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Research article

# A new approach to chemicals warehouse risk analysis using computational fluid dynamics simulation and fuzzy Bayesian network

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ABSTRACT

This study aims to assess the risk of chemicals warehouse using a Bayesian networks (BNs) and computational fluid dynamics (CFD). A methodology combining Bow-Tie (BT), fuzzy set theory (FST), and Bayesian network was employed, in which the BT was drawn for chemical spill scenarios. FST was utilized for the estimation of the basic events (BEs) occurrence probability, and the probability of interaction among a set of variables was obtained using BNs. Pool fire scenario radiation heat flux was evaluated using CFD code, fire dynamic simulator (FDS), and the solid flame model (SFM). Fail in forklift brake system (BE1), was the most significant cause for a chemical spill. Based on the CFD model, the heat flux is 31 $kW/m^2$ at a distance of 3.5 m from the fire, decreasing to 6.5 m gradually. The maximum safety distance of 4 m is predicted by the CFD for heat flux that exceeds 12.5 $kW/m^2$; however, SFM predicts approximately 4.5 m. According to the results, the amount of posterior risk is higher than the prior value. The framework presented in the chemicals warehouse for consequence analysis and dynamic risk assessment (DRA) of pool fire could be used for preventing the accidents and domino effects in the chemicals warehouse.

## 1. Introduction

Warehouses are one of the high risk fire areas in any industry due to the high volume of stored materials (Benintendi and Round, 2014). In the last half century, there have been many fatalities caused by fires and explosions in warehouses. Therefore, it is necessary for potential risk analysis (PRA) of chemicals warehouse in order to reduce their probability of occurrence. New approaches to risk assessment are required to inspect warehouses in order to provide appropriate preventive measures.

### 1.1. Uncertainty in risk assessment

In this study, uncertainty refers to a situation in which the occurrence probability of events cannot be measured, since there is not sufficient data in the chemicals warehouse. Various factors, such as poor attitude and belief in safety, incorrect implementation of safety procedures, various types of risk analysis methods, dynamic changes in process, environmental, human, and organizational parameters have caused many changes in the occurrence rate of events among industries (Ren et al., 2009). Therefore, the occurrence rate of events cannot be accurately predicted using classical methods.

There are various techniques for calculating the failure probability of event, such as statistical methods, using reliability data handbook (OREDA expert's judgment), and data obtained from past events. The individual case and taking into account different circumstances affect selecting an appropriate technique. However, several studies have suggested that the above methods can be used in combination with expert's judgment and fuzzy theory (Yazdi, 2017). Given that there is no data on basic events (BEs) in the chemicals warehouse in this study, it is therefore necessary to use fuzzy logic and experts' opinions to analyze and estimate risk in order to realistically examine the impact of factors affecting the occurrence of events (Yazdi et al., 2019a,b,c). Craftsmen have limited knowledge about the latest research methods; on the other hand, researchers in various industries are unfamiliar with all aspects of systems.

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Thus, industry-university interaction can facilitate the flow of knowledge, and can be useful for large companies (Lööf and Broström, 2008). The methods used in cause-consequence modeling have shortcomings and limitations that can affect the risk assessment results. Several techniques have been introduced for cause-and-consequence analysis and modeling. Some of these methods include barrier block diagram (Sklet, 2004), classification system and human factors analysis (Shappell and Wiegmann, 2000), management oversight and risk tree (Johnson, 1973), bow tie diagram (de Ruijter and Guldenmund, 2016), and Tripod Beta (Doran and Van Der Graaf, 1996). Among the methods of cause-and-consequence analysis and modeling, the BT model has been well proven as an efficient method, since, in a graphical model, it can combine the event causes and consequences (Khakzad et al., 2012). However, this method has two major problems in risk assessment, including static structure and uncertainty (Khakzad et al., 2013b). In this study, Bayesian network (BN) method and FST were used to reduce the uncertainty and eliminate the static structure of traditional methods.

### 1.2. Fuzzy Bayesian network (FBN)

FST was proposed by Lotfizade in 1965 (Zadeh, 1996). They believed that conventional probabilistic theories are not appropriate to determine the types of uncertainties that may exist in the real world (Yazdi et al., 2019). Accordingly, FST is an appropriate tool for conditions of uncertainty, where numerical probabilities are derived from possible qualitative expressions (Yazdi and Kabir, 2020). In this study, given that there were no resources in the chemicals warehouse for the BE failure rate or they did not have high reliability if they existed; considering these limitations and capabilities of FST, it was used to determine the BEs failure rate. BNs are inherently superior to other methods and have been widely praised by process safety experts due to their unique features in risk/accident analysis studies, especially in reducing uncertainty and updating the occurrence probability of events and final consequences of the events scenario, as well as being inherently dynamic in nature (Shi et al., 2020). BNs also have advantages over other models, including the ability to learn parameters or conditional probabilities, deductive and inductive reasoning, sensitivity analysis and consideration of events with common cause failures (Pollino and Henderson, 2010).

### 1.3. Numerical simulation of fire

One of the parts of risk assessment and modeling of accidents is numerical assessment of pool fire by computational fluid dynamics (CFD) (Rum et al., 2018). There are several methods for estimating fire risk, reducing fire risk, and designing fire protection systems (Fire, 2003). The International Association of Oil and Gas Producers (IOGP) has reported that fire risk can be estimated by two methods, including modeling methods with CFD and analytical relationships (Witlox, 2010). The numerical solution of Navier-Stokes discrete differential equations is used in field models or CFD models. The methods have some drawbacks, including flexibility in adapting to different applications and the need for high computational time, programming problems. The results of these models are more accurate than experimental methods by developing computer programs and codes for fire risk assessment (Sun et al., 2014). The FDS is one of these codes, providing information required for evaluating potential states as well as time resolution (Suardin et al., 2009).

### 1.4. Literature review and object

Table 1 reveals the models used in the field of risk assessment, which their advantages and disadvantages are presented based on the methods used.

Although many studies have been conducted on the safety of reservoirs in the chemical process industry, warehouses have not received much attention despite the numerous risks. FBN has been used in many studies; however, limited information has been reported on its use in risk assessment of the chemicals warehouse. The innovation of this study is more related to the place of study (chemicals warehouse) using a common integrated methodology rather than the development of a new methodology.

The present study approach is to numerically simulate the pool fire caused by isooctane in the chemicals warehouse and to determine the parameters affecting the severity of events using FDS. Therefore, this study was conducted with the following objectives:

1 Providing a method for DRA of the stored chemicals using fuzzy Bayesian network (FBN) and numerical fire simulation.
2 Cause and consequence modeling of accidents using BT diagrams and BNs.
3 Reducing uncertainty as much as possible in chemicals warehouse risk assessment using FST.
4 Finally, estimating risk according to the results of BNs, BT diagram, and numerical simulation in both posterior and prior modes.

## 2. Materials and methods

In the present study, integration of CFD and BN were used for risk assessment in chemicals warehouse. A realistic scenario of isooctane spill

**Table 1.** Methods used in risk assessment in recent years.

| Goal of study | Methods | Advantages | Disadvantages |
|---|---|---|---|
| Probabilistic risk assessment | Fuzzy fault tree (FFT) (Yazdi et al., 2019) | Using the Fuzzy Analytic Hierarchy Process (FAHP) to overcome uncertainty | This method only deals with the aspect of probability of occurrence in the field of risk |
| | FST and Bow tie (Zareia et al., 2019) | Using intuitionistic fuzzy numbers in the BT method to increase the accuracy of cause-effect modeling | |
| Quantitative risk assessment (QRA) | Fuzzy Bayesian network (FBN) (Yazdi and Kabir, 2020) | Using evidence theory, FST, and BNs to reduce uncertainty and update previous probabilities | This method only deals with the aspect of probability of occurrence in the field of risk |
| | Fuzzy DEMATEL and BN (Ahmadi et al., 2020) | In addition to technical discussions, this method uses technical factors in updating the probability of events | Leading performance indicators should be used for updating, which are not usually available in organizations |
| | Bow-Tie and consequence modeling (Bouafia et al., 2020) | Collective risk assessment using the combined method of BT and modeling with PHAST software | Modeling with PHAST software does not consider the effect of barriers |
| Dynamic risk assessment (DRA) | FST and dynamic Bayesian network (FDBN) (Guo et al., 2021) | Using DBN and fuzzy theory to reduce uncertainty over time | The severity parameter for determining the risk is not well defined |
| | CFD and Bayesian network (Jiang et al., 2021) | Reducing uncertainty and updating probability using BN method and CFD to investigate the relationship between gas release and risk assessment per unit time | Failure to consider population distribution to estimate risk |

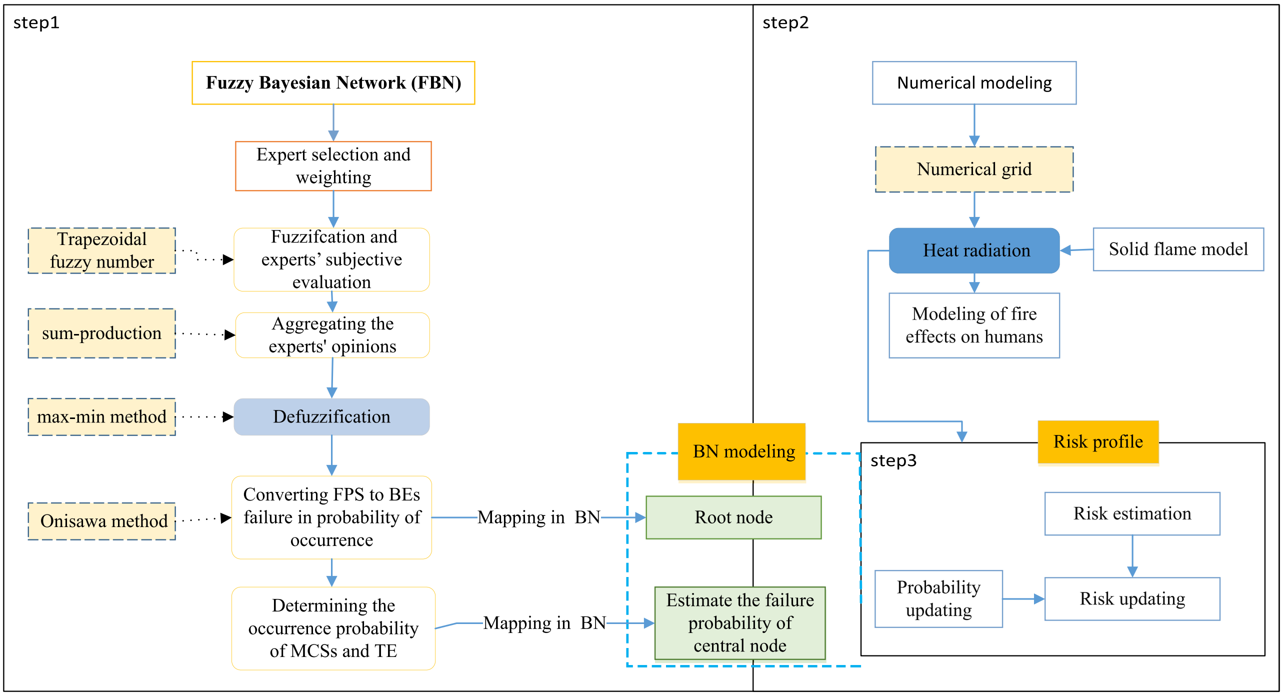


**Figure 1.** Steps of the research process for DRA.

due to forklift strike with the drum in a chemicals warehouse was considered in this study. The schematic diagram of the study methodology and details of each step are explained in Figure 1.

### 2.1. Step 1: fuzzy Bayesian network (FBN)

In this study, the chemical spill was identified as a high-frequency event in warehouses according to reported accidents, near-miss, and anomalies; therefore, the chemical spill was considered as a top event (TE). Also, the BT technique was utilized to find the BEs that affect the TE and to examine the control barriers and identify the consequences of the TE. In fact, this technique simultaneously illustrates how people, safety systems, and equipment work in the process of a given scenario, as well as the relationship between failure and its consequences (Omidvar et al., 2022). Then, FST was used to estimate BEs failure probability. This method was based on a 6-step design procedure as follows:

#### 2.1.1. Expert selection and weighting

When there is insufficient information, experts' opinion is used to determine the probability. In reality, experts might have various levels of expertise, working experience, and background. Therefore, they might subjectively assess different conditions due to various viewpoints. Hence, to represent different experts' relative quality a weighting factor is required (Rajakarunakaran et al., 2015). The current study used a heterogeneous group (including safety engineers and warehouse officials) to assess the probability (Lavasani et al., 2015a,b).

However, the failure probability of a particular BE can vary depending on different operational and environmental conditions. To overcome this challenge, aheterogeneous group of several experts can be a good alternative (Yazdi et al., 2019). Accordingly, to determine the BEs probability, an independent group of three experts with various expertise were used. Cooke et al., reported there are some factors for experts selection including experience of carrying out the same studies, the published papers number, and the qualification confirmation of experts by others (Cooke et al., 2008). Different experts might have a different level of work experience and expertise. The experts can examine BEs according to their knowledge and experience of the system. Goals and individual perspectives can affect expert's knowledge (Ford and Sterman, 1998). Therefore, they might possess different perceptions and subjectively assess events and a weight factor (WF) can be helpful to indicate the relative quality of experts, which, in this study, was calculated according to previous research studies (Lavasani et al., 2015; Renjith et al., 2010; Yazdi et al., 2017).

Three experts were appointed according to the recommendation of Ishikawa et al. (1993). The WF for each of the experts includes the total score of each expert divided by the sum of the scores of all the experts (Rajakarunakaran et al., 2015). The method of Ramzali et al. was used to weight the experts (Ramzali et al., 2015).

#### 2.1.2. Fuzzifcation and experts' subjective evaluation

To determine and quantify the weight of experts' viewpoints on the occurrence of BEs, seven linguistic terms were used (Saaty and Ozdemir, 2003). There are various fuzzy membership functions, for fuzzy flying linguistic terms, including triangular, trapezoidal, Gaussian and bell-shaped functions and proper membership functions are selected based on real situations (Markowski and Mannan, 2008). Recent studies have used trapezoidal and triangular fuzzy numbers (Yazdi et al., 2019); therefore, the present study used trapezoidal fuzzy numbers. Also, the variables including very low, low, fairly low, medium, fairly high, high, and very high were used to express the experts' opinions (Yazdi and Nedjati, 2022).

#### 2.1.3. Aggregating the experts' opinions

According to Liu et al. (2014), there is no guideline for prioritizing methods for consensus of experts' opinions. The present study used sum-production algorithm and Eq. (1) were used to obtain the group consensus of experts' opinions.

$$Z_i = \sum_{j=1}^{n} w_j f_{ij}, i = 1, 2, \ldots, m , j = 1, 2, \ldots, n \tag{1}$$

#### 2.1.4. Defuzzifcation

The obtained number from experts' opinions was still a possibility which should have been defuzzified. The defuzzification methods

**Table 2.** Isooctane pool fire simulation input parameters.

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Fuel | Isooctane C8H18 | Ambient temperature (K) | 294 |
| Pool diameter (m) | 5 | Burning rate (kg/m$^2$ s) | 0.073 |
| Combustion heat (kJ/kg) | 44500 (Hurley et al., 2015) | Special heat capacity of fuel (kJ/kg K) | 2.02 (Linstrom and Mallard, 2001) |
| HRR (kW/m$^2$) | 3248 | Domain size fire filed (m) | 16 × 34 × 6 |
| Density (kg/m$^3$) | 738 (Hurley et al., 2015) | Domain size far filed (m) | 24 × 55 × 6 |
| Radiative fraction | 0.35(McGrattan et al., 2000) | Total simulation time (s) | 300 |
| Co yield (kg/kg) | 0.022 (Hurley et al., 2015) | Grid resolution (*R*) | 4, 6/2, 8/2 |

**Table 3.** C1 and C2 coefficients (Book, 1992).

| Effect | $C_1$ | $C_2$ |
|---|---|---|
| First degree burn | −39.83 | 3.0186 |
| Second degree burn | −43.14 | −3.0186 |
| Death | −36.38 | 3.56 |

include mean max, max-min, bisector, center of area (CoA), and the center of the largest area weighted average (Yazdi and Kabir, 2017). Among these methods, COA and max-min are more known (Yazdi and Zarei, 2018). Therefore, this study used the developed max-min method provided by Chen and Hwang (1992) and Eq. (2) was used to calculate the fuzzy score (Yazdi, 2017).

$$\mathrm{FPS}(Z_i) = \left[\mathrm{FPS}_{\mathrm{Right}}\ (Z_i) + 1 - \mathrm{FPS}_{\mathrm{Left}}\ (Z_i)\right] / 2 \tag{2}$$

### 2.1.5. Converting FPS to BEs failure in probability of occurrence

The number obtained from the previous step needed to be transformed from a possibility to a probability distribution and to calculate the probability of failure the Onisawa equation Eq. (3) was utilized (Renjith et al., 2010). By addressing some characteristics this function is achieved, including human emotion proportion to the logarithmic value of a physical value (Omidvari et al., 2014).

$$FP = \begin{cases} \dfrac{1}{10^K} & \mathrm{FPS} \neq 0 \\ 0 & \mathrm{FPS} = 0 \end{cases} \quad \mathrm{K} = \left[\frac{1 - FPS}{FPS}\right]^{\frac{1}{3}} \times 2.301 \tag{3}$$

### 2.1.6. Determining the probability of occurrence of MCSs and TE

At this stage, according to Rajakarunakaran et al. (2015), the final event and the occurrence probability of each MCSs could be calculated using Eqs. (4) and (5).

$$P(MCS_j) = \prod_{i=1}^{n} FP(BE_i) \tag{4}$$

$$\mathrm{P(TE)} = 1 - \prod_{j=1}^{k}\left(1 - \mathrm{P}(\mathrm{MCS_j})\right) \tag{5}$$

### 2.1.7. BN method

This method is a graphical model for representing the probabilities of the variables. The BN is used for dynamic modeling of various event scenarios due to its flexible adaptive characteristic. Given that this model has a potential to update prior probabilities and consider failure causes, it can offer more reliable results for risk analysis in comparison with BT method (Zerrouki and Smadi, 2017). The diagram of BT was transferred based on the algorithm presented by Khakzad et al. to deal with the BT

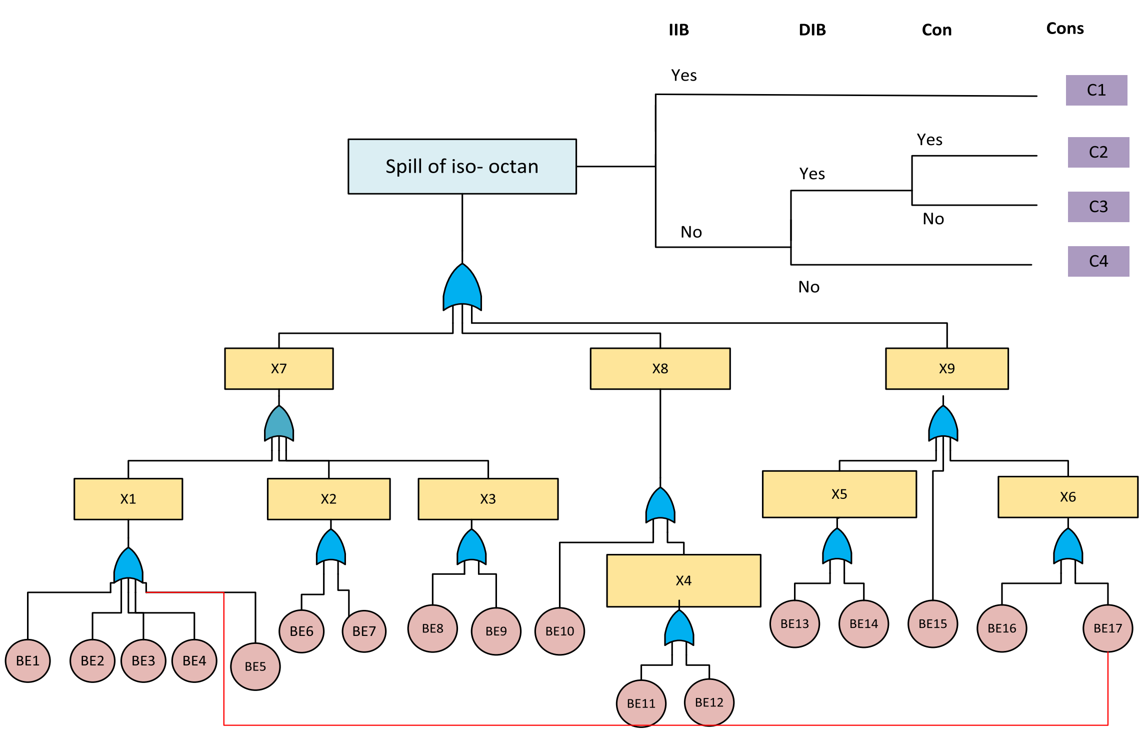


**Figure 2.** Modeling of the isooctane spill scenario in the chemicals warehouse using BT technique.

Table 4. Description of safety barriers, BEs and IEs, and consequences.

| Symbol | Description |
|---|---|
| BE1 | Fail in forklift brake system |
| BE2 | Fail in forklift control system |
| BE3 | Fail in forklift tiers |
| BE4 | Inadequate drivers education |
| BE5 | Lack of the pallet using |
| BE6 | Lack of the monitoring by warehouse keeper |
| BE7 | Lack of the monitoring by HSE staff |
| BE8 | Pallet jack strike caused by human error |
| BE9 | House keeping |
| BE10 | Forklift and drum strike |
| BE11 | Inappropriate the drum arrangement |
| BE12 | Fail in thermometer |
| BE13 | Lack of thermometer |
| BE14 | Fail in fan coil system |
| BE15 | Inappropriate ventilation system |
| BE16 | Lake of ventilation system |
| BE17 | Human error |
| X1 | Forklift strike |
| X2 | Pallet jack strike |
| X3 | Collision caused by adjacent drums |
| X4 | Inadequate monitoring system |
| X5 | Lack of temperature sensing |
| X6 | Fail in ventilation system |
| X7 | Strick |
| X8 | Worn out drum |
| X9 | Fail in control system |
| IIB | Immediate ignition barrier |
| DIB | Delay ignition barrier |
| Con | Confinement |
| Cons | Consequence |
| C1 | Pool fire |
| C2 | Vapor cloud explosion |
| C3 | Flash fire |
| C4 | Safe or toxic release |

limitations (Khakzad et al., 2013a). Using this algorithm, a qualitative model of cause-and-consequence is constructed in BNs (Khakzad et al., 2013a). For each intermediate or central node, the conditional probability table (CPT) was defined based on the gate types.

### 2.2. Step 2: Numerical modeling

Numerical simulations in this study were performed using CFD code FDS 6.5.1. The results of solid flame analytical model were compared with the CFD results. In this study, a fire simulation was considered based on a constant source of fire with a constant value of Mass Loss Rate per Unit Area (MLRPU) in a warehouse of chemicals. All surfaces (up, down, walls) were considered adiabatic. The barrels containing these materials were metal and the capacity of each barrel was 0.22 $m^3$ (height 0.85 m and diameter 0.37 m). The isooctane barrels were arranged in quadruple pallets, which a total of 8 pallets stacked in two rows were investigated. Table 2 shows the input parameters of the isooctane pool fire simulation.

In the case of a pool fire, the surface temperature of the fire is very close to the boiling temperature of the liquid fuel. The liquid heats up to its boiling temperature, then evaporates and burns in the vapor state. Thus the burning rate is equal to the mass of liquid burnt at the surface (Assael and Kakosimos, 2010). In this study, the equation provided by Mudan was used to calculate the burning rate (Mudan, 1984).

#### 2.2.1. Numerical grid

For proper simulation of fire, using the large eddy simulation, turbulent flow of which was simulated, and to model the predominant phenomena an estimation of the computational network cells dimensions was used. McGrattan et al. (2013a) defined the characteristic scale length and reported that to obtain sufficient accuracy for simulation this length has to be covered by at least 10 computational network cells. Using the released heat rate, the scale length is defined (McGrattan et al., 2013b). For sensitivity analysis, a longitudinal fire scale based on the amount of HRR must be determined. This value was determined using Eq. (6) (McGrattan et al., 2013b).

$$D^* = \left(\frac{\dot{Q}}{\rho_\infty c_p T_\infty \sqrt{g}}\right)^{2/3} \tag{6}$$

Using the dimensionless ratio of $\frac{D^*}{\delta_x}$, the mesh size and optimal domain was determined to obtain the characteristic diameter. The optimum range of $\frac{D^*}{\delta_x}$ was 4–16 (Sellami et al., 2018). In this study, three dimensionless ratios were considered for values (4, 6, 8) and 3 various mesh sizes (0.125, 0.833, 0.625) were studied and they were compared with analytical models.

#### 2.2.2. Solid flame model (SFM)

One of the most popular analytical models for estimating fire heat flux is SFM. Compared to the point source model, the results of SFM are more reliable even at distances close to the flame (Casal, 2017). In this study, given that the amount of received heat flux at the target point, the human factor, was considered, it was necessary to calculate the received heat flux value (Assael and Kakosimos, 2010).

#### 2.2.3. Modeling of fire effects on humans

The dose-response curve is commonly utilized to investigate the fire effects on humans. The dose-response equation is built up experimentally or from field data for parameters, such as heat radiation, pressure rise, heat, noise, toxic gas concentration, etc., and there are many methods for reproducing the dose-response curve. However, the method most widely used today is the probability function method. Eqs. (7) and (8) were used to calculate probability, injury (1st or 2nd degree burn) or death (Assael and Kakosimos, 2010).

$$P = F_k \frac{1}{2}\left[1 + erf\left(\frac{\mathrm{Pr} - 5}{\sqrt{2}}\right)\right], \mathrm{Pr} = C_1 + C_2 \ln D \tag{7}$$

$$D = t_{eff}(q')^{4/3}, t_{eff} = t_r + \frac{(x_0 - r)}{u} \tag{8}$$

In this study, reaction time was considered 5 s (Assael and Kakosimos, 2010). $u$ is 4 m/sand and $F_k$ is 0.95 for summer clothing. $C_1$ and $C_2$ coefficients are constant values represented in Table 3 (Assael and Kakosimos, 2010).

Table 5. Demographic information of the experts and allocated weighted scores for each expert.

| Experts | Title | Experience (year) | Education level | Age (year) | Weighted index | Weighted score of each experts |
|---|---|---|---|---|---|---|
| 1 | Engineer | ≤5 | Master | 30–39 | 10 | 0.27777 |
| 2 | Technician | 20–29 | Bachelor | ≥50 | 13 | 0.36111 |
| 3 | Junior academic | 6–9 | PhD | 30–39 | 13 | 0.36111 |

**Table 6.** Subjective assessment process, consensus of opinion, and BEs occurrence probability.

| Event | E1, E2, E3 | Fuzzy corresponding number | | | | Defuzzification of subjective BEs | K | Corresponding FPs |
|---|---|---|---|---|---|---|---|---|
| BE1 | M, M, FL | 0.327 | 0.427 | 0.463 | 0.563 | 0.325 | 2.936 | 0.00115878 |
| BE2 | FL, M, FH | 0.327 | 0.427 | 0.463 | 0.563 | 0.325 | 2.936 | 0.00115878 |
| BE3 | M, FH, H | 0.463 | 0.563 | 0.627 | 0.727 | 0.326 | 2.931 | 0.0011722 |
| BE4 | L, FH, M | 0.544 | 0.644 | 0.68 | 0.78 | 0.347 | 2.841 | 0.00144212 |
| BE5 | L, M, H | 0.353 | 0.453 | 0.489 | 0.589 | 0.327 | 2.927 | 0.00118304 |
| BE6 | L, M, VL | 0.425 | 0.525 | 0.525 | 0.625 | 0.351 | 2.824 | 0.00149968 |
| BE7 | L, L, M | 0.172 | 0.236 | 0.272 | 0.372 | 0.343 | 2.858 | 0.00138676 |
| BE8 | L, L, H | 0.208 | 0.308 | 0.308 | 0.408 | 0.329 | 2.918 | 0.00120781 |
| BE9 | L, H, H | 0.317 | 0.416 | 0.416 | 0.516 | 0.341 | 2.866 | 0.00136144 |
| BE10 | L, H, VH | 0.533 | 0.633 | 0.633 | 0.733 | 0.362 | 2.779 | 0.00166341 |
| BE11 | FL, FH, L | 0.569 | 0.669 | 0.705 | 0.769 | 0.369 | 2.752 | 0.00177011 |
| BE12 | FL, H, M | 0.272 | 0.372 | 0.436 | 0.536 | 0.306 | 3.023 | 0.00094842 |
| BE13 | FL, H, M | 0.453 | 0.552 | 0.58 | 0.68 | 0.342 | 2.862 | 0.00137404 |
| BE14 | M, FH, H | 0.544 | 0.644 | 0.68 | 0.78 | 0.347 | 2.841 | 0.00144212 |
| BE15 | M, H, VH | 0.652 | 0.752 | 0.788 | 0.852 | 0.376 | 2.724 | 0.00188799 |
| BE16 | FH, FH, FH | 0.5 | 0.599 | 0.699 | 0.799 | 0.314 | 2.986 | 0.00103276 |
| BE17 | L, VH, VH | 0.605 | 0.705 | 0.777 | 0.805 | 0.375 | 2.728 | 0.00187068 |

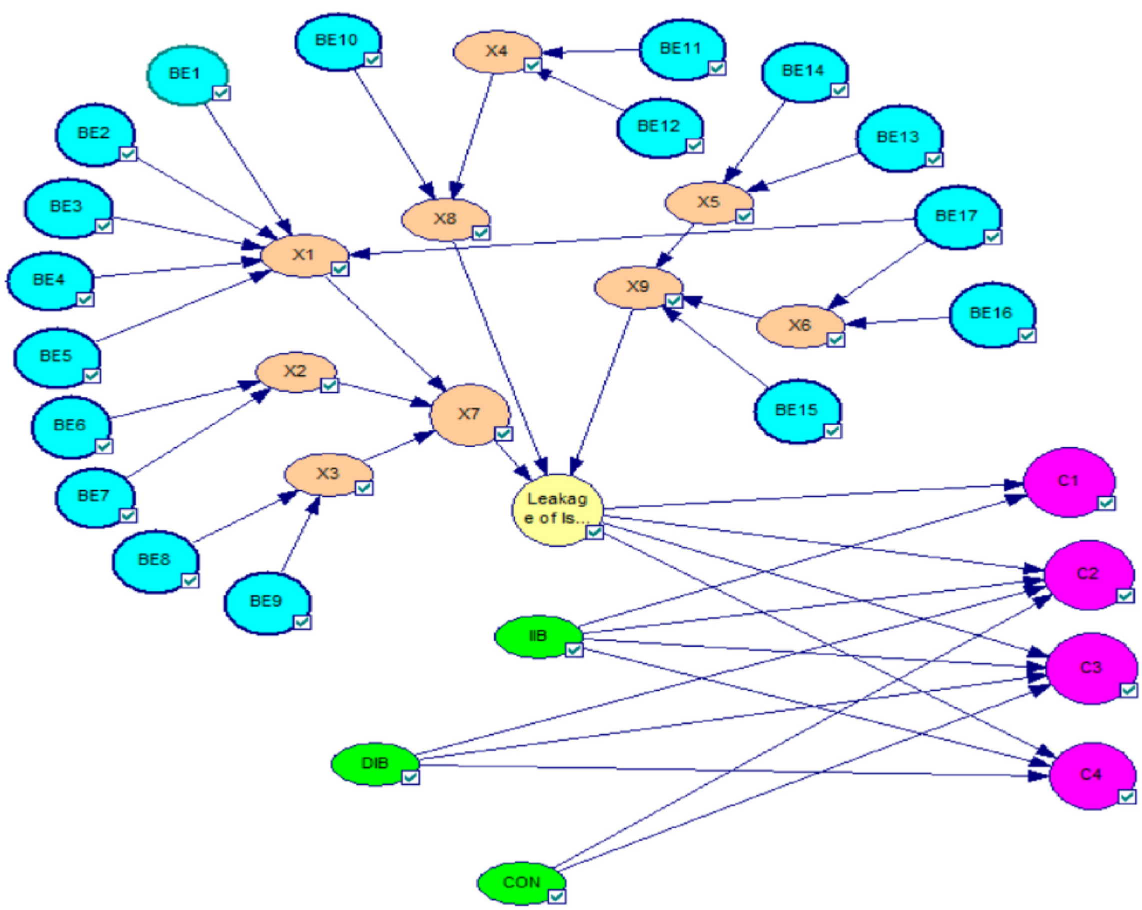


**Figure 3.** Bayesian network structure based on BT method.

*2.2.3.1. Step 3: Risk profile.* The risk is result of multiplying the probability of occurrence and the severity of each final consequence of event scenarios (Perlman et al., 2014). In this study, as an innovation, BNs were used to update the occurrence probability of final consequences and FDS code was used to find the severity of consequence. In this study, the mortality rate of each of the final consequences was considered as a criterion for evaluating the event scenario consequence. Finally, the number of people who will be killed is obtained using Eq. (9).

$$N = D_p AP \tag{9}$$

**Table 7.** Probability and ranking of BE in BT and BN.

| Event | Prior probability (BT) | Prior probability (BN) | Posterior probability (BN) | Ranking |
|---|---|---|---|---|
| BE1 | 1.15000E−03 | 1.15000E−03 | 4.81612E−02 | 12 |
| BE2 | 1.15000E−03 | 1.15000E−03 | 4.81612E−02 | 12 |
| BE3 | 1.17000E−03 | 1.17000E−03 | 4.89986E−02 | 11 |
| BE4 | 1.44000E−03 | 1.44000E−03 | 6.30606E−02 | 5 |
| BE5 | 1.87000E−03 | 1.87000E−03 | 7.83141E−02 | 2 |
| BE6 | 1.87000E−03 | 1.87000E−03 | 7.83141E−02 | 2 |
| BE7 | 1.36000E−03 | 1.36000E−03 | 5.69557E−02 | 9 |
| BE8 | 1.66000E−03 | 1.66000E−03 | 6.95195E−02 | 4 |
| BE9 | 1.77000E−03 | 1.77000E−03 | 7.41262E−02 | 3 |
| BE10 | 1.18000E−03 | 1.18000E−03 | 4.94175E−02 | 10 |
| BE11 | 1.38000E−03 | 1.38000E−03 | 5.77933E−02 | 8 |
| BE12 | 1.49000E−03 | 1.49000E−03 | 6.24000E−02 | 6 |
| BE13 | 1.37000E−03 | 1.37000E−03 | 5.73745E−02 | 15 |
| BE14 | 9.40000E−04 | 9.40000E−04 | 3.93665E−02 | 14 |
| BE15 | 1.44000E−03 | 1.44000E−03 | 6.03606E−02 | 7 |
| BE16 | 1.88000E−03 | 1.88000E−03 | 7.87329E−02 | 1 |
| BE17 | 1.03000E−03 | 1.03000E−03 | 4.31356E−02 | 13 |

## 3. Results

### 3.1. BT modeling

Chemicals spill into the drum containers is one of the major hazards and the most frequent occurrence in risk identification in warehouses. Taking into account three protective layers, with the presence of operational staff and safety experts of the chemicals warehouse, the BT diagram was drawn up for the spill of isooctane in the warehouse. Figure 2 displays the diagram of BT resulting from isooctane spill. The BT diagram fault tree was qualitatively drawn up, the results of which indicated that 26 causes, consisting of 17 BEs and 9 intermediate events (IEs) caused the isooctane spill in the chemicals warehouse. The TE scenario is the spill of isooctane from chemical barrels in the warehouse in the presence of ignition sources and the failure of safety barriers (immediate ignition, delay ignition, confined space) can lead to four consequences, including vapor cloud explosion (VCE), flash fire, pool fire, and release of chemicals into the warehouse environment. Table 4 demonstrates the qualitative description of safety barriers, BEs and IEs, and BT model consequences.

### 3.2. Fuzzy set theory

BEs failure was determined in the probability of occurrence based on a seven-point rating scale by three experts chosen according to Ishikawa et al. Demographic details of experts are presented in Table 5. The occurrence probability of 17 was obtained through the forms and experts' interviews. Table 6 shows the BEs failure rate using the FST.

### 3.3. Bayesian modeling

Due to the limitations of the BT technique for updating prior probabilities and considering common causes, the BT diagram was plotted in the BNs according to Figure 3. Table 7 represents the posterior and prior probability of BEs in the BT and BN methods. The BT model inductive results indicated that the TE occurrence probability is equal to 2.387819E−02. Whereas, the BN model revealed that the TE occurrence probability is equal to 2.4883691E−02, which is more than the BT model. The BEs posterior probability is shown in the fourth column of Table 7. One of the most important BEs affecting the TE occurrence can be identified by updating the BEs probability. Table 7 reveals the BE rankings based on the posterior probability values in the BNs. Accordingly, BE16, lake of ventilation system, is the most critical BE and then BE5, BE6, and BE9 are in next ranks, respectively. The BE14 and BE17 events are recognized as the minor important events, and the BE13 event, lack of thermometer, is recognized as the least important event in the TE. The probability of safety barriers failure in databases (National Institute of Public Health and the Environment (RIVM) Centre for External Safety, 2009) and studies has been used in the form of Table 8 (Vílchez et al., 2011). The probability values of the final events are represented in Table 8. The table shows that a pool fire with a probability of 2.38711E−03 will be the most probable consequence of isooctane spill in the chemicals warehouse.

**Table 8.** Probability of consequences and safety barrier of BN.

| Variable | | Probability |
|---|---|---|
| | Pool fire | 2.38711E−03 |
| Consequences | VCE | 8.591E−04 |
| | Flash fire | 8.591E−04 |
| | Safe or Toxic release | 1.43269E−03 |
| | Immediate ignition barrier | 0.1 |
| Safety barrier | Delay ignition barrier | 0.6 |
| | Confinement | 0.6 |

### 3.4. Fire modeling

Numerical simulation using FDS 6.5.1 code was performed for isooctane pool fire. the present study used structured meshes and time step $10^{-2}$. A 32 GB memory system and 64 cores/CPU E5-2690V4@2.6GHz (2processors) in Shahid Beheshti University of Medical Sciences, Tehran, Iran were used to perform simulation. The analysis of the results was done according to the target point heat flux. When the simulation reached an quasi steady state (after 20 s), the heat flux at 10 frequencies was calculated for the average heat flux around the fire and compared to the SFM results (Ahmadi et al., 2019). The results obtained by CFD method were compared with the SFM results (Table 9). At the distance of Y/D = 03 the value of heat flux based on the CFD method was 43.5 kW/m$^2$ (R = 4). At R = 6, this value was obtained 42.3 kW/m$^2$ and at R = 8 was equal to 40.5 kW/m$^2$. The heat flux value was is 31.52 kW/m$^2$ at the distance of Y/D = 03 in the SFM. Figure 4 shows the pool fire development in second 20. By increasing flame height the heat flux increases; therefore, the maximum heat flux is 1000 kW/m$^2$.

#### 3.4.1. Numerical gridding

The current study investigated 3 different mesh sizes (0.125, 0.833, and 0.625) and compared them with analytical models. The amount of heat flux measured at 2 m above the ground was measured by FDS and analytical models. The predicted results were compared with those of the analytical models using Eq. (10).

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{pred,i} - y_{\exp,i}\right)^2} \tag{10}$$

In this equation, $y_{pred,i}$ is the predicted value and $y_{\exp,i}$ is the value obtained from the analytical model data and n is the number of measurements. The simulation results were compared with FDS and SFM in

**Table 9.** Comparison of CFD simulation results with analytical models.

| Distance | Heat flux (kW/m$^2$) | | | |
|---|---|---|---|---|
| | FDS | | | SFM |
| | R = 8 | R = 6 | R = 4 | |
| Y/D = 0.3 | 40.5 | 42.3 | 43.5 | 31.52 |
| Y/D = 1.3 | 1.67 | 1.62 | 1.47 | 9.54 |
| Y/D = 1.7 | 0.609 | 0.539 | 0.408 | 7.2 |
| Y/D = 3.3 | 0.608 | 0.571 | 0.57 | 3.37 |
| Y/D = 3.7 | 0.713 | 0.634 | 0.565 | 2.8 |

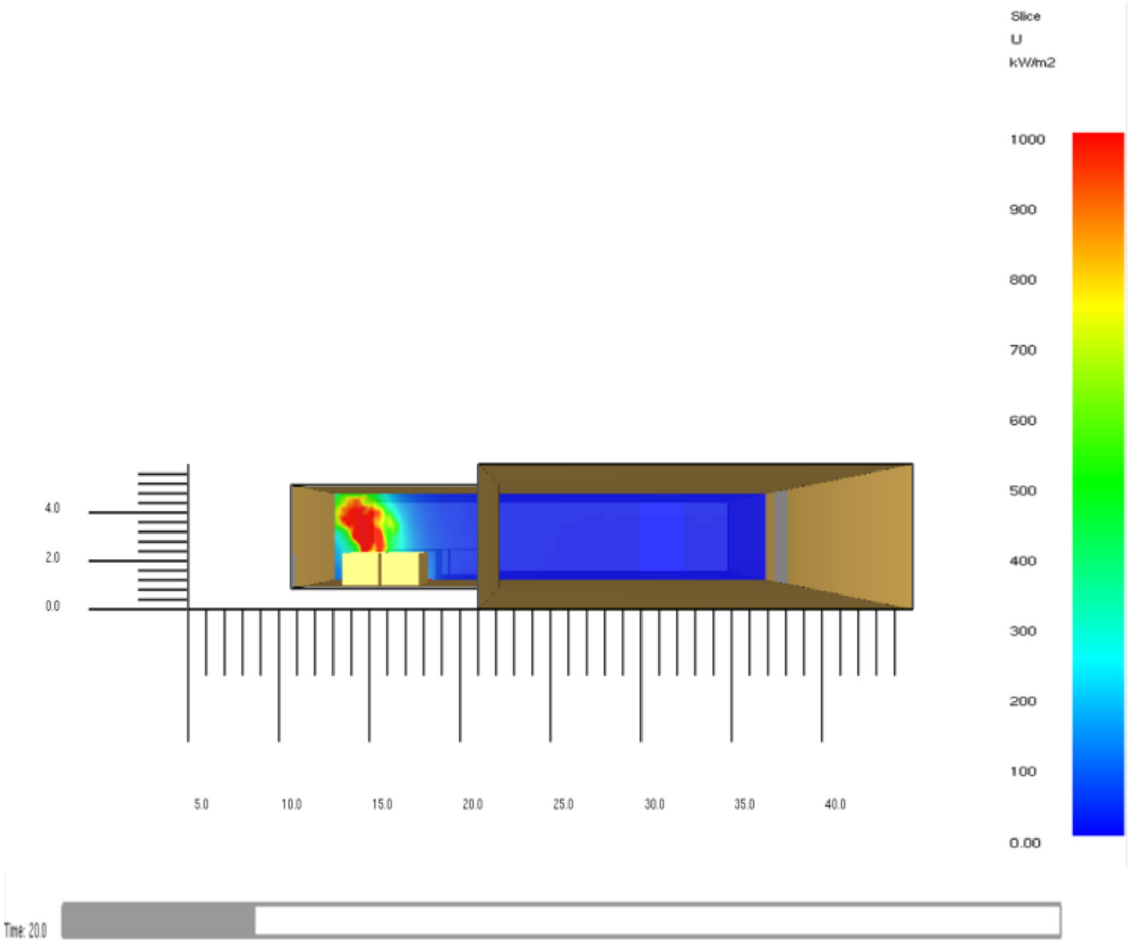


**Figure 4.** Pool fire development in second 20.

**Table 10.** SFM.

| Grid resolution(R) | Mesh size | Number of cells | RMSE of heat flux (kW/m$^2$) | Simulation time (min) |
|---|---|---|---|---|
| 4 | 0.125 | 2178048 | 7.32 | 3456 |
| 6 | 0.0833 | 6147072 | 6.87 | 8366 |
| 8 | 0.0625 | 13876224 | 6.29 | 4008 |

three meshes (Table 10). The results of this comparison showed that the maximum error value is related to mesh size 0.125 m with a value of 7.32% and the minimum error value is related to mesh size 0.0625 m with a value of 6.29%. The error value in the mesh size selected in this study (mesh size of 0.0833 m) is 6.87%. The comparison indicated that 0.0625 mesh size had better results compared to others, while, numerical simulation with 0.0625 mesh size requires approximately 5 times the mesh size of 0.125 m. Therefore, considering the optimum accuracy and timing, the mesh size of 0.0833 was chosen for numerical simulation.

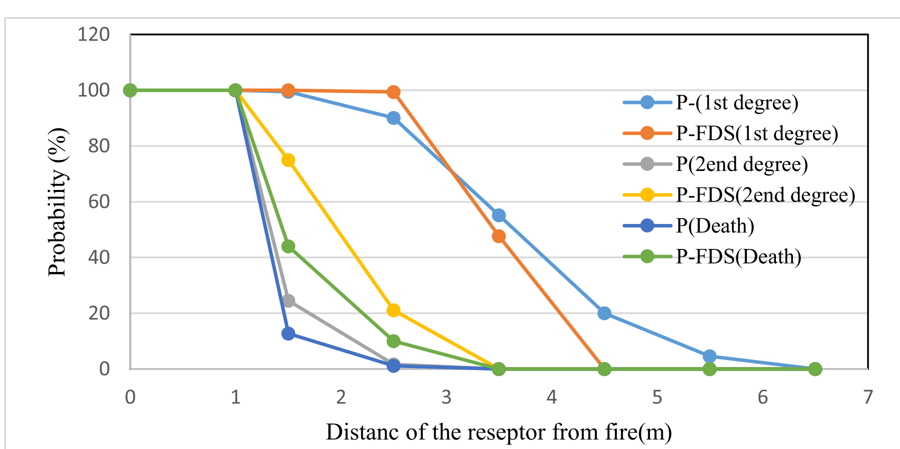


**Figure 5.** Probability of effects on humans in the SFM and CFD.

Table 11. Consequences risk profile with BN and FDS approach.

| Consequences | Frequency (event/years) | | Impacted area | Population distribution | Probability of death | Severity | Risk | |
|---|---|---|---|---|---|---|---|---|
| | Prior | Posterior | | | | | Prior | Posterior |
| Pool fire | 2.38711E−03 | 0.1 | 38 | 0.001 | 0.3 | 0.01 | 2.38711E−05 | 1.000E−03 |

### 3.5. Modeling of the fire effects on humans

The effect of probability based on the numerical simulation and SFM results is presented in Figure 5. Accordingly, the maximum safety distance is 6.5 m and the maximum death probability according to SFM is at a distance of 1.5 m. The CFD model, however, predicts a maximum safety distance of 3.5 m. Due to the exposure time, the range of vulnerability is 1.5–6.5 m from the fire based on these two models. In the CFD model, the heat flux is 31 $kW/m^2$ at a distance of 3.5 m from the fire, decreasing to 6.5 m gradually. The SFM predicts the maximum safety distance of approximately 4.5 m, while the CFD predicts 4 m for heat flux exceeding 12.5 $kW/m^2$.

### 3.6. Risk estimation

According to the studies regarding the criterion for evaluating fire consequence, heat flux is 4 $kW/m^2$ (pain threshold in 20 s) and 37.5 $kW/m^2$ (100% death in 1 min or 1% death in 10 s). The average population density inside the warehouse is 3 people. Table11 represents the results of isooctane spill risk assessment in the chemicals warehouse. The results showed that the amount of posterior risk is higher than the prior value. This increase is due to the ability of BNs in deductive reasoning, which is of great importance in DRA. This advantage makes the structure of the network dynamic and allows updating root events assuming the occurrence of isooctane spills in the chemicals warehouse.

## 4. Discussion

The performance of safety barriers and their failure against the accident scenario were quantitatively and qualitatively assessed before the final consequences and after the event scenario. Based on the BT model, the TE probability (isooctane spill) was calculated 2.387819E−02; moreover, the most probability (2.38711E−03) was identified for pool fire as a final (Table 8). Although the capabilities of the BT model have been proven in event modeling (Chen and Wang, 2019), studies have pointed out the limitations and shortcomings of this method in DRA (Zarei et al., 2016). The present study used the BN method to remove the BT method shortcomings and limitations. According to inductive reasoning results, isooctane spill occurrence probability in the BN and BT methods is 2.4883691E−02 and 2.387819E−02, respectively. The difference might be due to the consideration of conditional dependence between BEs and IEs of the same cause, which is consistent with the study by Yuan et al., in 2015 (Yuan et al., 2015). In risk analysis, deductive reasoning is of importance and the BN method is able to perform it. The probability of a BE occurring by receiving event precursor information can be updated using this kind of reasoning (Kjaerulff and Madsen, 2008).

If the latest pre-incident data on chemicals warehouse events are used over time, the model data will be closer to reality and a native DRA model will be created. In this way, the uncertainty in the results and model reduces compared to when non-specific data are used. The most critical BE can be identified by updating the BEs probability. In this study, the events Fail in forklift brake system (BE1) are considered as the most critical events with the largest contribution to the isooctane spill event occurrence. The issue deduced from determining the importance of BEs is that in addition to allocating resources for inspection, maintenance, and testing, it can be used to remove equipment from the chemicals warehouse or to determine repair time. The present study used FST to decrease the BEs uncertainty. The combination of fuzzy method and BN method (FBN) besides having all the features of BNs are able to utilize the capabilities of fuzzy theory to reduce uncertainties in studies of risk assessment (Yan et al., 2016). The application of FST to estimate the probability of BEs identified in spill can lead to the reduction of uncertainties. Given that an appropriate database is not available for such BEs, the application of the theory in combination with the BNs leads to the elimination of uncertainties. It is possible to quantitatively and dynamically model the scenarios leading to warehouse events. Regarding fuzzy BT in the chemicals warehouse (such as the effects of fire alarm systems, leakage control systems, etc.) no study has been conducted on control barriers; therefore, this issue can be investigated in future studies.

The findings of predicting heat flux resulting from pool fire with a diameter of 5 m by SFM and FDS are shown in Figure 5. Accordingly, the mesh size of 0.0625 m is most compatible with the results of SFM. Based on Figure 5, the heat flux predicted by the FDS at the distance of $Y/D = 0.3$ is overestimated. At distances farther from the pool fire, the values predicted by the FDS are somewhat close to each other compared to the SFM. Table 9 reveals that at the distance of $Y/D = 3.7$ m from the pool fire, there are the lowest difference between the amount of the heat flux predicted by the FDS and SFM. The results of simulation indicate that the amount of received thermal radiation at a distance of 4 m is 20 $kW/m^2$. In order to identify domino events, the escalation vector threshold is an important criterion. Escalation vectors larger than the threshold can cause damage to adjacent units (Khakzad et al., 2013a). When the physical effects caused by the escalation vector are less than the threshold value of the adjacent equipment vulnerability, it is assumed that domino event does not occur. There are different values in each reference, and sometimes in the violation of the limits of vulnerability. The highest threshold reported is for thermal radiation of 38 $kW/m^2$ (Kletz, 1980) and for blast pressure of 70 kPa (Khan and Abbasi, 1998). It is recommended that threshold values of 50 and 15 $kW/m^2$ for more than 10 min be expressed for under pressure and atmospheric tanks, respectively (Cozzani et al., 2006). As can be seen in Table 11, the area affected by the thermal radiation of pool fire a circular with a radius of 3.5 m is approximately 38 $m^2$. The estimated risk numbers in prior and posterior approaches are 2.38711E−05 and 1.000E−03, respectively. These values are in the unacceptable range compared to the UK risk criterion, which is more applicable in indoor and outdoor environments. According to the UK criterion, the range of acceptable risk criterion is $10^{-6}$, tolerable range is $10^{-5}$, and unacceptable range is $10^{-4}$. Therefore, the necessary measures should be prioritized to implement preventive strategies in this range. In this study, given these barrels contain atmospheric pressure chemicals the threshold value for the domino effects was set at 15 $kW/m^2$. Accordingly, in the case of occurring fire in isooctane barrels, the domino fire also occurs in other chemicals. Based on the HSE association instruction, the minimum distance between tanks containing chemicals with a capacity less than 1 $m^3$ is at least 1 m. If the barrels are grouped together, the total barrel volume will be less than 3 $m^3$. Given the volume of a group of barrels, the distance between the barrels containing isooctane and other materials will be at least 1 m (Executive, 2015). The volume of barrels containing isooctane is 2.4 $m^3$ and the volume of adjacent barrels containing glycol amine is 4.6 $m^3$. Therefore, the minimum distance between these materials should be at least 5 m due to their incompatibility.

## 5. Conclusion

Lack of proper database in the chemicals warehouse to assess the probability of risk and map the cause-effect model and DRA is a challenge in DRA in the chemicals warehouse. In this study, BT diagram was used for cause-effect modeling of the isooctane spill in the chemicals warehouse. The BT model was transferred to the BN to update the probability of BEs and to fix the defect of the BT diagram. Given the lack of a proper database in the chemicals warehouse and the reduction of uncertainty, fuzzy theory was used. To identify the severity of possible consequences, numerical simulation and FDS code were used, and finally, according to the results of BNs and numerical simulation, the risk number was estimated in both posterior and prior modes.

The SFM results were compared with the results of numerical simulation. Compared to the SFM, the maximum predicted error in the desired mesh size was 6.87% in the CFD model. The results of CFD and SFM were utilized to examine the effects of pool fire on humans (1st degree burns, 2nd degree burns, and deaths). Modeling of the effects of pool fire on a warehouse of chemicals showed the vulnerability range of 1.5–6.5 m in the chemicals warehouse. The estimated risk number in two prior and posterior approaches is in the non-acceptable range compared to the UK risk criterion. Identifying the events responsible for the occurrence of events, appropriate managerial and supervisory measures can also be used in the framework presented in the chemicals warehouse for consequence analysis and DRA of pool fire could be used for prevention of the accidents and domino effects in the chemicals warehouse. Therefore, in order to use the method presented in this study, future studies are recommended as follows.

- Safety assessment of control barriers in the chemicals warehouse and determining the emergency ventilation efficacy in smoke control using numerical simulation.
- Estimating dynamic risk of flash fire and vapor cloud in the chemicals warehouse and assessing the effect of ventilation systems.

## Declarations

### Author contribution statement

Mohammad Javad Jafari; Mostafa Pouyakian; Parvaneh Mozaffari; Fereydoon Laal; Heidar mohamadi; Masoud Taheri Pour; Saber Moradi Hanifi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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### Data availability statement

No data was used for the research described in the article.

### Declaration of interest's statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

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