Quantitative risk assessment and management of hydrogen leaks from offshore rocket launching platforms

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Abstract—Liquid hydrogen in cryogenic condition can incidentally leak from offshore rocket launching platforms, leading to catastrophic impacts. Risk assessment and management of hydrogen leaks are required to prevent such accidents. The aim of the paper is to develop a methodology for quantitative risk assessment on hydrogen leak hazards from offshore rocket launching platforms during their filling process. A set of credible leak scenarios are chosen using Latin Hypercube Sampling (LHS) technique. The flows of hydrogen leaks for the selected scenarios are simulated using Computational Fluid Dynamics (CFD) method. A probabilistic model for predicting hydrogen leaks is established based on the computed results, where a long short-term memory (LSTM) network is used. Individual risks are defined as likelihood of explosion and fire due to hydrogen leaks. As an illustrative example, the developed methodology was applied to a hypothetical offshore rocket launching platform, confirming that the hydrogen leak risk level of the platform meets the ALARP (As Low As Reasonably Practicable) criteria. Risk mitigation options are also discussed to reduce the risk level.

Keywords-quantitative risk assessment; long short-term memory network; offshore rocket launching platform

1. Introduction

The offshore rocket launching can overcome the geographical limitations of the traditional land-based launching. However, the severe marine environment poses a significant threat to the propellant filling system, which can result in propellant leakage, leading to fire and explosion. Statistics show that more than 64% of aerospace accidents are explosion and fire caused by accidental leaks of propellant [1]. Effective risk assessment can mitigate the risk of leakage and avoid catastrophic accidents.

The objective of offshore risk assessment is to ensure high safety and reliability of the system [2][3][4]. Most of the studies can get highly reliable results largely depending on a clear understanding of the system and its operating environment. For example, the risk assessment of offshore wind turbines based on failure model effect analysis (FMEA) [5]. With the advancement of techniques, the focus on risk assessment has shifted to quantitative assessment that can provides more accurate results[6][7]. This methodology utilizes computational fluid dynamics (CFD) to characterize load time profiles and other techniques to calculate the possible consequence of the accidents. Although a more accurate methodology is provided for propellant leakage risk assessment, there are still some drawbacks. For example, it is time-consuming to perform necessary CFD calculations, e.g. more than several hours [8]; it is not sure if the risk assessment can cover all the possible scenarios; it is difficult to cope with the extreme accidents with low probabilities and large effects, some of which are difficult to selected by digital techniques, e.g. earthquake.

To deal with the above-mentioned problems, Paik et al. [6] proposed a risk assessment methodology based on Latin Hypercube Sampling (LHS) technique to consider possible scenarios. API [9] suggests screening out high-risk accidents as typical scenarios. While most of them primarily concentrate on typical scenarios rather than the specific extreme accidents. A data-driven approach has been proposed and applied, which combines CFD simulations and machine learning models to predict gas leakage in a more efficient manner [10]. A back propagation (BP) model minimizing the objective function is first developed to predict gas dispersion. On this basis, other machine learning models are developed based on the above model, such as support vector machine (SVM), long short-term memory (LSTM), radial basis function (RBF). Because of the time dependency of leakage accidents, the LSTM network is suitable for capturing the temporal link between input and output variables, and can accurately describe the actual leakage scenario [8]. For instance, a prediction for stock trends [11], a forecasting model of wind speed [12].

Inspired by the above studies, the present study utilizes machine learning models to address the problems of extreme accidents in the risk assessment. After hazard identification, a simulation database provided by CFD is used for the training of LSTM-based prediction model. The integrity of hazard scenarios is guaranteed by the performance of prediction model. Finally, the risk assessment, including consequence and frequency analysis, is performed by applying the damage model. A case study is performed to illustrate the applicability and effectiveness of the method.

The following section introduces the methodology used to assess the risk of leakage scenarios. Section 3 presents the application of the approach in a case study of leakage accidents on an offshore rocket launching platform. Section 4 provides the results. Conclusions are summarized in section 5.

2. METHODOLOGY

2.1. Framework

Figure 1 shows the QRA procedure for the propellant filling system, which involves the identification of potential hazards and the quantification and assessment of risks. The fire and explosion mainly depend on gas concentration, and the CFD method is used to determine the gas cloud feature parameters. Various leakage scenarios are generated using a sampling method, considering the uncertainty of wind direction, wind speed, leak position and leakage rate. The machine learning-based prediction model is developed based on a database generated from CFD simulations. Consequence assessment of fire and explosion is conducted using empirical models. The risk assessment, which takes into account the frequency and consequence of the accident, is performed, and a criterion is used to judge whether or not the risk control measures should be applied. The accident frequency is calculated by multiplying the component's failure frequency by the ignition probability.

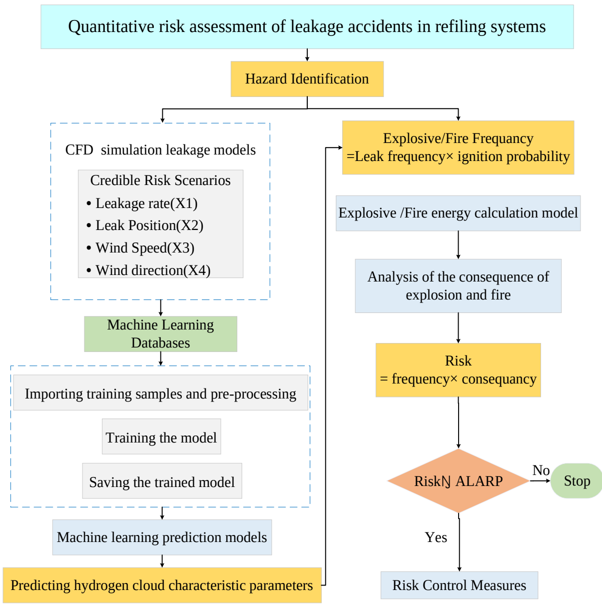


Figure 1. Quantitative risk assessment process for filling system

2.2. Hazard Identification

FMEA is widely used in hazard identification for complex systems including ocean engineering [5]. When performing hazard identification for the entire system, it is crucial to consider the intricate connections between different components involved in the propellant filling system. It is recommended to assess the components with high Risk Priority Numbers (RPNs), which are the product of the severity (S), occurrence (O), detection (D).

$$RPN = S \times O \times D \tag{1}$$

2.3. Scenarios for Gas Leakage

Latin hypercube sampling (LHS) is usually used to generate scenarios involving several random variables[13]. Historical data can provide statistical parameters for random variables such as leakage rate, wind speed, and wind direction. The equipment with the highest RPN is selected to determine the leakage location. Equation (2) is used to perform random sampling from the probability density function (PDF), ensuring a good coverage of the range of values.

$$x_i = F^{-1}\left(\frac{m_i - 0.5}{N}\right) \tag{2}$$

where N is the sample size, m_i is the i th element in the sample, F^{-1} is the inverse function of the cumulative distribution function.

2.4. The Long Short-Term Memory Network

The LSTM network is used to predict the leakage characteristics, which is trained based on CFD simulation results. The problem of gradient explosion or disappearance, also referred to as long-range dependence, can be effectively resolved by employing the LSTM network, which is a specialized type of recurrent neural network [14]. Figure 2 shows the LSTM circuit unit structure, where i_t, f_t, and o_t are the input, forgotten, and output gate, respectively. It controls the path of information transmission through several gates. The three gates are calculated as follows.

$$i_t = \sigma(W_i x_t + U_t h_{t-1} + b_i) \tag{3}$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{4}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$\tilde{c}_t = \tanh(W_c x_t + H_f h_{t\text{-}1} + b_C) \tag{6}$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{7}$$

$$h_t = o_t * \tanh(c_t) \tag{8}$$

where σ is the sigmoid activation function with values from 0~1, *tanh* is the hyperbolic tangent function with output values from -1~1, x_t is the input value at the current moment, h_{t-1} is the state at the previous moment, W is the weight matrix; b is the bias vector.

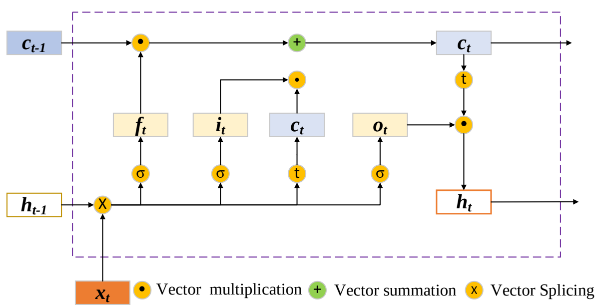


Figure 2. LSTM circular cell structure

2.5. Frequency Analysis

LH2 leakage accident can occur in three different ways, as shown in Figure 3. The first one is an immediate ignition, which may lead to a jet fire depending on the ignition probability. The second one involves delayed ignition, where an explosion can occur and the accident progression is dependent on the timing of the ignition. The third one occurs when there is no ignition source, and no significant harm occurs as the fuel is non-toxic. If the leakage is detected and isolated, the consequence can be avoided. The HyRAM database [15] provides a default value of 0.9 for successful detection and isolation, and 0.1 for failed. The frequency of fire and explosion can be calculated using the following equation.

$$F_{Jetfire} = f_{total} \times P(\overline{Isolated}) \times P_i \tag{9}$$

$$f_{Exp} = f_{total} \times P(\overline{Isolated}) \times P_d \tag{10}$$

$$f_{total} = N \times f_{leak} \tag{11}$$

where N is the number of components of the same category, f_{leak} is the component leak frequency, $P(\overline{Isolated})$ is the probability of failed leakage detection and isolation before ignition, P_i and P_d are the probability of immediate and delayed ignition respectively that depend on the leakage rate. Value of the parameter is provided in HyRAM [15].

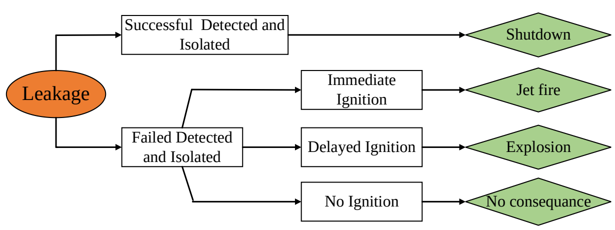


Figure 3. LH2 leakage event tree

The low viscosity of hydrogen makes joints, pipes and valves more susceptible to leakage [16]. The frequencies of fire and explosion for each category are presented in Table 1.

Table 1. Frequency of fire and explosion

Category	Leakage frequency	Type of accident	Frequency
Joints	8*6.96E-6	Jet fire	2.95E-7
		Explosion	1.50E-7
Pipe	4*9.12E-7	Jet fire	1.93E-8
		Explosion	9.84E-9
Valves	28*4.13E-5	Jet fire	6.12E-6
		Explosion	3.12E-6

2.6. Consequence Analysis

1) Overpressure

The so-called Boiling liquid expanding vapor explosion (BLEVE) is a classical accident scenario for LH2 leakage. The LH2 explosion is a physical, not a chemical. Overpressure is the primary outcome, resulting in structural damage and human fatalities [17]. The energy of LH2 explosion can be calculated as:

$$E_m = \gamma[C_v(P_g - P_s)(V / R_g - \alpha m)] \tag{12}$$

where γ is the correction factor, 1.8, C_v is the specific heat capacity at constant volume, J·kg^{-1}·K^{-1}, P_g is the pressure of hydrogen, MPa, P_s is the surfing pressure, MPa, V is the volume of hydrogen, m^3, R_g is the gas constant of hydrogen, 4157 J·kg^{-1}·K^{-1}, α is coefficient, 1.9155×10^{-6} K·Pa^{-1}, m is mass of hydrogen, kg.

Explosive energy is equal to TNT equivalent.

$$W = E_m / Q_{TNT} \tag{13}$$

where Q_{TNT} is the detonation heat, 4500 kJ/kg.

Combined with the distance from the leak source, the shockwave overpressure is calculated as follows.

$$\Delta p_s = \frac{0.108W^{1/3}}{r} - \frac{0.114W^{2/3}}{r^2} + \frac{1.772W}{r^3} \tag{14}$$

where r is the distance from the leak source, m.

2) Thermal flux

To trigger LH2 fire and explosion, three conditions must be satisfied: concentration threshold, flame accelerator and ignition source. Hydrogen flammability ranges have been defined by different standards, leading to fire or explosion consequences. A flammable concentration within the range of 4~75 % is selected. By combining with the distance from the leak source, the heat flux can be calculated using the hydrocarbon ignition model [18][19], which is expressed as follows.

$$q = [5777.3P_g^{0.32} m^{2/3}(1 - 0.058\ln r)] / r^2 \tag{15}$$

3. Case Study

3.1. Hazard Identification

The filling system can be divided into two main parts based on their structure and function: the liquid system and the gas system. The gas system is subdivided into three subsystems: storage tank pressure boosting system, propellant blow-off system and pneumatic valve control system. It consists of several components such as high-pressure cylinders, pipelines, filters, valves, and filling pumps.

In this study, liquid hydrogen and liquid oxygen are used as the propellant for the filling system. The storage tank pressure boosting system assists the propellant blow-off system to remove impurities before filling, and pressurizes the liquid hydrogen storage tank to ensure filling tasks. The propellant blow-off system's function is to remove flammable gases before or after filling. The pneumatic valve control system controls the pressure and flow rate during filling. The liquid system is responsible for the actual propellant filling process and is composed of storage tanks, level gauges, valves, flow gauges, filters, flanges, and other related components. The filling process is divided into four phases:

a) Low flow rate filling phase: avoid rapid cooling of the storage tank in the hot state, and prevent overpressure.
b) High flow rate filling phase: storage tank is pre-cooled to a certain level, increasing the flow rate to reduce time.
c) Reducing flow rate filling phase: filling to a certain level, reduce the filling flow rate to ensure filling accuracy.
d) Replenishment phase: replenish the propellant consumed by evaporation during parking.

Based on the subdivision of the filling system, the main leakage failure modes are identified. For each failure mode, there are several reasons. The PRN for each reason is calculated using (1). The PRN for each failure mode is obtained by summing the PRNs for all the reasons. The FMEA results are shown in Table 3. Only the failure modes with high RPNs are considered in the present study.

Table 3 FMEA results

Failure modes	**Causes of failure**	**RPN**
Level gauge failure	1. Poor quality	32
	2. reed switch damage	
Valve failure	1. Corrosion	18
Filling pump failure	1. cavitation	40
	2. poor contact of return relay	
Flow gauge failure	1. Pulse interference	18
	2. instrumentation failure	
	3. PLC failure	
Seals failure	1. Corrosion	18
Pressure sensor failure	1. Quality problems	16
Filler flap failure	1. Mechanical failure	14
Connection valve failure	1. Poor sealing	14
Storage tank rupture	1. Pressure instability	12
Flange failure	1. Poor sealing	15

3.2. Leakage Simulation

The Odyssey platform [20], which has dimensions of 160 × 92 × 81 m is considered in the simulation. Monitor points (MPs) are placed throughout the model to record hydrogen dynamic behavior, as shown in Figure 4.

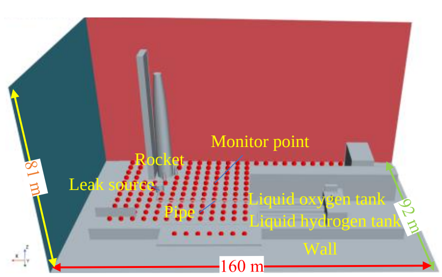


Figure 4. Geometric model

It can be seen from Figure 4 that, the distance between the gas monitors is calculated to be 7 m using the characteristic length [21] defined by:

$$L = \sqrt[3]{Min(V_j)},\quad j = 1, \dots, N \tag{16}$$

where V_j is the volume of the cloud at the flammable concentration, m^3, N is the sample size. The flammable cloud volumes for all simulated scenarios are shown in Figure 5.

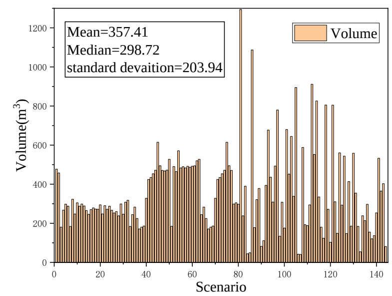


Figure 5. Flammable cloud volume

The 150 scenarios were generated by LHS. The statistical descriptors of the random variables are listed in Table 5.

Table 5. Statistical descriptors

Random variable	**Distribution type**	**Mean**	**Standard deviation**	**Reference**
Wind speed	Normal	4.28	1.86	--
Wind direction	Normal	175.1	100.3	[22]
Leak rate	Weibull	0.86	0.43	[23]

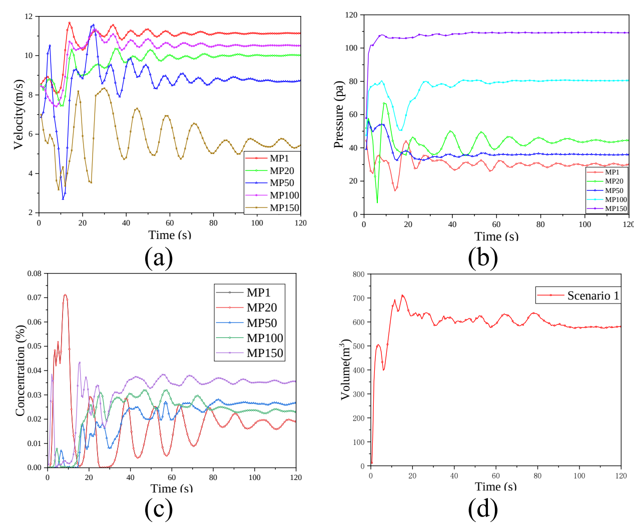


Figure 6. Time history of LH2 diffusion variables: (a) leak rate; (b) pressure; (c) concentration; (d) hydrogen cloud volume

The dispersion modeling is performed using the CFD software STAR-CCM+ that has been validated in several LH2 dispersion [24][25]. The ideal compressible model is used to solve dispersion problems assuming all LH_2 evaporates. The polyhedral mesh is used to grid the computational domain, the leakage hole is refined and the other regions are sparse.

It is assumed that leak occurs in the pipelines as shown in Figure 4. The time histories of the hydrogen diffusion variables for a leakage scenario are shown in Figure 6. It can be seen from Figure 6 that, since the monitors are placed at different places, the output will be different. It is worth mentioning that all of the diffusion variables reach an approximately steady state after about 80 seconds.

3.3. Prediction Model based on LSTM

Compared to traditional diffusion models, such as Gaussian diffusion models and CFD models, machine learning models have demonstrated higher efficiency in predicting gas diffusion. Among machine learning prediction models, the LSTM model has shown excellent performance in gas diffusion prediction with time sequence. The LSTM model consists of four parts: sequence input, LSTM layer, fully connected layer, and regression output.

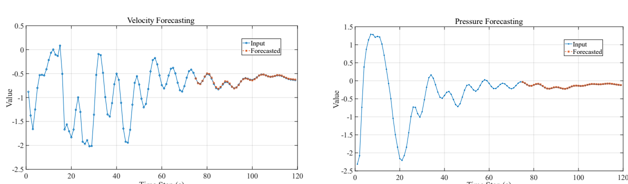
To ensure the accuracy of the results, the input data are standardized to reduce the difference. The LSTM layer with 128 hidden units further improves the accuracy of the results. The output size of the fully connected layer corresponds to the quantity of input data channels. To predict diffusion states for m+1 to m+x seconds, the first m seconds of the diffusion variables are chosen as input. The accuracy of the model is evaluated using the root mean square error.

$$\mathrm{RMSE} = [\frac{1}{n}\sum_{i=1}^{n}(C_i - D_i)^2]^{1/2} \tag{17}$$

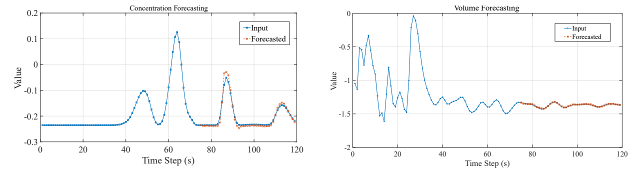
where C_i and D_i are the true value and predicted value per MP respectively, n is the number of MPs. The RMSE of diffusion variables is listed in Table 6. It is concluded that when the minimum batch size is 10 and the maximum epoch is 200, the model has the best prediction result and shortest running time. A leakage scenario with wind speed of 2.929m/s, wind direction of 70.516° and leakage rate of 0.212kg/m^3 is chosen to verify the accuracy the prediction model, and to determine the risk. The prediction results of MP 20 are compared with results from CFD simulation as shown in Figure 7. It can be seen from the figure that the agreement between the predicted and simulated results is good.

Table 6. The RMSE of diffusion variables

Diffusion variable	**RMSE**
Velocity	9.718
Pressure	15.030
Concentration	7.821
Volume	14.193



(a) (b)

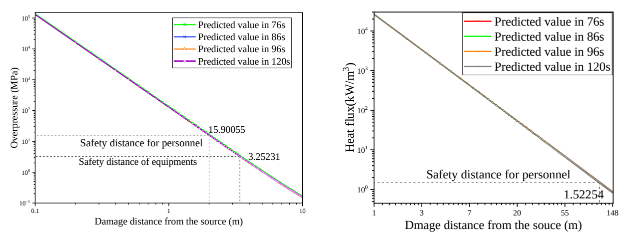


(c) (d)

Figure 7. Prediction results: (a) leakage rate ; (b) pressure; (c) concentration; (d) hydrogen cloud volume

3.4. Consequence Analysis

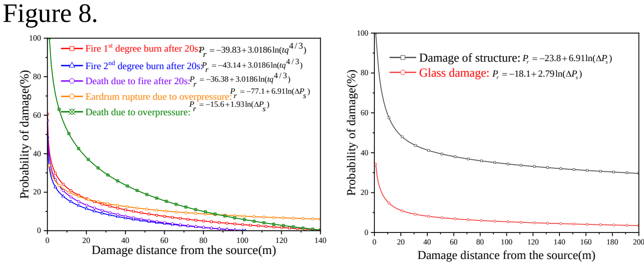
The occurrence of explosion and fire is the result of the interaction between gas and ignition sources. As a consequence of such accidents, overpressure and thermal flux can pose significant safety risks. Combining (14) and (15) and the prediction data of MP 20, as shown in Figure 7, the overpressure and thermal flux at different distances from the leak source are calculated, as shown in Figure 8.



(a) (b)

Figure 8. (a) overpressure; (b) thermal flux as a function of distance from the source

It can be seen from Figure 6 that the hydrogen diffusion state is stable for about 80 seconds. Therefore, there is little variation in the overpressure and thermal flux with time after 80 seconds. According to overpressure and heat flux damage criteria for personnel and structures[26][27], the personnel and equipment safety distance is calculated, as shown in Figure 8.



(a) (b)

Figure 9. Probability of damage for personnel and structure: (a) damage probability for personnel; (b) damage probability for structure

Figure 9 shows the probability of damage for personnel and structure. The probability of damage Pr can be calculated by combing the overpressure ΔP_s or heat flux q (shown on Figure 8) and the distance from leakage source r. The equations for the probability calculation is provided in [28].

4. Risk Calculation

4.1 Individual Risks

The IR can be calculated as:

$$IR = \sum_{i=1}^{R} f_i \times p_i \tag{18}$$

where f_i is the probability of failure events, p_i is the probability of death due to failure events, R is the total number of failure events.

It can be seen from Eq. (18) that, the IR can be calculated by the outcome of Section 2.5 and Section 3.4. By adding together all accident scenarios that could happen for each component, the IR is shown in Figure 10 (a). It stands for the probability of an individual death at the platform 24 hours per day, 365 days per year, and it is visually represented by risk contours. The risk varies with the distance to MP 20.

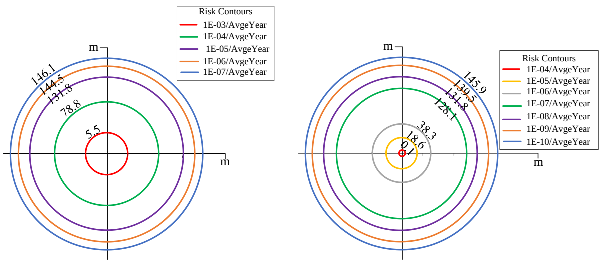


Figure 10. Individual risks: (a) Initial risk, (b) Reduced risk with mitigation options

According to the IR acceptability guideline [29], a risk of 10^{-6}/year is acceptable. Nevertheless, the platform is almost completely covered by the counter representing 10^{-6}/year. It indicates that the risk of filling missions is unacceptable. The protective measures should be taken to make the platform within the As Low As Reasonably Practicable (ALARP) region. It can be seen from Eq. (18) that, the IR is impacted by the failure probability. Therefore, the valve which has high initial failure probability must be monitored carefully.

4.2 Risk Mitigation Options

To minimize the consequence of accidents, protective measures such as monitors and blast walls should be implemented. Table 1 demonstrates that valves are a key factor in risk assessment. In order to prevent fire, explosion and the domino effect, monitors and blast walls are erected next to leak-prone equipment (such as tanks, pipelines). This safeguard ensures that any leak from monitoring equipment will be quickly identified and isolated. The updated IR is shown in Figure 10(b). The current highest risk value for IR is 10^{-4}/year, and the risk range is 0.1 m. In accordance with ALARP recommendations, the risk has been reduced by a factor of 10 compared to the previous example, and the risk range has been condensed.

In general, the use of hydrogen presents various risks, including fire, explosion, and asphyxiation. These risks are less likely to occur on land but are more likely in open areas, particularly at sea, where they can result in more dangerous situations. Gas monitors are currently one of the most effective and popular techniques to reduce risks. These monitors are designed to detect hydrogen and notify staff members to take timely action to prevent potentially fatal accidents and injuries, as is the case with LH2. As shown in Figure 10(b), after implementing protective measures, the IR has been significantly reduced compared to the previous state.

5. Conclusions

In the present study, a machine learning based approach is proposed to address the main challenges of risk assessment. The applicability of this methodology is illustrated in a case study. The LSTM model has been used for the prediction of LH2 dispersion characteristics. The developed prediction model aims to cover all relevant accident scenarios. The proposed approach can provide the dispersion characteristics of different phases, which are valuable for keeping track of accident development. Moreover, the combination of LSTM and CFD can efficiently predict various hazards that may occur during the filling process in a short period. The initial forecasting may not be optimal due to the lack of data, but as more simulations are done and the prediction model is developed, it can be used to integrally and rapidly assess numerous unexpected scenarios that may arise.

The proposed methodology can be used for other industries like process plants, which makes it a valuable tool for mitigating the risk of leakage. One limitation of the current methodology is the lack of considering the uncertainty between modeling and simulation, which could be considered in the future.

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