \\ -W(PT130) & P(PT130=0) \end{bmatrix} \end{aligned} \quad (11)$$

$$\begin{aligned} &W(PICB)=(1-P(LIC128AV=0).P(LIC128BV=0)).(W(PT130).P(PIC130B=1)\\ &+W(PIC130B).P(PT130=1))=1.006E-5/h=0.0882/\ year \end{aligned} \quad (12)$$

The occurrence frequency of PICB failure is 0.0882/year.

4. Results and Discussion

The results of BN analysis to predict the scenario occurrence frequency and its consequences by deductive reasoning are shown in Table 5. As can be seen, there are six consequences. The most destructive accidents consequences are a catastrophic rupture of D108 with an explosion and pump cavitation with the possibility of a pool fire. The level of severity is chosen by expert judgment using an aggregation (choose the max level G between the four targets: personnel, environment, public, and production/goods) in the severity ranking criterion. After risk evaluation by the risk matrix in Table 6, the previous risks are in the tolerable zone with a low occurrence. The tolerable zone means that the risk is acceptable, but it should be a prevention or protection measure in the case of an emergency and follow efficient scheduled maintenance.

To improve the safety, the company set up a semi-automatic water deluge system involving a D108 balloon to avoid increasing pressure in the case of a nearby fire as well as P105A/B pumps.

The authors applied sensitivity analysis to improve the safety of the process by BN analysis.

Table 5. Consequences frequencies

Number	Consequences	Consequence frequency (/year)
1	Safe situation	0.326
2	Release gas into the atmosphere	4.3E-2
3	Catastrophic rupture of D108 with an explosion, process shutdown	1.6E-7
4	Safe situation	7.8E-2
5	Stopping pumps with short process stop	1.02E-2
6	Cavitation pumps with the possibility of pool fire, process shutdown	1.18E-7

Table 6. Risk evaluation

Consequence	Gravity	Probability	Risk zone
Catastrophic rupture of D108 with an explosion, process shutdown	G4	P1 (improbable)	Tolerable
Cavitation pumps with the possibility of pool fire, process shutdown	G3	P1 (improbable)	Tolerable

4.1. Sensitivity Analysis

The posterior probability of each node Xi is calculated given the failure of the regulatory system (FIC and PICB) in Figures 8 and 9. The results are shown in Table 7. After updating the frequency of the consequences, the previous consequences or risks remained in the tolerable zone.

As can be seen from Figure 10, the results are shown that the probabilities of X_4 and X_5 represent the largest increase in RoV, thus representing the most critical basic events contributing to accidents. In this case, it is necessary to install a parallel configuration (e.g. 1002 configuration) at the PT130 transmitter, especially because it is a common critical element that helps in the occurrence of both scenarios.

Table 7. Events and consequences with probabilities updating

Symbols	Description	Prior (BN)	Posteriors (BN)
Events:			
X1	FT143 failed	1E-5	0.027
X2	FIC143 failed	4.4E-5	0.118
X3	FIC143V failed	3.2E-3	0.856
X4	PT130 failed	9.6E-6	0.179
X5	PIC130B failed	4.4E-5	0.819
X6	LIC128AV failed	3.2E-3	0.002
X7	LIC128BV failed	3.2E-3	0.002
Safety barriers:			
Barrier 1	Alarm-operator failed	0.116	0.116
Barrier 2	Pressure system controller failed	3.74E-4	3.74E-4
Barrier 3 (PSV110)	Pressure safety valve failed	0.01	0.01
Barrier 2 (LZL-128)	Safety instrumented system failed	1.15E-5	1.15E-5
Consequences:			
C1	Safe situation	0.326	0.8835
C2	Release gas into the atmosphere	4.3E-2	0.1165
C3	Catastrophic rupture of D108 with an explosion	1.6E-7	4.35E-07
C4	Safe situation	7.8E-2	0.8835
C5	Stopping pumps with short process stop	1.02E-2	0.1165
C6	Cavitation pumps with the possibility of pool fire	1.18E-7	1.34E-06

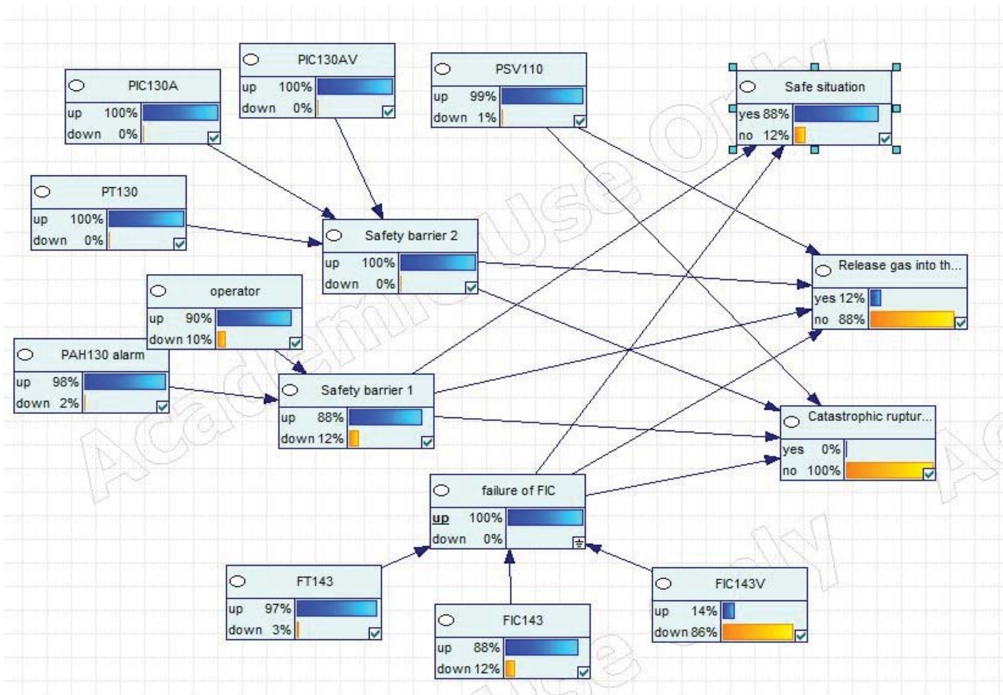

Figure 8. Updating probabilities for the BN model for the first scenario

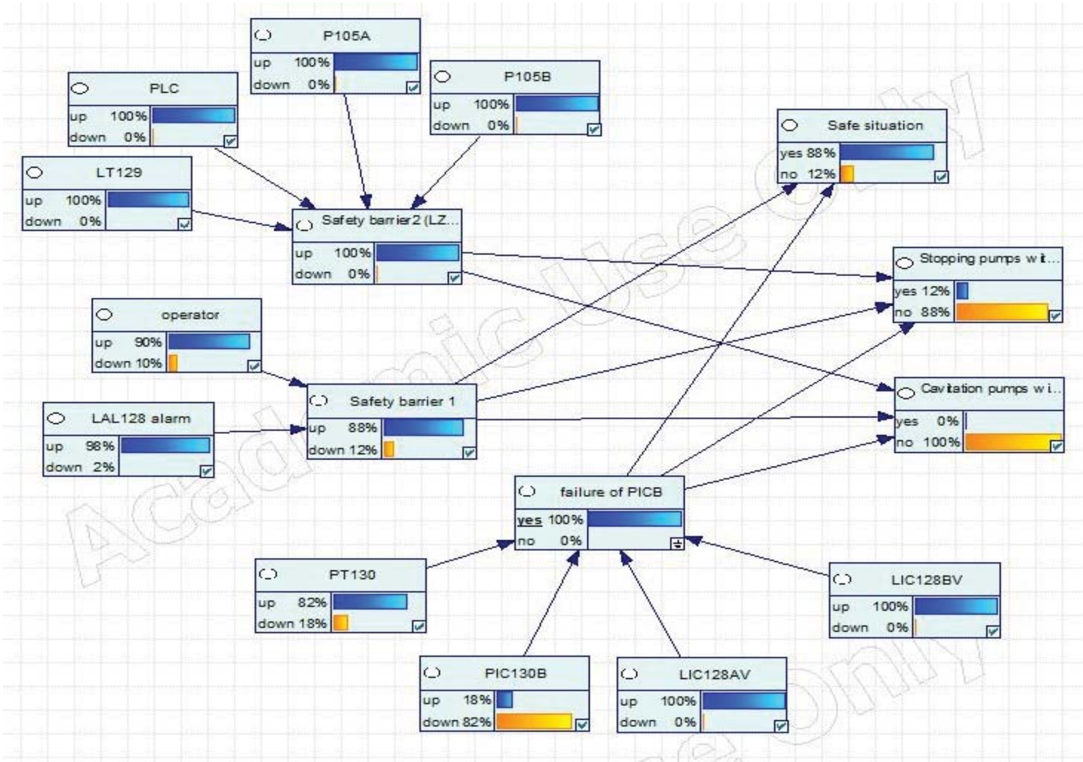

Figure 9. Updating probabilities for the BN model for the second scenario

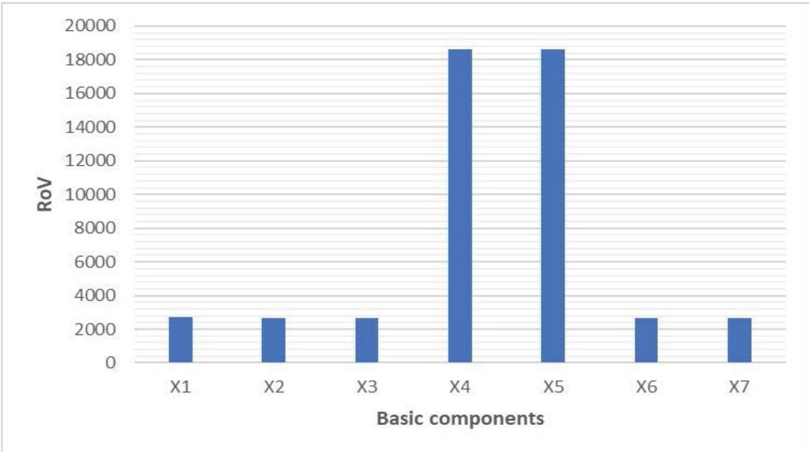

Figure 10. RoV of basic events

5. Conclusion

This paper has presented an application of the Bayesian network to safety risk modeling for the gas refinery subsystem. The proposed framework combines the Bayesian network (risk assessment) and risk matrix (residual risk evaluation). This approach enables the assessment of the residual risk, which is defined as a combination of occurrence frequency and severity. The accident scenario is modeled by the BT diagram in order to identify all possible accident consequences and their causes. The BT was mapped to BN to perform both uncertainty handling and probability updating. The mapped BN is able to consider conditional dependency among events. A transformation operator is used to compute the occurrence frequency of unwanted event failure. This frequency propagates in the BN and assesses the accident consequences as a frequency value and not as a probability value. Sensitivity analysis was used for identifying the most critical basic events leading to the accident. The results demonstrated that pressure transmitter (PT130) and logic solver (PIC130B) were the most important critical basic events because they were common between more than one subsystem. This study considered a complex system as binary states. In the future, we plan to apply the approach proposed with the multi-states system and take into account the epistemic and aleatory uncertainties in the risk model.

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