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Bayesian Network Integration of Event Tree and SLIM-Based Human Reliability for Fire and Explosion Risk Assessment: BP-Husky Toledo Refinery Case Study

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ABSTRACT

The oil and gas processing industry is critical for meeting global energy demand, yet it remains vulnerable to high-consequence accidents such as fires and explosions. This study presents a probabilistic risk assessment of a vapour cloud explosion and fire case at the BP-Husky Toledo Refinery using accident investigation report data. The objective is to obtain a more comprehensive representation of accident risk by integrating the performance of physical safety barriers and human reliability within a single analytical framework. Physical escalation pathways and consequence scenarios are modelled using event tree analysis, while human error likelihood is evaluated using the success likelihood index method based on identified error modes and performance shaping factors. Both components are then integrated using a Bayesian network to quantify consequence probabilities and examine the effect of adding a human error barrier and proposed barrier improvements. The results show that the consequence distribution is dominated by near-miss outcomes (approximately 57%) with smaller probabilities for flash fire (about 14%), vapour cloud explosion (about 13%), and rupture (about 16%). Incorporating the human error barrier produces only marginal changes in these probabilities. Nevertheless, the integrated approach improves clarity in linking specific human error mechanisms and barrier performance to overall risk and supports structured evaluation of barrier improvements for accident prevention.

Keywords
Event tree analysis; Success likelihood index method; Human reliability analysis; Bayesian network; Process safety barriers; Vapour cloud explosion

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INTRODUCTION

The oil and gas processing sector is crucial for fulfilling global energy requirements. Nevertheless, it is also broadly acknowledged as a high-risk domain for occupational safety. This is mostly attributable to the combustible characteristics of hydrocarbons, elevated pressure operating conditions, and the intricacy of processing systems. A multitude of incidents has been documented within the oil and gas business, encompassing many forms of accidents. Between 2014 and 2024, the United States, a nation with significant oil and gas operations, documented several safety events [1]. The yearly incidence of events varied throughout this timeframe, signifying that risk persists and recurs. This highlights the necessity for thorough and ongoing focus on safety within the oil and gas sector. In natural gas pipeline and processing contexts, consequence modeling generally addresses two primary outcomes: fire and explosion [2]. Pool fires are commonly documented in fire scenarios, especially in cases involving the storage and release of flammable liquids [3].

Moreover, accident data reveal that fatalities stem from various causes, including transportation incidents (approximately 42%), contact with equipment or objects (25%), fires or explosions (14%), exposure to hazardous environments (9%), and falls from heights (8%) [4]. These patterns indicate that safety risks arise from intricate interactions among technical conditions, job behaviors, and organizational factors. Consequently, a comprehensive mitigation approach that encompasses technological, managerial, and behavioral dimensions is necessary to diminish both the number and severity of incidents, while also promoting the long-term goal of zero accidents.

Physical barriers provide a strategic function as the primary line of defense by obstructing direct contact between workers and sources of hazards, while also mitigating escalation during abnormal situations. The lack or ineffectiveness of physical barriers can elevate the probability of incidents; thus, the performance of barriers need careful consideration in the risk assessment procedure. A systematic analytical method is required to assess the efficacy of physical barriers, using Event Tree Analysis (ETA). ETA facilitates the systematic delineation of escalation pathways and consequence scenarios contingent upon the efficacy or ineffectiveness of safety functions. Jiang et al. integrated Fault Tree Analysis (FTA) and Event Tree Analysis (ETA), demonstrating that hydrocarbon leaks on offshore platforms can lead to many consequence scenarios, from safe conditions to uncontrolled releases [5]. The escalation level was significantly impacted by the efficacy of barriers, including leak protection, leak detection, automatic shutdown, and manual shutdown [5]. Likewise, Lee [6] utilized ETA and indicated that hydrocarbon leaks could progress from safe situations to catastrophic scenarios, including significant flames or explosions, contingent upon the efficacy of detection, protection, and mitigation measures. Layered failures across barriers greatly elevate the likelihood of severe outcomes, underscoring the necessity of enhancing barrier dependability to avert large occurrences and facilitate the goal of zero accidents [6].

While physical barriers serve as the principal line of defense, their existence alone cannot eradicate the potential for accidents, as human error continues to be a pivotal factor in operational safety. In risk modeling, human error is often inadequately reflected despite its significant impact to accidents. Empirical research indicates that human error is responsible for approximately 60–80% of significant accidents, whereas system faults contribute to roughly 20–40% [7]. This suggests that human variables may significantly influence industrial accidents and so necessitate explicit consideration in risk analysis and management. Rozuhan [8] evaluated the probabilistic risk of hydrocarbon discharge in offshore facilities that may result in flames or explosions. The research combined ETA with human reliability analysis (HRA) and modeled the integrated system using a Bayesian network (BN) to assess the influence of human error on total risk [8]. Tananta and Ramadhani assessed Hazard Risk Assessment (HRA) for fire and explosion hazards at gas stations by integrating Fault Tree Analysis (FTA) with the Success Likelihood Index Method (SLIM) [9]. Their findings found sixteen fundamental reasons, prominently including human-related issues such as procedural non-compliance and operator negligence. The maximum documented human error probability (HEP) was 0.0392 for errors associated with comprehending refuelling processes, although other errors stayed below acceptable thresholds [9]. The findings indicate that, despite a seemingly minor quantitative contribution, human-related issues are essential and must be addressed through training, enhanced compliance with standard operating procedures (SOPs), supervision, and regular inspections.

This research examines a vapor cloud explosion and fire incident at the BP-Husky Toledo Refinery in Toledo, Ohio, United States [10]. Prior research, notably by Khakzad [11] and Bui et al. [12], has illustrated various methodologies for risk assessments within the oil and gas sector. A prevalent technique is Bow-Tie Analysis (BTA), which combines Fault Tree Analysis (FTA) to ascertain initiating causes and Event Tree Analysis (ETA) to delineate the progression of consequences. BTA effectively maps escalation paths and identifies preventive and mitigative barriers; findings frequently indicate that equipment failure, human mistake, and inadequate control mechanisms are primary contributors to accidents [11]. Another method is Quantitative Risk Assessment (QRA), which often commences with hazard identification (e.g., Hazard Identification/HAZID) and is succeeded by frequency and consequence studies utilizing historical data and modeling tools. Quantitative Risk Assessment (QRA) results frequently identify hydrocarbon leaks as significant risk scenarios with the potential for catastrophic fires and explosions, underscoring the necessity for early detection systems, fire protection measures, and stringent operational protocols [12].

This study examines two complementary components to offer a more thorough depiction of risk: physical barriers and barriers related to human mistake. Human error is evaluated by SLIM, whereas ETA is utilized to build consequence scenarios depending on the processed fluid, the efficacy of safety functions, and additional pertinent aspects [13]. The aspects are subsequently integrated through a Bayesian network (BN) to elucidate their interdependencies and to predict accident probabilities while concurrently considering both contributions. The integration of physical barrier performance and human reliability within a unified analytical framework is still relatively rare; thus, this study aims to provide a novel perspective on industrial safety risk assessment.

This study intends to do a comprehensive investigation of the factors leading to fire and explosion incidents at the BP-Husky Toledo Refinery by utilizing SLIM and ETA combined via a Bayesian network (BN). The primary aim is to discover and assess the roles of human error and system failure, integrating both to achieve a holistic understanding of how physical and human-error barriers affect accident likelihood.

Event Tree Analysis (ETA)

Event Tree Analysis (ETA) is an inductive risk assessment technique employed to model an accident scenario, commencing with an initiating event and advancing through succeeding events or safety functions that may either succeed or fail, ultimately resulting in various end states or outcomes [14]. The approach is typically depicted as a branching structure, where each branch represents an alternate sequence of events subsequent to the starting event. This framework facilitates the thorough delineation of escalation routes, extending from benign results to the most catastrophic disaster situations. ETA was initially created and utilized by the U.S. Nuclear Regulatory Commission for probabilistic risk assessments of nuclear power plants, and it has since been extensively embraced in high-risk sectors including oil and gas, chemicals, and energy [15].

Figure 1 illustrates the Event Tree structure, depicting the correlation between the originating event and various potential consequence pathways. Figure 1 illustrates the typical application of the Event Tree Analysis (ETA) approach. A precipitating incident (PIE) activates the event tree, further scenario progression relies on the efficacy of successive safety barriers. Barrier 1 may either succeed (PB1s) or fail (PB1f); for each scenario, Barrier 2 may subsequently succeed (PB2s) or fail (PB2f), resulting in four potential outcomes (A–D). This method allows for the tracing of each consequence path originating from the initial event, contingent upon the efficacy or ineffectiveness of the safety barriers involved. Generally, paths exhibiting a greater number of barrier failures tend to signify more severe effects, while pathways with effective barriers reflect regulated or reduced scenarios. The likelihood of each outcome is determined by multiplying the chance of the initiating event by the probability of success or failure of each subsequent event in the event tree branch [16][17]. This quantification enables ETA to assess the impact of barrier performance on the probability of various consequence scenarios [16].

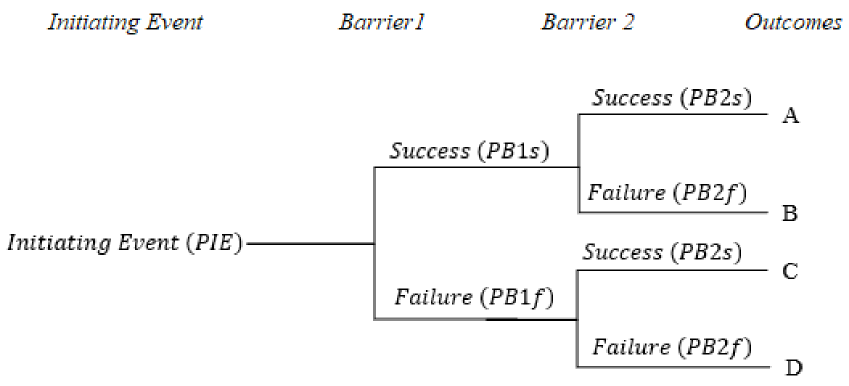


Figure 1. Visual Representation of Event Tree Structure [16]

Success Likelihood Index Method (SLIM)

The Success Likelihood Index Method (SLIM) is a Human Reliability Analysis (HRA) method that analyses the likelihood of human error occurring in a given situation based on the combined effects of some Performance Shaping Factors (PSF), which, although relatively small, can collectively significantly affect the probability of error [18]. The procedure for applying the Success Likelihood Index Method (SLIM) can be explained through the following systematic steps.

1. Define error modes and PSF

   Determining failure modes is carried out through a comprehensive identification process covering all stages of the task, considering potential oversights or errors. Once errors have been identified, the next step is to determine the relevant Performance Shaping Factors (PSF) and the potential risks they may pose.

2. Assigning weights to PSF

   Assigning weights to PSF is an important step because PSF significantly influences the level of success or failure in an analysis. The weighting process is carried out by assigning a value to each PSF in the range of 0 to 100, where the highest weight is given to the factor considered to be the most influential, followed by other factors according to their level of importance.

3. Ranking PSF

   Ranking PSF for each error mode is necessary to assess the extent to which these factors contribute to minimising the possibility of human error. The ranking assessment for each PSF is conducted independently, so that it does not depend on the values or rankings assigned to other PSFs.

4. Estimating the Success Likelihood Index (SLI)

   After the weighting and ranking stages have been carried out, the next step is estimating the Success Likelihood Index (SLI) value for each PSF. This calculation is done by multiplying the normalised PSF weight by the ranking value given to each PSF. The total SLI value is then obtained by summing the results of the multiplication of each PSF that has been analysed.

5. Converting SLI values into Human Error Probability (HEP)

   The SLI value obtained in the previous stage still represents a relative figure regarding the possibility of errors occurring, so it needs to be converted into a probability. This conversion process is carried out by standardising the SLI value using the following equation.

$$\log(POS_i) = a(SLI_i) + b \tag{1}$$

Equation 1 is used to estimate the logarithmic probability of success (POS). To do so, constants a and b are estimated by considering the best-case and worst-case scenarios.

Then, Equation 2 is used to estimate the final probability of success, while human error probability (HEP) is estimated using Equation 3.

$$POS = 10^{\log POS} \quad (2)$$

$$HEP = 1 - POS \quad (3)$$

Bayesian Network (BN)

A Bayesian Network (BN) is a probabilistic graphical model that represents relationships between variables in the form of a Directed Acyclic Graph (DAG) [19]. This model is based on probability theory and is used to support decision-making in conditions of uncertainty [20]. The probability of an event occurring, taking into account other events that have already occurred, is known as conditional probability [21]. The DAG structure in BN consists of two main components: nodes and arcs. Nodes represent variables and their relationships, while arcs indicate the direction of cause-and-effect relationships between variables in the network.

METHOD

This study applies the Success Likelihood Index Method (SLIM) and Event Tree Analysis (ETA) to analyse the contribution of human error barriers and physical barriers in fire and explosion incidents at PT BP Husky Toledo Refinery. In the SLIM approach, error-causing factors are identified through error modes and Performance Shaping Factors (PSFs), such as lack of experience, limited training, and absence of clear operational procedures. These factors are then weighted, assessed, and processed to obtain a Human Error Probability (HEP) value. Meanwhile, Event Tree Analysis (ETA) is used to evaluate errors from a physical system perspective, with failure scenario modelling that identifies impacts on the entire system. The data for determining each barrier is obtained from the process units through which the fluid passes during the sequence of events leading to the incident. Next, an integration between physical and human error barriers is achieved through the Bayesian Network (BN) approach, providing a comprehensive picture of the interaction between the two types of barriers and an estimate of the accident probability resulting from their combined effect. The methodological framework used in this study is shown in Figure 2, which illustrates the main stages of applying SLIM, ETA, and BN in assessing the probability of human error and system error.

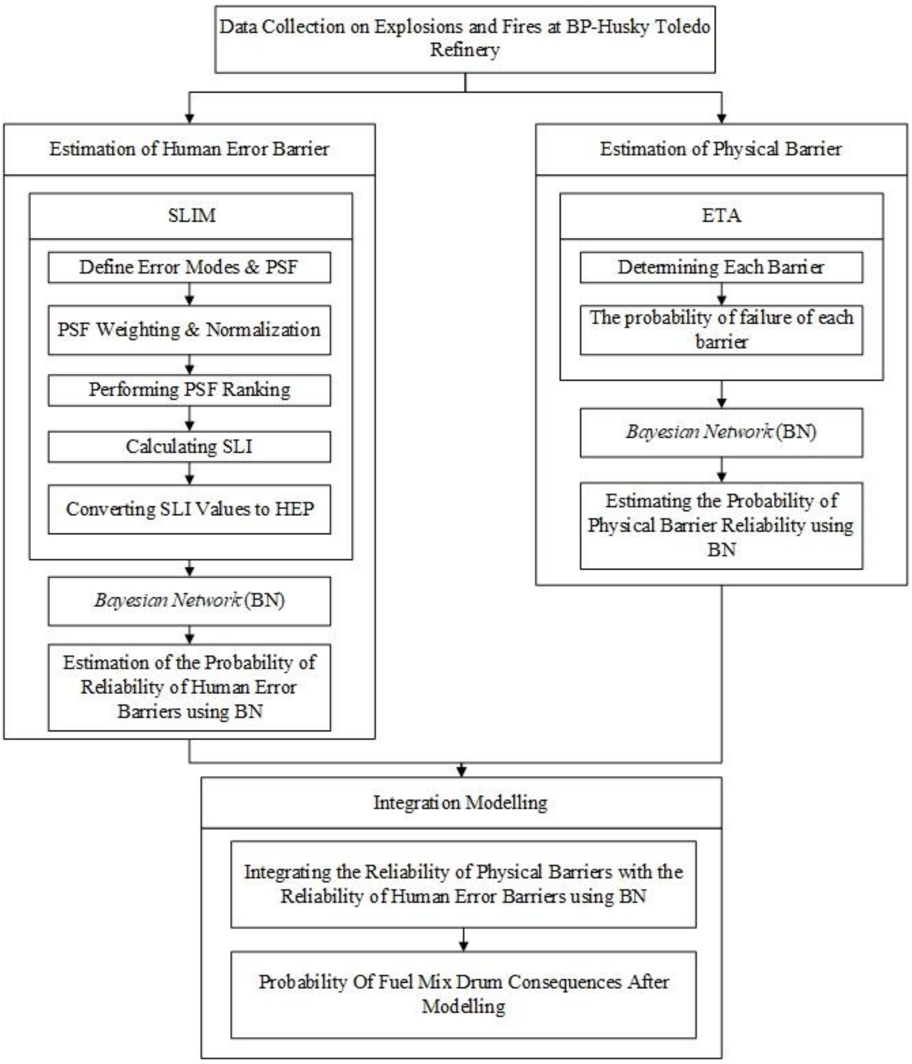


Figure 2. Conceptual Model

RESULT AND DISCUSSION

Integrating human error and physical barriers in the case of explosions and fires at the BP Husky Toledo Refinery produced outputs in the form of estimates of human error probabilities and probabilities of physical system aspects, accompanied by recommendations to reduce the probability of errors occurring in physical systems.

Result

The initial step in this research is data collection, which serves as the basis for getting the information needed to accomplish the research objectives. Data on the causes of the fire and explosion at the BP Husky Toledo Refinery were obtained from accident investigation reports, as shown in Table 1.

Table 1. Error Modes

NO.	ERROR MODES	Reference
1	When reading the water level sensor on the overhead accumulateer drum unit, the operator made an error.	[10]
2	The operator made a mistake while draining naphtha from the Fuel Gas Mix Drum unit.	[10]

3	The morning shift operator did not convey information about the activities carried out to the night shift operator.	[10]

Table 1 presents several failure modes identified in the fire and explosion incident at the BP Husky Toledo Refinery. Based on the data collected, the accident was analysed by classifying the causes of failure into three main categories: technical, human, and management factors. The next step was to conduct a Human Reliability Assessment (HRA) using the Success Likelihood Index Method (SLIM) to measure the probability of human error.

After identifying various error modes in the explosion and fire incident at the BP-Husky Toledo Refinery, the next step was determining the Performance Shaping Factors (PSF) affecting human performance. The PSFs used in this case are presented in Table 2.

Table 2. PSF Description

PSF	DESCRIPTION	Reference
Training	Operators did not receive retraining after the change in the type of water level sensor, resulting in limited operator knowledge about how the new sensor works.	[10]
Experience	Two workers who are inexperienced in performing drainage increase the probability of human error (HEP).	[10]
Procedure	Two operators drained the Fuel Gas Mix Drum unit without clear procedures on how to do so, resulting in mishandling that caused a fire and explosion.	[10]

The calculation process for each Success Likelihood Index (SLI), as shown in Table 3, is performed by multiplying the normalised weight of each Performance Shaping Factor (PSF) by its rank in each error mode, then summing the results of these multiplications. The SLI value ranges from 0 to 100, where 0 represents a high probability of failure, while 100 indicates a high probability of success in the analysed task step.

Table 3. SLI Calculation Based on PSF Weight and Error Modes

PSF	Normalised Weight	EM1	EM2	EM3	Reference
Training	0.37	90	70	60	[9] [22]
Experience	0.33	70	80	50	[9][22]
Procedure	0.30	85	90	70	[23]
SLI	1	81.90	79.30	59.70	

Table 4 presents the results of Human Error Probability (HEP) calculations based on various error modes, considering the best-case and worst-case scenarios. These calculations are based on constants ‘a’ and ‘b’ used to determine the logarithm of the probability of success, which is then converted into a probability of success value and HEP. The table shows that error modes with a lower probability of success have a higher HEP value, indicating a greater failure rate.

Table 4. HEP Value Calculation

Error Modes	HEP for the Best Case	HEP for the Worst Case	"a" Constant Value	"b" Constant Value	Log (Probability of Success)	Probability of Success	Human Error Probability
1	0.0740	0.2400	0.0009	-0.1192	-0.0489	0.8935	0.1065
2	0.0039	0.2200	0.0011	-0.1079	-0.0237	0.9469	0.0531
3	0.0033	0.2000	0.0010	-0.0969	-0.0399	0.9122	0.0878

After obtaining the Human Error Probability (HEP) value, the analysis continues by evaluating physical system aspects using Event Tree Analysis (ETA). The ETA method is used to describe various possible failure scenarios that may occur.

Figure 3 presents various possible failure scenarios along with the probability of each scenario. The probability values for physical system aspects were obtained based on data from OREDA and IOGP [24][25]. Potential consequences of these scenarios include near misses, flash fires, vapour cloud explosions, and ruptures.

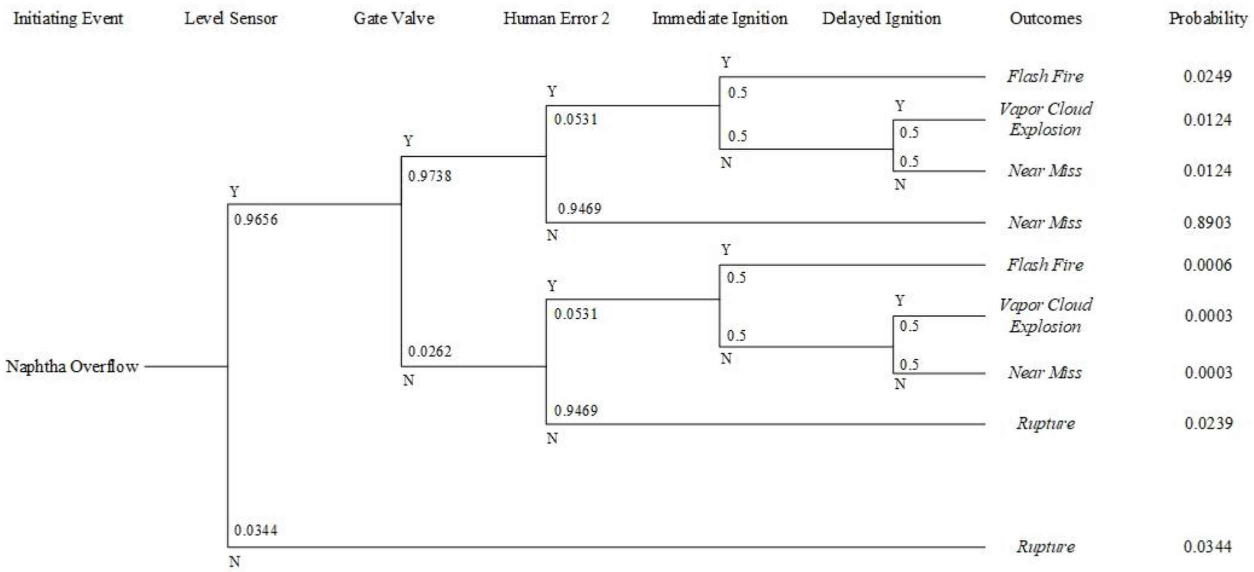


Figure 3. Event Tree Analysis

Subsequently, the probability values of physical and human error barriers are incorporated into the Bayesian Network to thoroughly elucidate the cause-and-effect relationship and assess the likelihood of accidents by merging both barrier types.

Figures 4 and 5 present the outcomes of the Genie software investigation about physical and human error barriers in Bayesian Networks (BN). The probability of consequences derived from the Directed Acyclic Graph (DAG) for the physical barrier BN indicates that the likelihood of a Near Miss is approximately 57%, Flash Fire is about 14%, Vapour Cloud Explosion is roughly 13%, and Rupture is around 16%. Simultaneously, the likelihood of errors leading to fluid leaking was determined to be 7% inside the human error barrier Directed Acyclic Graph (DAG). The research results indicate that each error mode exerts a distinct level of influence, with error mode 1 contributing the most at approximately 31%, followed by error mode 2 and error mode 3, each at around 30%.

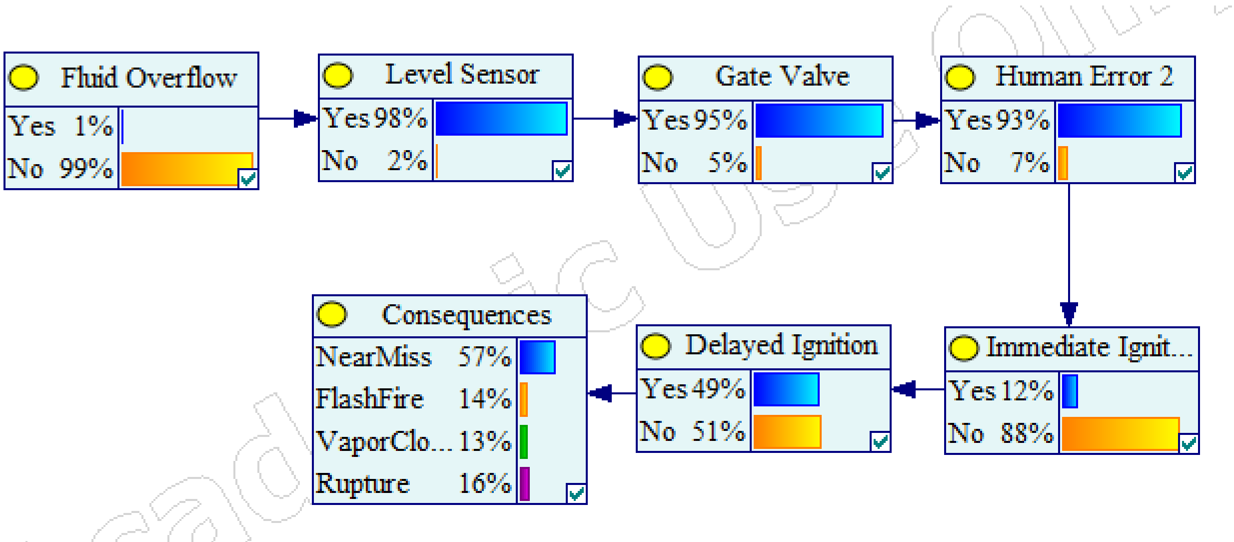


Figure 4. Bayesian Network Physical Barrier

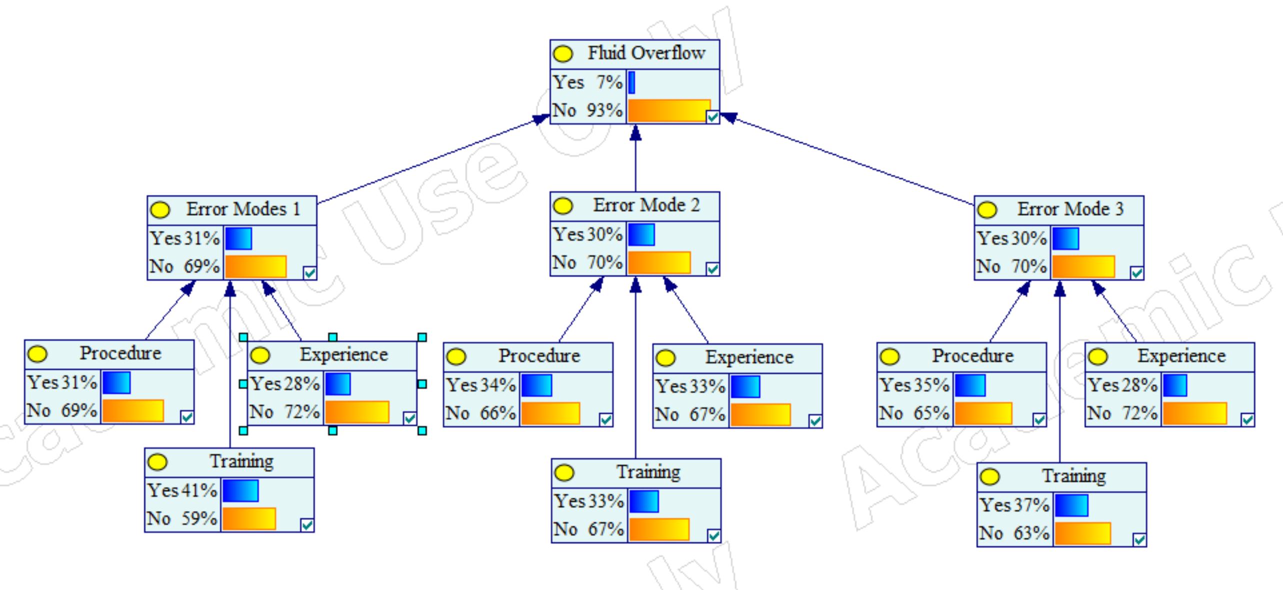


Figure 5. Bayesian Network Human Error Barrier

As shown in Figure 6, the integration of physical barriers and human error barriers provides a comprehensive overview of the interaction between these two types of barriers. This integration enables a more thorough evaluation of the probability of accidents occurring, while highlighting the relative contribution of technical and human factors in influencing the overall risk level of the system.

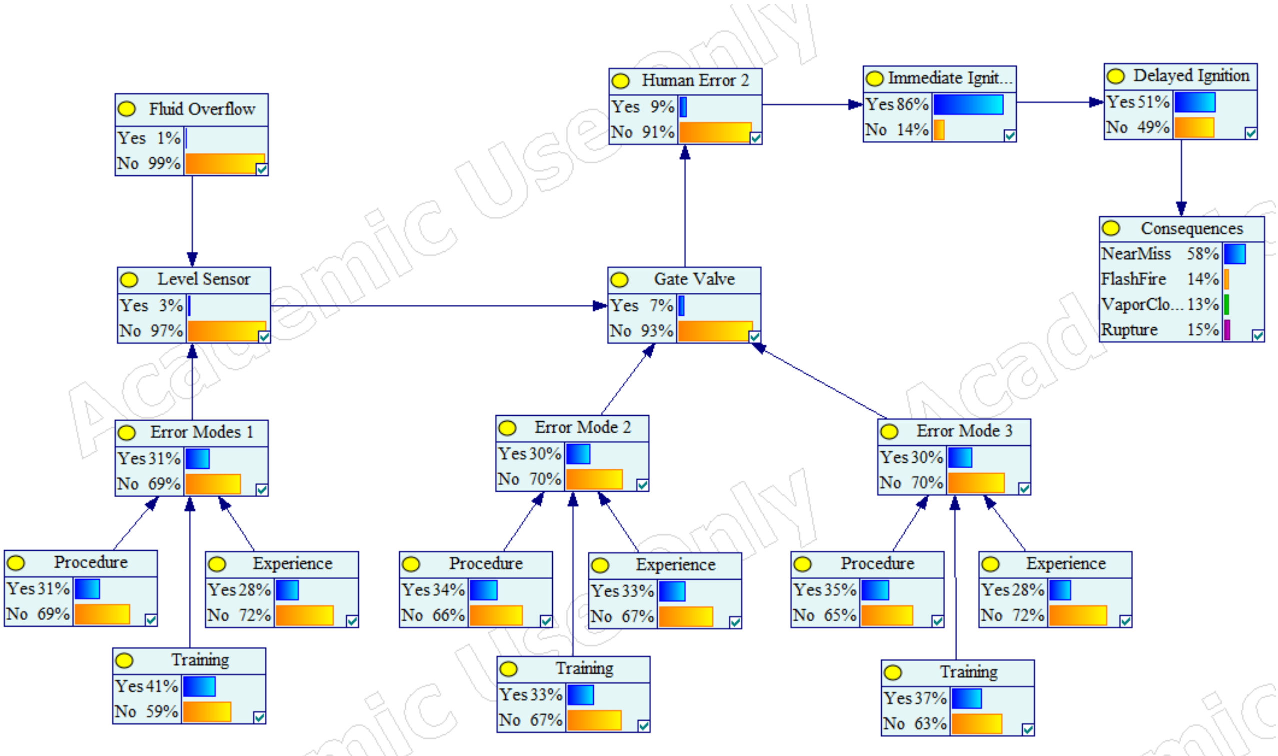


Figure 6. Bayesian Network Integration

Upon acquiring the analytical data from the current physical barriers, the subsequent stage involves their integration with the proposed physical barriers outlined in the CSB report [10]. This approach involves reorganizing the Event Tree Analysis (ETA) with the suggested barriers, subsequently incorporating human error barriers to achieve a more holistic understanding of risk likelihood. Figure 7 displays the revised ETA.

Figures 8 and 9 illustrate that the Event Tree Analysis (ETA) and Bayesian Network (BN) employing the suggested barriers yielded four potential outcomes: near miss, flash fire, vapor cloud explosion, and rupture. The probability values for each consequence were derived using physical system aspect data acquired from OREDA and IOGP [24][25]. One enhancement to this proposed barrier was replacing the gate valve with an automated valve, so augmenting the system's efficacy in averting failure escalation.

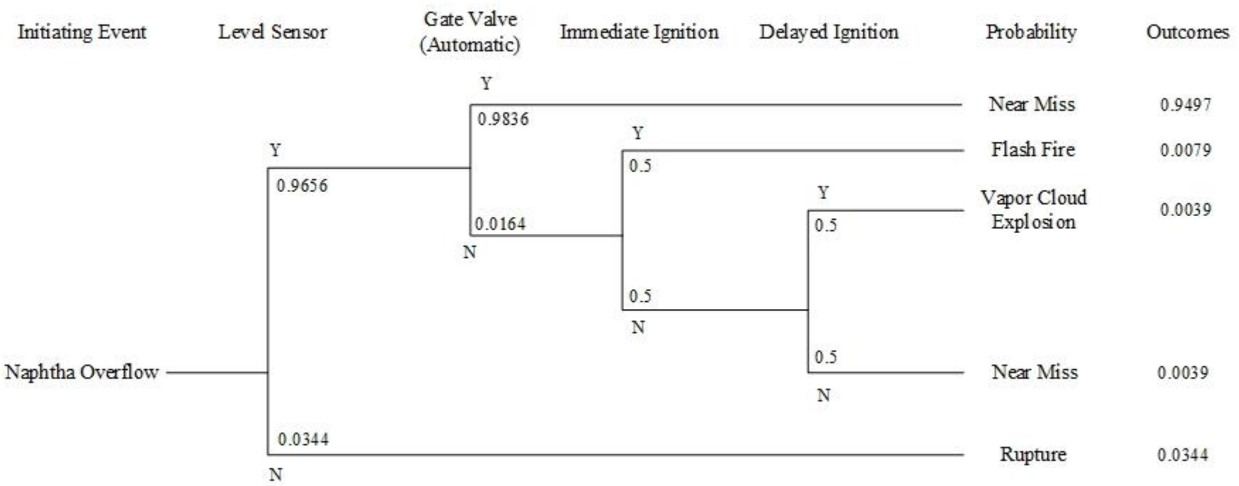


Figure 7. Event Tree Analysis Recommendation

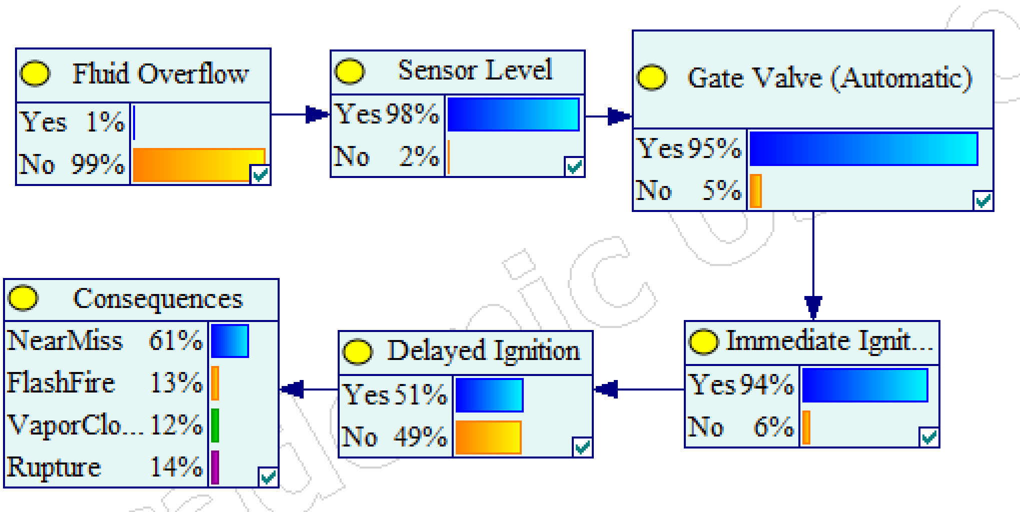


Figure 8. Bayesian Network Physical Barrier Recommendation

Figure 9 shows the results of the Bayesian Network (BN) representing the integration between physical barrier recommendations and human error barriers.

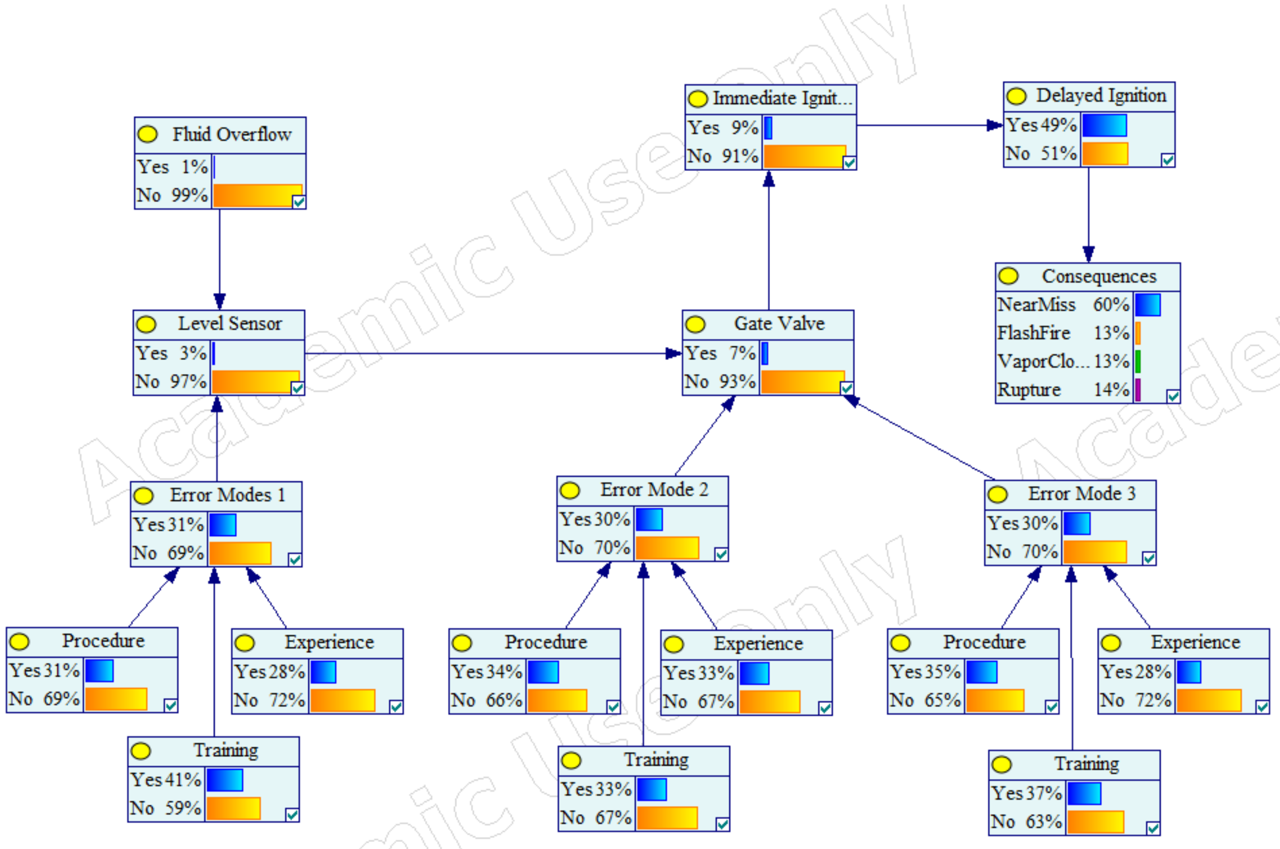


Figure 9. Bayesian Network Integration Recommendation

Discussion

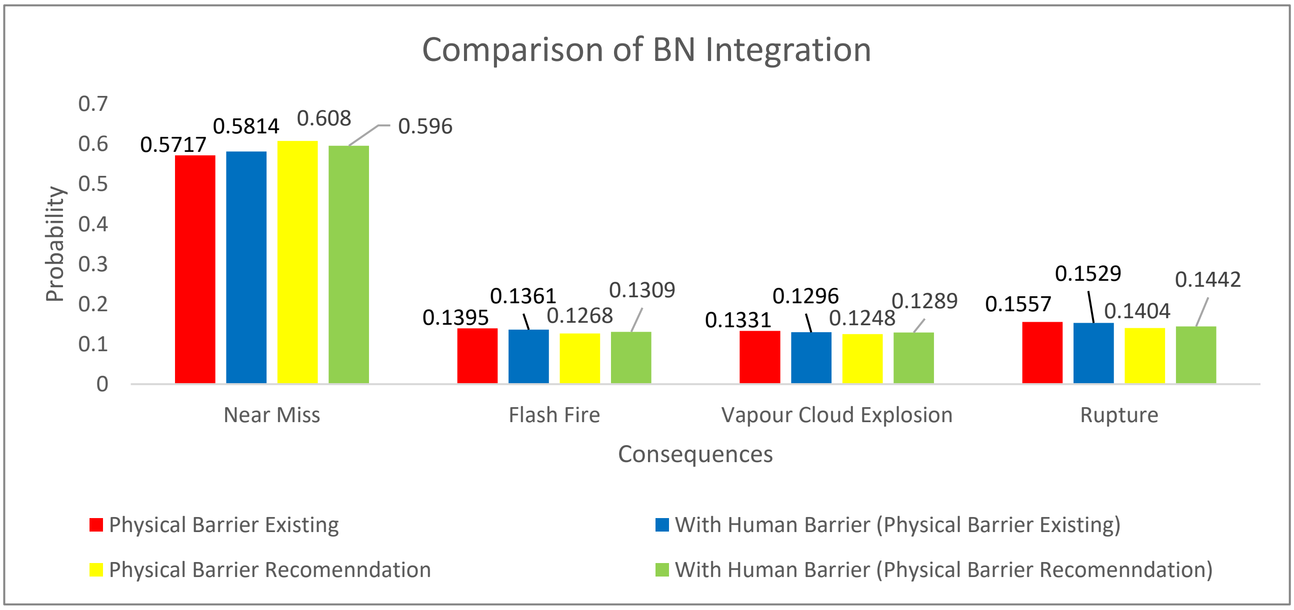
This study aimed to achieve a more comprehensive risk representation by incorporating physical barriers (ETA) and human-error-related barriers (SLIM) into a Bayesian network (BN) architecture. The findings suggest that the integrated framework effectively elucidates the interaction between technical and human contributions; yet, the supplementary human error barrier results in only negligible alterations to consequence probabilities. This section analyzes the implications of these results, correlates them with the discovered error processes, and contextualizes the findings in relation to prior research.

From the standpoint of human reliability, the identified error modes (Table 1) are directly associated with the accident narrative in the investigation report, encompassing operator misinterpretation of the water level sensor, errors during naphtha drainage, and inadequate shift handover communication [10]. These modes align with prevalent operational weaknesses in high-risk businesses, where atypical conditions and non-standard activities often impede operator performance. The Performance Shaping Factors (PSFs) delineated in Table 2, training, experience, and procedure, offer a credible rationale for the occurrence of these mistake patterns. The absence of retraining after a sensor modification and the lack of explicit draining protocols might significantly impair situational awareness and decision-making quality during crucial phases [10]. In SLIM, the PSFs are weighted and ranked (Table 3), and the resultant Human Error Probability (HEP) values (Table 4) demonstrate that the error modes do not contribute uniformly; one mode displays a higher HEP than the others, suggesting that a targeted intervention is likely to be more efficacious than generic training. This corresponds with the overarching principle of HRA approaches, which posits that performance is influenced by various contextual elements, such as competence, task clarity, and supervision—and that these elements can collectively alter error likelihood, even when each looks insignificant independently [18]. Comparable findings have been documented in SLIM-based systems, wherein procedural discipline and operator comprehension are identified as significant factors influencing mistake probability, hence necessitating prioritization for risk mitigation [9][23].

Moreover, from the standpoint of physical systems, the event tree models (Figures 3 and 7) illustrate that the progression of accidents is contingent upon the sequential efficacy of barriers, aligning with the fundamental principles of Event Tree Analysis (ETA). The consequence probabilities obtained from the physical barrier model are founded on reliability and ignition-related information [24][25], which offer a systematic framework for assessing the probability of various escalation routes. In Figures 4 and 6 (current physical barriers), the predominant outcome is the near-miss scenario, but flash fire, vapor cloud explosion, and rupture transpire with non-negligible probability. Analyzing these results through barrier logic, the near-miss condition can be perceived as instances where barrier functions (e.g., isolation, detection, shutdown, mitigation) operate adequately to avert escalation. This conclusion aligns with previous quantitative risk analyses indicating that combinations of barrier success and failure significantly affect the progression from a leak or release to severe fire or explosion scenarios [5][6]. Consequently, even in the presence of human error, the distribution of "system-level" consequences may predominantly be influenced by the reliability of engineering safeguards and ignition-related conditions depicted in the ETA/BN framework.

The recommended-barrier scenario (Figures 7–9) offers further insight: the implementation of the CSB-recommended modifications, such as substituting a gate valve with an automated valve, aims to enhance isolation efficacy and avert escalation [10]. Figure 10 illustrates this enhancement through a transition towards less severe outcomes: the near-miss chance escalates in the scenario with the proposed physical barrier, yet the probabilities of flash fire, vapor cloud explosion, and rupture diminish. This trend aligns with the hypothesis that enhancing a preventative or mitigative barrier elevates the likelihood of containing a release scenario prior to its escalation into fire or explosion consequences [5][6]. The alterations are notably moderate rather than extreme, which is justifiable considering that the probabilities of consequences result from various conditional events along the scenario pathways; enhancing one barrier affects only a segment of the overall path probability, while other barriers and conditional events continue to influence the final distribution [24][25].

A key finding of this study is that integrating the human error barrier into the BN produces only slight shifts in the consequence probabilities for both the existing and recommended physical barrier configurations (Figures 5, 6, 8, 9, and 10). This suggests that, within the current model structure and parameterization, the human-error-related contribution acts as an additional layer but does not dominate the consequence distribution. This outcome is consistent with Rozuhan et al. [8], who also reported that adding a human error barrier changed a safe-condition probability only modestly (from 0.9873 to approximately 0.9672). One plausible interpretation is that the physical barrier pathways and their conditional probabilities already determine much of the scenario outcome space, while the human-error barrier, modelled as a single integrated element in the BN, adjusts the outcome probabilities only incrementally. This does not contradict the broader empirical observation that human error can contribute substantially to major accidents [7]; rather, it indicates that the magnitude of the human contribution estimated by the model depends on (i) how human actions are represented (e.g., aggregated vs. task-specific nodes), and (ii) how strongly those nodes are connected to escalation pathways in the integrated BN. In other words, the present modelling approach may capture human contribution as an auxiliary modifier rather than a primary driver of escalation probabilities.



Despite the relatively small quantitative effect on consequence probabilities, integrating SLIM with ETA via BN remains practically valuable. First, the SLIM outputs identify which human performance factors most plausibly increase error likelihood (Tables 2–4), enabling targeted recommendations such as retraining after instrument changes, establishing clear procedures for abnormal draining operations, and strengthening shift handover protocols [10]. Second, the integrated BN provides a transparent structure for "what-if" evaluation: changes to either physical barriers (Figures 7–9) or human factors (Tables 2–4) can be propagated to observe their influence on consequence likelihoods (Figure 10). For future work, the discussion above indicates that using alternative HRA techniques and/or a more granular representation of human tasks may yield a different sensitivity of consequences to human factors, which is consistent with the diversity of HRA methods and their modelling assumptions [13][18]. Further validation using different parameter sources or modelling strategies may also improve confidence in the quantified influence of human barriers.

CONCLUSION AND RECOMMENDATION

Conclusion

This study formulated and implemented a comprehensive framework that amalgamates Event Tree Analysis (ETA) for physical barriers with the Success Likelihood Index Method (SLIM) for human reliability, which were then synthesized using a Bayesian Network (BN) to evaluate the likelihood of fire- and explosion-related outcomes at the BP-Husky Toledo Refinery. The BN results reveal that the consequence distribution is predominantly characterized by near-miss outcomes (about 57%), although flash fire (≈14%), vapor cloud explosion (≈13%), and rupture (≈16%) represent significant escalation scenarios. Following the incorporation of the human error barrier, the general distribution exhibits only slight alterations (near miss ≈58% and rupture ≈15%, whereas flash fire and vapor cloud explosion persist at approximately 14% and 13%, respectively). The findings indicate that, given the examined scenario and model structure, the incorporation of a human error barrier does not substantially diminish the odds of consequences. Nonetheless, this does not undermine the need of incorporating human and physical boundaries. The integrated ETA–SLIM–BN methodology offers a more thorough depiction of risk by considering human reliability as an extra layer of protection that enhances engineered safeguards. The approach facilitates a systematic "what-if" analysis of barrier enhancements and human-factor interventions, providing a more definitive foundation for prioritizing risk mitigation strategies and bolstering overall system resilience in high-hazard processing facilities.

Recommendation

Future research should assess the amalgamation of human and physical barriers through supplementary Human Reliability Analysis (HRA) methodologies and different modeling frameworks. Specifically, since SLIM-based integration resulted in minor alterations in consequence probabilities, juxtaposing SLIM with alternative HRA methodologies and modeling human actions in a more task-specific manner within the Bayesian Network may yield a more nuanced and accurate assessment of human impact on overall system risk. Subsequent research may enhance validation via supplementary case studies and parameter-sensitivity analysis to bolster confidence in the measured impact of human obstacles on escalation results.

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