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A Methodology for Risk Analysis Based on Hybrid Bayesian Networks: Application to the Regasification System of Liquefied Natural Gas Onboard a Floating Storage and Regasification Unit

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This article presents an iterative six-step risk analysis methodology based on hybrid Bayesian networks (BNs). In typical risk analysis, systems are usually modeled as discrete and Boolean variables with constant failure rates via fault trees. Nevertheless, in many cases, it is not possible to perform an efficient analysis using only discrete and Boolean variables. The approach put forward by the proposed methodology makes use of BNs and incorporates recent developments that facilitate the use of continuous variables whose values may have any probability distributions. Thus, this approach makes the methodology particularly useful in cases where the available data for quantification of hazardous events probabilities are scarce or nonexistent, there is dependence among events, or when nonbinary events are involved. The methodology is applied to the risk analysis of a regasification system of liquefied natural gas (LNG) on board an FSRU (floating, storage, and regasification unit). LNG is becoming an important energy source option and the world's capacity to produce LNG is surging. Large reserves of natural gas exist worldwide, particularly in areas where the resources exceed the demand. Thus, this natural gas is liquefied for shipping and the storage and regasification process usually occurs at onshore plants. However, a new option for LNG storage and regasification has been proposed: the FSRU. As very few FSRUs have been put into operation, relevant failure data on FSRU systems are scarce. The results show the usefulness of the proposed methodology for cases where the risk analysis must be performed under considerable uncertainty.

KEY WORDS: Bayesian networks; FSRU; LNG regasification; reliability analysis; risk analysis

1. INTRODUCTION

Bayesian networks (BNs) provide powerful probabilistic methods to build causal relationships between events and model the failure modes of a system, facilitating the creation of a rational framework for a decision analysis under risk. This article proposes a methodology to perform risk analysis using BNs and, as an application, perform the risk analysis of flammable substance leakage in a regasification system on board a floating, storage and regasification unit (FSRU).

The risk could be presented as the product of the probability of the occurrence of undesired events and the magnitude of their consequences. Traditionally, fault tree analysis (FTA) is used to estimate

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the probability of an event. FTA can be used in both qualitative and quantitative analyses. Using a qualitative approach, FTA can determine the logic leading to any event, while the quantitative approach assesses the probability of the occurrence of the top and intermediary events. However, FTA has some limitations: only binary variables are used, conditional dependencies are not represented, a diagnostic analysis is not possible, and multistate or continuous variables are not properly modeled. Since BNs do not have these limitations, it is possible to conduct a more realistic analysis using this method.[1]

A BN is a direct acyclic graph (DAG) in which the nodes are the variables and the arcs represent conditional dependencies;[2] thus, the events are not necessarily independent, as it is assumed when FT is used. The BN qualitative analysis determines the relationships between the nodes, and the quantitative analysis can be performed in two ways: a predictive analysis, in which the probability of any node is calculated based on its parent nodes and the conditional dependencies, or a diagnostic analysis, in which the probability of any set of variables is calculated based on some evidence.[3–5]

In addition, the BN can also represent uncertain knowledge, which is important for systems with no failure history, such as new or recent processes. Moreover, the BN facilitates the modeling of continuous variables, while FT is only capable to deal with discrete (binary) variables and it is not complex to model common cause failures (CCF) using BNs.

As FT is traditionally used to estimate the probability of the occurrence of events, this study proposes the conversion of FT into BNs to take advantage of the familiarity that most analysts have with FT, although it is possible to build the BN directly from the analysis of the system.

To perform the risk analysis of leakage in the liquefied natural gas (LNG) regasification system onboard an FSRU, this article estimates the probabilities of the undesired events using a BN and then estimates the consequences of the analyzed events. The consequence is a measure of the impact of the undesired events, and the range of effects might include harm to people, damage to equipment and land, or facility contamination; however, in this study, the focus is the harm to people. The consequences of the leakage are quantified using models available in the literature that evaluate the discharge, pool formation, and its evaporation; dispersion; and the thermal radiation generated through potential fires or explosions.[6–15]

The first regasification system on board an LNG carrier was recently introduced in Brazil, and an FSRU has been used as an offshore terminal to store and regasify the LNG; thus, the analysis of this system is important. As a pioneering process, regasification on board an FSRU carries some additional uncertainties and the risk analysis of this system is justified.

LNG is becoming an important energy source option, and the demand for energy of all types has increased. In addition, the world's capacity to produce LNG is surging. Large reserves of natural gas exist worldwide, particularly in areas in which there is no market or where the resources exceed the demand; this natural gas is liquefied for shipping to areas where there is a demand. Thus, the storage and regasification process usually occurs at onshore plants, where the LNG is stored in a double-walled storage tank under atmospheric pressure until needed. Subsequently, LNG is pumped at a higher pressure and warmed until it returns to a gas state. A new option for LNG storage and regasification has been proposed: the FSRU. The FSRU provides an economic and flexible option for the storage and regasification process, as an FSRU costs less than an onshore facility of a similar capacity, thereby providing a faster return on the capital invested because the time typically used for planning is saved and the construction time is reduced, assuming the conversion of an existing LNG carrier. FSRUs are also a flexible solution, as they can be moved from one demand area to another, which is an attractive feature in countries with seasonal demand or where there is an unstable market. Additionally, the FSRU might significantly reduce the total risk compared with an onshore plant, which considerably impacts neighboring areas and populations (this risk might be even worse due to the possibility of terrorist attacks).

This article proposes a methodology to perform quantitative risk analysis based on BNs and explores the capabilities of a recently developed extension of BNs to evaluate risks. This article also applies the proposed methodology to a real case analyzing a regasification system onboard an FSRU.

2. COMPARATIVE ANALYSIS BETWEEN BNS AND FT

The BN is used in this study to estimate the probability of the occurrence of undesired events.

An overview of FT and BN is presented, followed by a brief explanation of the conversion of FT into BN. Benefits and limitations of both techniques are presented.

2.1. Fault Tree Analysis (FTA)

FTA is a widely used technique for the dependability modeling of large systems. According to ABS,[16] FTA is a deductive analysis that graphically models (using Boolean logic) the combinations of equipment failures, human errors, and external events that cause specific mishaps. FTA uses a diagram to verify the causes of an event; and knowing the failure rates, it is possible to calculate the probability of the undesired event (top event) that was selected for qualitative and quantitative analysis. An FTA assumes that all events are binary events (working or not working), one event is statistically independent from all others, and the relationships among the events and their causes can be represented using logical AND and OR gates. Other gates are formed through the association of AND and OR gates, that is, the NOR gate, which is the negation of an OR gate, where the output occurs if none of the inputs occur. In addition, although FT provides an efficient method for representing the causes of symptoms and simultaneously considers the existence of several faults, this method is incapable of determining the sequential ordering of component failures that lead to system failures. Thus, dynamic fault trees (DFT) were developed to address these limitations, in which the analytical solution is obtained through conversion into the equivalent Markov process, where a state-space model is generated by the combination of the occurrence of all possible events and their transition probabilities (defined by the component failure rates). However, this approach has two significant limitations: the state space grows exponentially with the increasing number of modeled events, and it is difficult to model variables that exhibit nonexponential failure distributions.[1] Assumptions that might limit analyses using FT and DFT are not necessary when a BN is used, which facilitates the inclusion of multistates, continuous variables, and local conditional dependencies and considers the sequential ordering of the occurrence of the components' failures.

2.2. Bayesian Networks (BNs)

Neapolitan[2] defines the BN as a graphical structure for representing probabilistic relationships among a large number of variables and making probabilistic inferences using those variables. A BN is a DAG with the nodes representing the variables and arcs representing their conditional dependencies. The BN qualitative analysis determines the relationships among the nodes, while the quantitative analysis might be performed in two ways: a predictive analysis or a diagnostic analysis. The predictive analysis calculates the probability of any node based on parent nodes and conditional dependencies, while the diagnostic analysis calculates the probability of any set of variables given some evidence. The nodes and arcs are the qualitative components of the networks and provide a set of conditional independence assumptions that can be represented through a graph notion called d-separation, where each arc built from variable X to Y is directly dependent, that is, a cause-effect relationship.

If the variables are discrete, then the probabilistic relationship of each node X with its respective parents pa (X) is defined using a conditional probability table (CPT). For continuous variables, the conditional probability distribution (CPD), which represents conditional probability density functions, defines this probabilistic relationship, and the quantitative analysis is based on a conditional independence assumption. Considering three random variables X, Y, and Z, X is conditionally independent of Y given Z if $P(X,Y|Z) = P(X|Z)P(Y|Z)$. The joint probability distribution of a set of variables, based on their conditional independence, can be factorized as shown in Equation (1):

$$P\left[x_1, x_2, ..., x_n\right] = \prod_{i=1}^{n} P\left[x_i \,|\, Parent\,(x_i)\right]. \quad (1)$$

The graphical representation is the bridging of the gap between (high-level) conditional independence statements encoded in the model and (low-level) constraints, which enforce the CPD.[3]

Given some evidence, the beliefs are recalculated to indicate their impact on the network. The possibility of using evidence from the system to reassess the probabilities of network events is another important feature of BNs, which is useful to determine critical points in the system. Classical methods of inference of a BN for this purpose involve the computation of the posterior marginal probability distribution of each component, the posterior joint probability distribution of subsets of components, and the posterior joint probability distribution of the set of all nodes. Jones *et al.* proposed that the analysis and propagation of evidence, using BN, are useful to explore or preview system behaviors that are unknown or require more attention.(4)

In recent years, the number of studies presenting the use of BNs in risk analysis has increased;(16–22) traditional models, such as fault trees and block diagrams, have been replaced with discrete BN. However, the efficient application of BNs in risk assessment requires the use of hybrid models formed with discrete and continuous variables. The evaluation of hybrid networks offers a challenge, as inference algorithms have limitations, such as dealing with state-space explosion and finding an appropriate discretization. However, a new and efficient dynamic discretization of the domain and an iterative approximation method to refine discretization in the regions that contribute more to the structure of the density functions associated with a robust propagation algorithm have been proposed by Marquez *et al.*(1) In this approach, the BN considers any probability distribution function, unlike the traditional tools, which, in practice, consider only exponential distributions; these considerations are implemented in the commercial BN software package, AgenaRisk,(23) which is used in this study. There are other commercial tools for the calculation of BNs, such as Netica(24) and Hugin.(25) However, these tools do not apply the dynamic discretization mentioned above, and thus, the software AgenaRisk was used in this study. It is worth noting that this method is approximate and the accuracy of the results should be verified according to the scenario evaluated. Marquez *et al.*(1) present a comparison between numerical and BN results of eight examples and Neil *et al.*(26) discuss about the accuracy of hybrid BN. Additionally, in the Appendix, an example is presented and discussed to better illustrate this issue. Moreover, Jensen and Nielsen(27) is an excellent reference for the theoretical aspects of BNs and algorithms.

Notably, BNs are efficient to model multistate variables, local dependencies, CCFs, and limited or incomplete knowledge. Multistate variables and local dependencies are important to generate a more realistic model, whereas traditional tools typically use only binary variables and are unable to represent local dependencies (e.g., to represent how the malfunction of one piece of equipment affects other equipment). CCFs affect the reliability system because they cause the failure of more than one component, which can render redundancy protection useless (details concerning CCFs have been previously reported by Fleming,(28) Smith,(29) and TNO(30)). Occasionally, there are not enough or satisfactory statistical data available about the system to perform a reliability analysis; thus, BN analysts ask relevant questions to a group of specialists and explain the assumptions that are encoded in the model, and domain experts supply their knowledge to the analysts.(31,32)

The risk analysis presented in this article explores the benefits of the BN, such as modeling with continuous variables, the propagation of evidence, and the representation of local dependencies; such approach would not be possible with the use of FT, due to the limitations presented in item 0.

2.3. Converting an FT into a BN

Although it is possible to build the BN directly from the analysis of the system, the conversion of an FT into a BN takes advantage of the familiarity that most analysts have with FT to build the first version of the BN of the system under consideration.

Converting FT into a BN is not a complex process, and any analysis performed using FT can also be performed with BN inference.(3,7) However, as mentioned earlier, BNs offer some additional advantages, such as the possibility of including local dependencies, multistate variables, uncertainty, and dependencies among elements that can be included in the BN after the conversion.

The first step to translate an FT into a BN is to create a corresponding node(5)for each event and base elements (primary event/component) in the FT. Even if the same base element is represented more than once in the FT, only one node must be created in the BN. The second step is to connect the nodes as the gates are connected in FT. The third step is building a CPT for each node according to the logic gates in the FT. In Figs. 1 (a) and (b) the CPT is assigned to nodes connected through AND and OR gates. The gates represent deterministic relationships; therefore, the entries are either 0 or 1, where 1 denotes a failure and 0 denotes working. The other FT gates must be converted into OR and AND gates before converting FT into BN. Moreover, the logic gates might not be deterministic;(1) if there is uncertainty associated with the event, this uncertainty might be considered on CPT, as shown in Fig. 1(c). Lampis and Andrews(17) and Martins *et al.*(20) translate an FT into a BN that is used to develop a system fault diagnostics.

Additionally, BN facilitates the use of continuous variables; in this case, the prior probabilities are replaced with probability density functions, and the

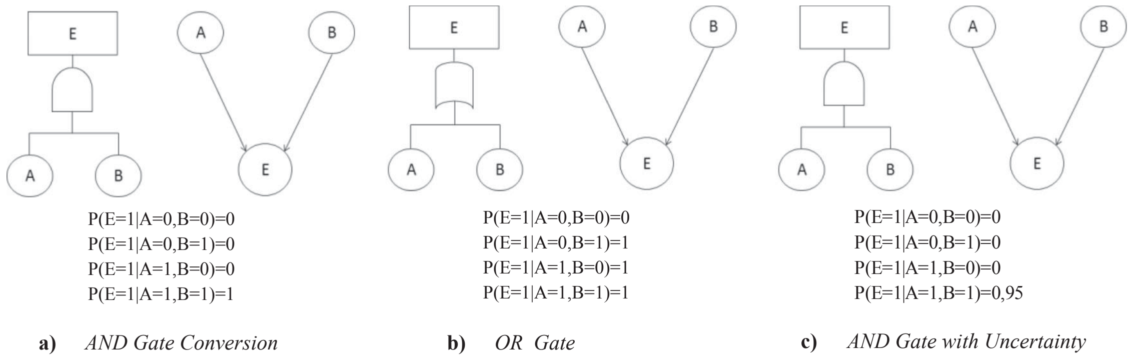

Fig. 1. Converting an FT into a BN.

relationships between components are represented through basic constructs, such as the AND and OR gates used in FT.[1] The AND gate, where the output will fail when all input components fail, has a probability of output failure in the time interval $[0, t]$, given by:

$$\begin{aligned} P(\zeta_{\text{AND}} \leq t) &= P(\zeta_1 \leq t, \cdots \ldots, \zeta_n \leq t) \\ &= P(\max\{\zeta_i\} \leq t), \end{aligned} \tag{2}$$

where ζ_{AND} is the time to failure (TTF) of AND gate and ζ_i is the TTF of component i.

The OR gate, where the output will fail if at least one input component fails, has a probability of output failure in the time interval $[0, t]$, given by:

$$\begin{aligned} P(\zeta_{\text{OR}} \leq t) &= 1 - P(\zeta_1 > t, \cdots \ldots, \zeta_n > t) \\ &= P(\min\{\zeta_i\} \leq t), \end{aligned} \tag{3}$$

where ζ_{OR} is the TTF of OR gate and ζ_i is the TTF of component i.

3. PROPOSED METHODOLOGY

The proposed methodology is a combination of different techniques based on the proposals of different authors,[1,3,6,12] which resulted in the formation of an iterative six-step methodology: familiarization, qualitative analysis, probabilsity estimation for undesired events, consequences analysis, risk evaluation, and mitigation measures.

Step 1—Familiarization

In this step, the available information concerning the system and its operation must be collected. The review of the existing data (documentation and expert opinion) should be performed and, if possible, a visit to the site where the system is or will be installed is also recommended.

Step 2—Qualitative analysis

In the second step, the relationship between the system components must be identified. The qualitative analysis must provide a clear view of the system and identify the relationships between system elements; in the proposed methodology, this representation should be accomplished by building a hybrid BN. As mentioned in Section 2.3, the BN can be built by the conversion of an FT into a BN or directly.

Step 3—Undesired events probability estimation

In the estimation of the probability of undesired events, the priori probabilities are included in the BN, the associated conditional probabilities are defined, and the joint probability of a set of variables is evaluated. If there is any evidence, then it is included in the BN, and the conditional probabilities are evaluated. In this step, a criticality analysis and an analysis of different scenarios may be performed by evaluating the posterior probabilities, which allows for an improvement of the analysis through an evaluation that is not possible using traditional tools, such as FT. The criticality analysis aims at finding the set of components or subsystems that have greater influence in the system behavior. The analysis of different scenarios can be used to model any situation of interest, such as the impact of including redundancies, the impact of a component fault, the system behavior over time, or any other condition that affects the system and can cause a undesired event. It allows, for example, including information about previous operation time of a piece of equipment that may increase the probability of an undesired event over time (note that this is not possible in an FT analysis).

Step 4—Consequences analysis

The consequence is the measure of the impact of the undesired events, and this article estimates the consequences of the leakage of flammable substances from the regasification system onboard an FSRU. The analysis will focus on harm to people due to the effects of fires that can occur as a consequence of the leakage of propane or natural gas from the regasification system.

When a flammable liquid is released from a storage tank or pipeline, a liquid pool might form. As the pool forms, some of the liquid will evaporate and disperse. If the flammable vapor encounters an ignition source while its concentration is between the lower and upper flammability limits (LFLs and UFLs), a flash fire will occur, and the flame can travel back to the spill, resulting in a pool fire. A pool fire involves burning of the vapor above the liquid pool as it evaporates from the pool and mixes with air. This sequence is described by Pitblado *et al.*(6)

In the case of flash fire, the potential to injure individuals is restricted within the ignited gas cloud, and for pool fire, the potential for fatalities reflects the exposure to heat radiation. To estimate the consequences, we will consider whether the vapor cloud encounters an ignition source, which occurs when the concentration equals the LFL, and reaches the maximum dispersion area (i.e., the most pessimistic scenario).

At this point, it is important to note that the scenarios described in this study consider that there is no immediate ignition; however, if an immediate ignition occurs and the flammable substance is released in the form of jet, then a jet fire will form. As in the case of the pool fire, the potential for fatalities reflects the exposure to heat radiation. Different consequences models are used to estimate the consequences according to the scenario. The models used to perform the consequences analysis of the real case studied in this article are presented in Section 4.4.

Step 5—Risk evaluation

In the fifth step of the proposed methodology, the product of the probability of the occurrence of undesired events and the magnitude of their consequences is used to calculate the risk. When the focus is on harm to people, the overall risk might be quantified in terms of individual or societal risks. The societal risk represents the risk to the community (the specific population affected by the consequences analyzed), while the individual risk represents the risk to an individual at a specific point.

These values are useful to make decisions about the location of terminals where the FSRU might operate. As reported in TNO(33) and Worthington,(34) in case of a flash fire, the potential of fatalities is restricted to the area within the ignited gas cloud but with a 100% probability, and in the case of a pool fire, the potential for fatalities reflects the exposure to thermal radiation with a 100% probability within an area with a radiation magnitude greater than or equal to 35 kW/m^2. In areas with less than 35 kW/m^2 of radiation, the probability of death is evaluated using the Probit function, which converts a dose level to a probability of death as a function of the radiation level and the exposure time (see Worthington(34)).

Step 6—Mitigation measures

Finally, in the last step, the BNs are used to identify critical components and propose mitigation measures. BN facilitates the analysis and propagation of evidence and examination of different scenarios. Given any evidence, such as a system failure, the beliefs are recalculated to indicate its impact on the network. At this point, the process returns to step 3, and the subsequent steps in the process are repeated until the desired level of risk is obtained.

Fig. 2 presents an overview of the methodology steps, which is divided into two parts: the first enumerates the tasks performed in each step, and the second lists the means suggested for these tasks.

4. APPLICATION OF THE PROPOSED METHODOLOGY

In this section, the risk analysis of a leak in the LNG regasification system onboard an FSRU is performed using the methodology described in the previous section. First, information collected about the system is presented. Then, a qualitative analysis is performed. Subsequently, the undesired events (leaks) probabilities are estimated for a given mission time using BN, followed by a quantitative consequences analysis. Finally, the risk is evaluated, mitigation measures are proposed, and the risk is revaluated.

	Step 1 *Familiarization*	Step 2 *Qualitative Analysis*	Step 3 *Undesired Events Probability Estimation*	Step 4 *Consequences Analysis*	Step 5 *Risk Evaluation*	Step 6 *Mitigation Measures*
Tasks	Understand the system and identify possible scenarios to which the system will be submitted.	Represent physically and functionally the system; Represent the relationships between system elements.	Complete the BN with quantitative data (priories, CPT and density functions); Estimate the probability density of the undesired events; Include evidence in the BN and evaluate the conditional probabilities.	Estimate the probable consequences of the undesired events.	Evaluate the risk associated with the facility or system analyzed. (This article is focused on the individual risk.)	Identify critical components and then propose mitigation measures.
Means	Data review; Interviews with experts.	Functional tree; Unifilar diagram; Block diagram; Fault tree; Bayesian network.	Bayesian network (inference).	Discharge, pool formation dispersion, flash fire, and pool fire models.	Association of steps 3 and 4.	Bayesian network (inference considering evidence).

Fig. 2. Methodology summary.

4.1. Familiarization

Typically, vessels are used for LNG transportation; however, in recent years, these vessels also began to participate in the regasification and direct supply to net pipes. The regasification process onboard an FSRU creates additional hazards to the operation of LNG vessels because, in addition to LNG, compressed gas and the presence of propane have been added to the process. Accidents in this process might reach the storage tanks, generating severe consequences. Natacci *et al.* report the consequences of a catastrophic rupture of one, two and three LNG tanks.[35]

In the vessel studied, a cascade system was used to regasify the LNG. In this system, the LNG is heated in two stages. In the first stage, a propane compact heat exchanger (HE1) is used to heat the LNG, and its temperature is increased from −162 °C to −10 °C; at this stage, the natural gas is already vaporized, but this temperature is too low for delivery to the pipeline. In the next stage, sea water is used to heat the gas in a shell-and-tube heat exchanger (HE2), and the temperature reaches 15 °C. The first stage uses no water due to the possibility of freezing when in direct contact with the LNG. Subsequently, the natural gas passes through an accumulator, and if there is still a portion of liquid, then this liquid is returned to the tank through gravity. Next, the gas is compressed and delivered to the gas pipeline. The propane used in the first phase works in a closed loop. When the propane leaves the LNG heat exchanger HE1, its temperature is approximately –5 °C, and it is liquefied (propane at 4.7 bar liquefies at approximately –5 °C). Hence, the propane is pumped into a titanium heat exchanger (HE3) and vaporizes when heated to 10 °C using sea water at 4.7 bar. The propane is subsequently returned to the LNG exchanger HE1. This system must have an effective thermal insulation to avoid an unexpected heat gain of the LNG or propane inside the tubing, which could result in gas expansion and tubing rupture. Schleder *et al.* have provided a more detailed description of this regasification system.[36] A diagram of the system is shown in Fig. 3, and the nomenclature used is presented in Table I. A thermal insulation for each heat exchanger is also considered (I1, I2, and I3).

4.2. Qualitative Analysis

The qualitative analysis must provide a clear view of the system and identify the relationships between system elements, which might be

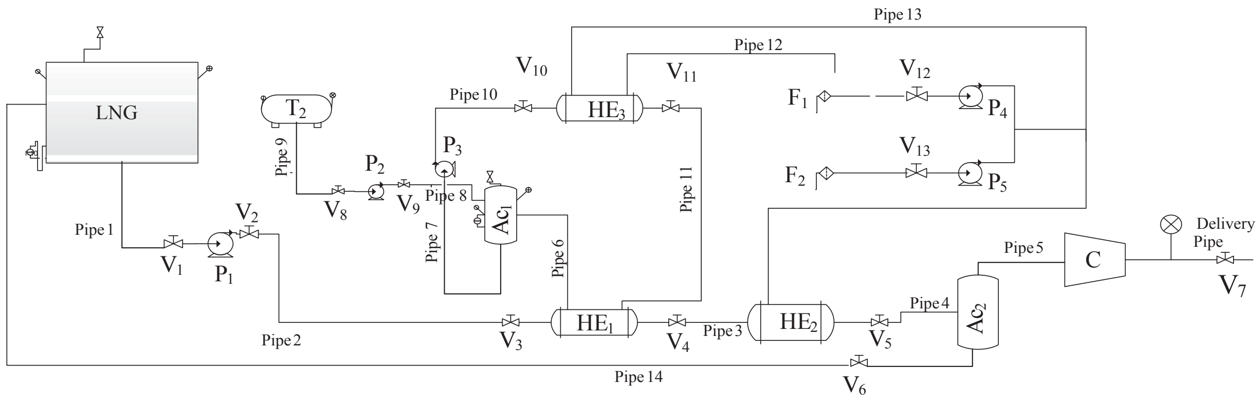

Fig. 3. Unifilar diagram of the regasification system studied.

Table I. Unifilar Diagram Nomenclatures

Item	Description	Item	Description
T2	Propane storage tank	P2, P3	Propane pumps
V1, V2, V3, V6, V8, V9, V10, V11, V12, V13	Gate valves for liquid	P4, P5	Water pumps
V4, V5, V7	Gate valves for gas	Pipes 1, 2, 3, 4, 5, 12, 13, 14	Pipes with 8”
P1	LNG supply pump	Pipes 6, 7, 8, 9, 10, 11	Pipes with 3”
Ac2	LNG accumulator	Delivery pipe	Pipe with 12”
HE1	Propane/LNG compact heat exchanger	Ac1	Propane accumulator
C	Compressor	HE2	Sea water/LNG shell-tube heat exchanger
F1 e F2	Water filter	HE3	Propane/sea water titanium heat exchanger

accomplished using a block diagram or a fault tree, followed by conversion into BN, as previously proposed.[37] A BN might also be generated directly from the system analysis.

Considering the diagram of the system shown in Fig. 3, a preliminary hazard analysis[38] showed that the major risks associated with this process are explosions and fires as a result of LNG or propane leaks. Based on this notion, FTs for the top events, “LNG Leak” and “Propane Leak,” were built and converted into BN using the procedure explained in Section 2.3—“Converting FT into BN.”

In the FT construction, the following assumptions were considered:

- The components present binary failure modes (fault with leak/no-fault);
- Relationships between events and causes are represented through logical AND and OR gates;
- Failures are statistically independent.

Due to the limited amount of information concerning failures rates, some assumptions were necessary to perform the analysis. First, the leakages were divided in two types: medium leaks, which assumes leaks equivalent to holes with diameters equal to 100 mm or less for natural gas pipes and 50 mm or less for propane pipes, and catastrophic leaks, assuming leaks equivalent to holes with diameters greater than 100 mm for natural gas pipes and than 50 mm for propane pipes, which are treated as catastrophic ruptures in the pipeline. Because there are no available databases[39,40] concerning significant frequencies of occurrence of the total rupture or total loss of containment for the other components of the system, only the pipelines were considered for the catastrophic leakages. Thus, an FT was built for each of the following top events: natural gas medium leak, natural gas catastrophic leak, propane medium leak, and propane catastrophic leak.

Fig. 4 presents the FT of a natural gas medium leak that could represent a gas leak, a liquid (LNG)

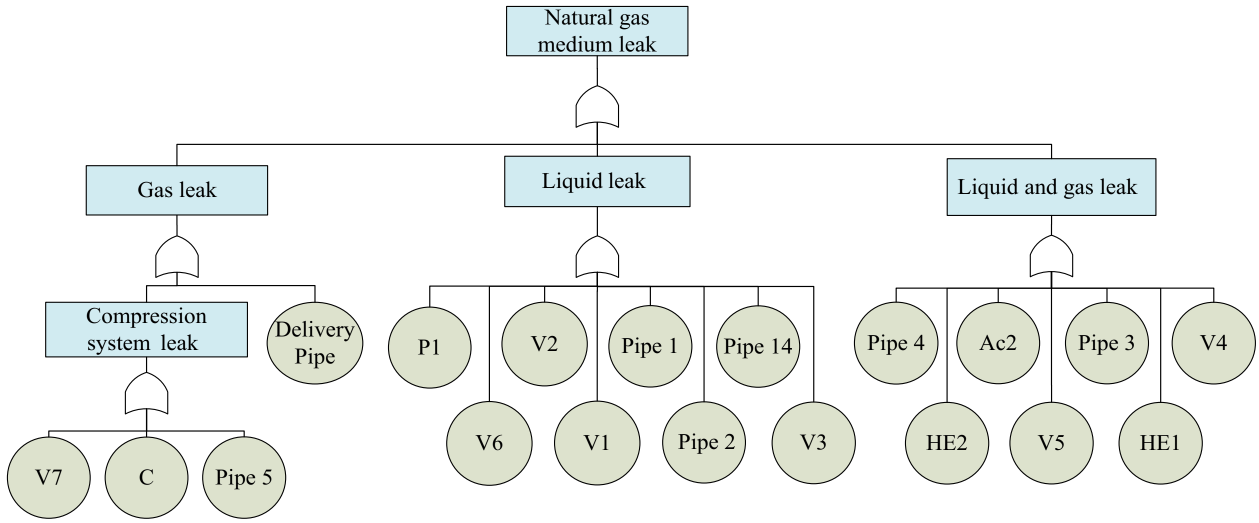

Fig. 4. Fault tree representing a natural gas medium leak (leaks equivalent to holes with diameters equal to 100 mm or less).

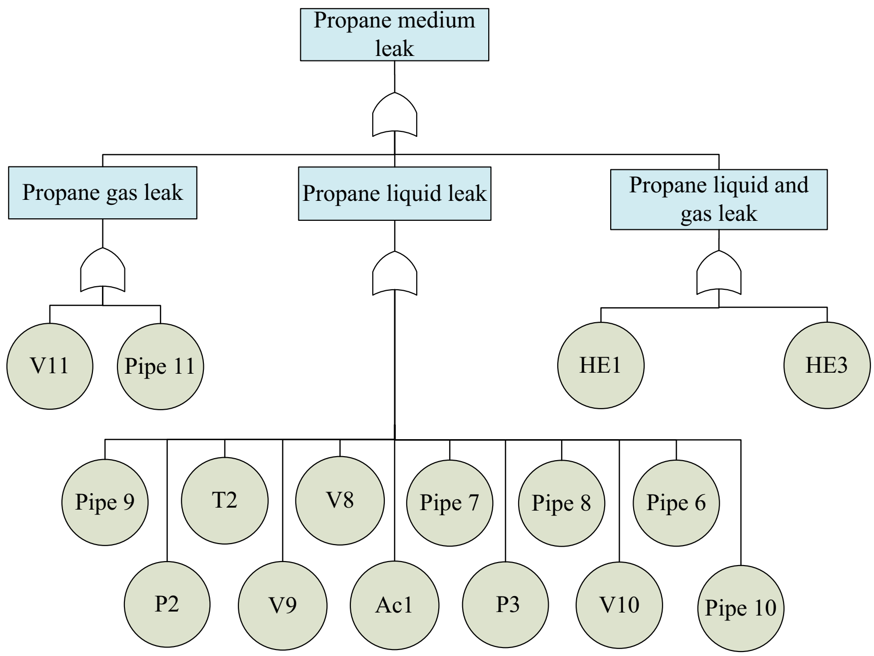

Fig. 5. Fault tree representing a propane medium leak (leaks equivalent to holes with diameters equal to 50 mm or less).

leak, or the simultaneous leaking of gas and liquid (two-phase leak). Not all equipment shown in Fig. 3 is present in this FT, as some of these pieces of equipment did not contribute to the top event.

Another relevant assumption is that the LNG storage tanks are outside of the scope of this study because the LNG tank is not a component of the regasification system. However, the propane storage tank is part of the system, and thus, a leakage in the propane tank was analyzed. Only a catastrophic rupture was considered due to the lack of available information concerning the failures rates. Natacci *et al.* report more details concerning the rupture of LNG tanks.[35]

Fig. 5 presents the FT of a propane medium leak that could also represent a gas leak, a liquid leak, or the simultaneous leaking of gas and liquid.

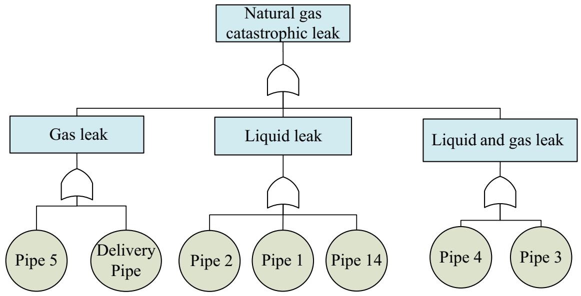

Fig. 6. Fault tree representing a natural gas catastrophic leak (leaks equivalent to holes with diameters greater than 100 mm).

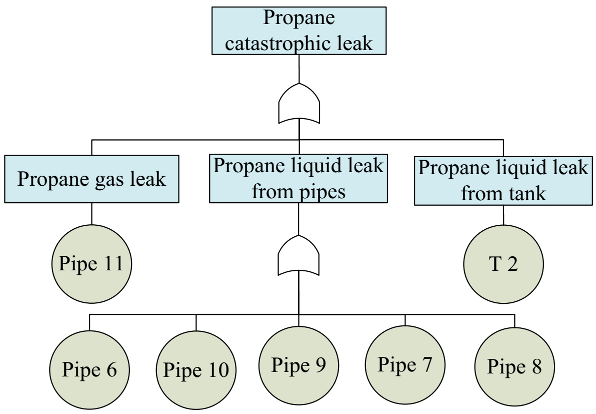

Fig. 7. Fault tree representing a propane catastrophic leak (leaks equivalent to holes with diameters greater than 50 mm).

As previously discussed, it was assumed that only the pipelines and the propane storage tank are subject to catastrophic ruptures and, consequently, Figs. 6 and 7, which present fault trees for catastrophic leaks, only include pipelines and the propane storage tank.

4.2.1. Converting Leak FT into BN

The first step to translate an FT into a BN is creating a corresponding continuous node for each event and base element (primary event/component) in the FT, representing the TTF of the basic components or subsystems. The second step involves the subsequent connection of the nodes in BN in a manner similar to the connection of gates in FT. In addition, discrete nodes might be included to represent the state of the system or subsystem. The BN could be generated through the conversion of a previous FT into a BN or directly from the system analysis. Notably, even when the BN is built from a previous FT, the limitations associated with FT, as presented in Sections 2.1 and 2.2, are not present in the resulting BN. Thus, the BN can be improved after converting the FT, facilitating the inclusion of continuous variables and local dependencies.

The regasification system has local dependences between heat exchangers and insulators. The failure probability distributions of the nodes "Heat Exchanger LNG/Propane" (HE1), "Heat Exchanger LNG/Water" (HE2), and "Heat Exchanger Propane/Water" (HE3) change if the their insulation fails. If the insulation fails, then the heat exchanger failure probability increases. This variable has a conditional dependence, which cannot be addressed using traditional approaches, such as FT. Although it is not possible to represent local dependence in FT analysis, this dependence can be modeled in a simple way using BNs. To include local dependence in the model, an arc was built between these nodes. Using this approach, it is possible to model how the malfunction of equipment affects other equipment. In addition, it is also possible to include the CCF in the BN to obtain a more realistic model.[3,31] However, in the case presented here, failure rates due to CCF are reflected in the failure rates of the components.

Figs. 8–11 illustrate the corresponding BN for each FT from Figs. 4–7, respectively. Following the steps presented in Section 2.3 and the considerations of the preceding two paragraphs, the construction of these BNs can be summarized as follows:

- corresponding nodes were created for each event and base element in the FT;
- the nodes were connected by arcs as they were connected by the gates in FT (the arcs represent conditional dependencies among the nodes);
- discrete nodes ("gas leak probability," "liquid leak probability," and "liquid and gas leak probability") were included to represent the leak probabilities for a specific mission time;
- arcs representing local dependences were included.

Notably, in BN, there are extra intermediate nodes, which are built to facilitate the quantitative analysis in the next step. The top nodes represent a leak in the regasification system. However, as different types of leaks (gas, liquid, or two-phase leakage) have different consequences, the nodes "gas leak probability," "liquid leak probability," and "liquid and gas leak probability," considering a given mission time, are the nodes of interest to estimate the risk associated with the regasification system. These

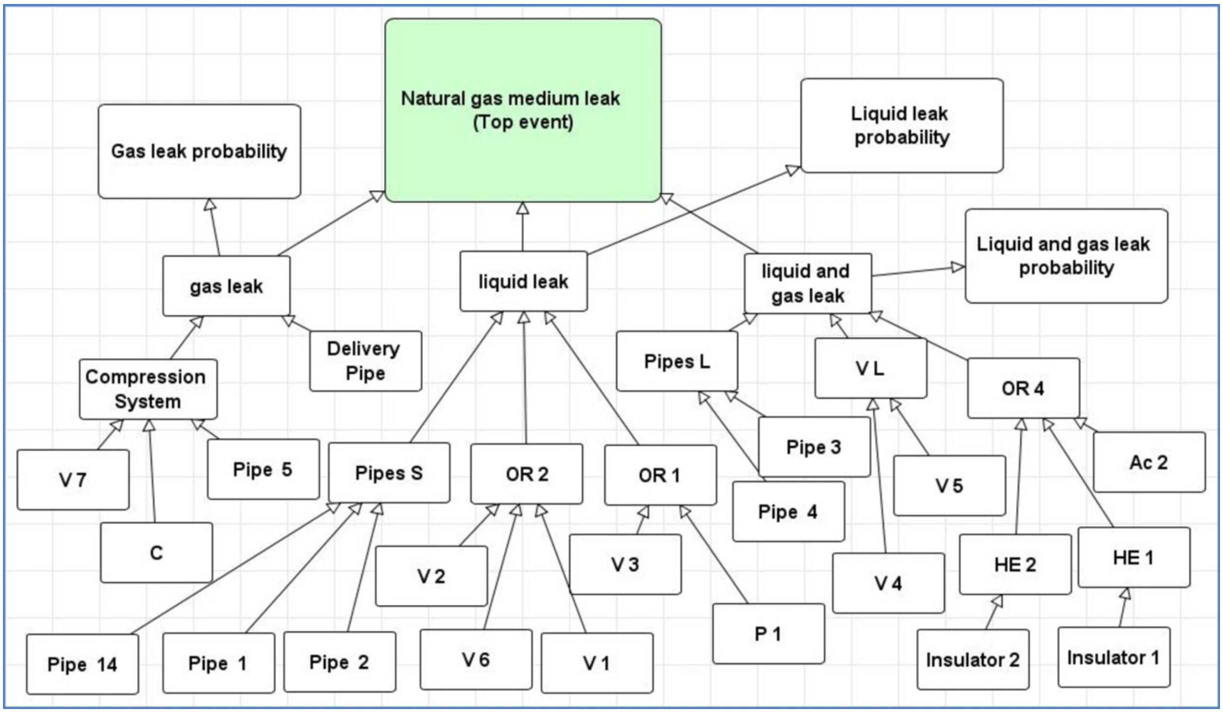

Fig. 8. BN representing a natural gas medium leak (corresponding to FT from Fig. 4).

probabilities will be multiplied by the corresponding consequences to estimate the risk associated with the regasification system. Below these nodes are the subsystems involving the basic components that might fail and cause leaks.

4.3. Undesired Events Probability Estimation

The BN shown herein was built and executed to evaluate the probability of the undesired events using the commercial tool AgenaRisk, which is available on the Agena site.[23] In BN, quantitative analysis begins with the inclusion of the priori probabilities of the root nodes, which can be obtained using empirical data or expert opinion. Subsequently, the relationships between nodes must be specified according to Equations (2) and (3). Finally, the joint probability of the network is obtained, which, in this study, facilitates the determination of the leak probability for a given mission time.

The root nodes that represent the basic components are characterized using probability density functions that represent the TTF of each basic component. Recalling that only the faults that cause leaks are considered, the goal is to calculate the risks associated with leaks. A similar analysis might be performed to evaluate the system reliability through adjustments in the BN and the probability density functions as in Schleder *et al.*[36]

Although the constructed BN is able to deal with any distribution, it was considered that the components have constant failure rates (λ) due to the lack of more specific data, which means that the TTF distributions were assumed to be exponential. Thus, the probability of a component to fail at a given mission time t is calculated as $P(f) = 1 - e^{-\lambda t}$, except for the insulators. The mission time was assumed as 96 hours, which is the time required to regasify all the stored gas in the FSRU tanks. In order to define the failure rates for the basic components, the statistical data presented in Refs. 39 and 40 were used, considering only the information for failures associated with leakage. Table II presents the obtained failure rates associated with leakage for each basic component, except for the insulators.

Empirical or field (failure) data were not available for the insulators, but their TTF distribution can be determined using expert judgment. Thus, BN analysts ask relevant questions to a group of specialists and explain the assumptions that are encoded in the model, and the domain experts supply knowledge to the BN analysts. In the current study, as suggested

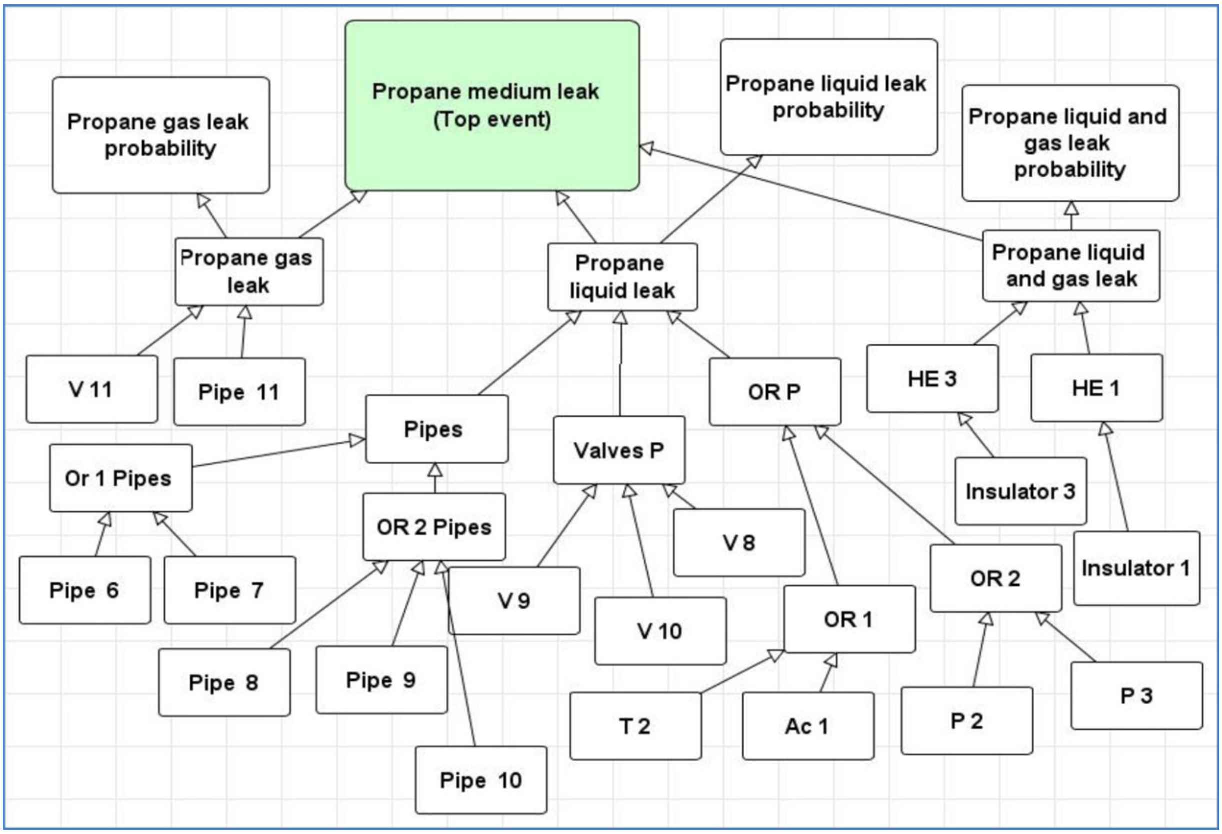

Fig. 9. BN representing a propane medium leak (corresponding to FT from Fig. 5).

by the specialists, for the insulator node, a Weibull distribution was assumed, with a shape factor of s = 6 and a scale factor of $\beta = 1/10{,}000$ hours. This distribution could not be considered if the analysis had used an FT.

The rupture rate suggested by the Health and Safety Executive (HSE)[40] was used to evaluate the BN for catastrophic leak, which was equal to 6.709×10^{-10}/m.hr for pipes with a diameter equal or greater than 8 inches and 2.285×10^{-10}/m.hr for pipes with a diameter equal or greater than 3 but less than 8 inches. Only the catastrophic rupture of the pipes and the propane storage tank were considered in the evaluation of catastrophic leakages.

As discussed in the previous section, local dependencies between the heat exchangers and insulation were considered in the developed BN. To represent these dependencies, the failure rates of the heat exchangers were adjusted: first, the failure rate of the exchanger was considered with respect to working insulation (failure rate showed in Table II), and a higher failure rate was considered for the heat exchanger if the insulation fails. Thus, for the heat exchanger HE1, the failure rate increased from 1.500×10^{-7} to 1.900×10^{-7} when the insulation failed, and similar results were obtained for the other two heat exchangers. These failure rates are shown in Table III.

When the BNs are completed with all parameters, the inference is performed. The top events provide the time distribution to the leak in the regasification system and the probabilities for the target nodes (which represent leaks probabilities) for a mission time of 96 hours are obtained. These probabilities are presented in Table IV. No maintenance actions were considered during this period.

4.4. Quantitative Consequence Analysis

As described in the application case, the regasification system uses propane to heat the LNG. Ramos *et al.*[41] reported that the primary hazards associated with LNG are the pool and the flash fires. Since propane is also flammable, this article assumes that

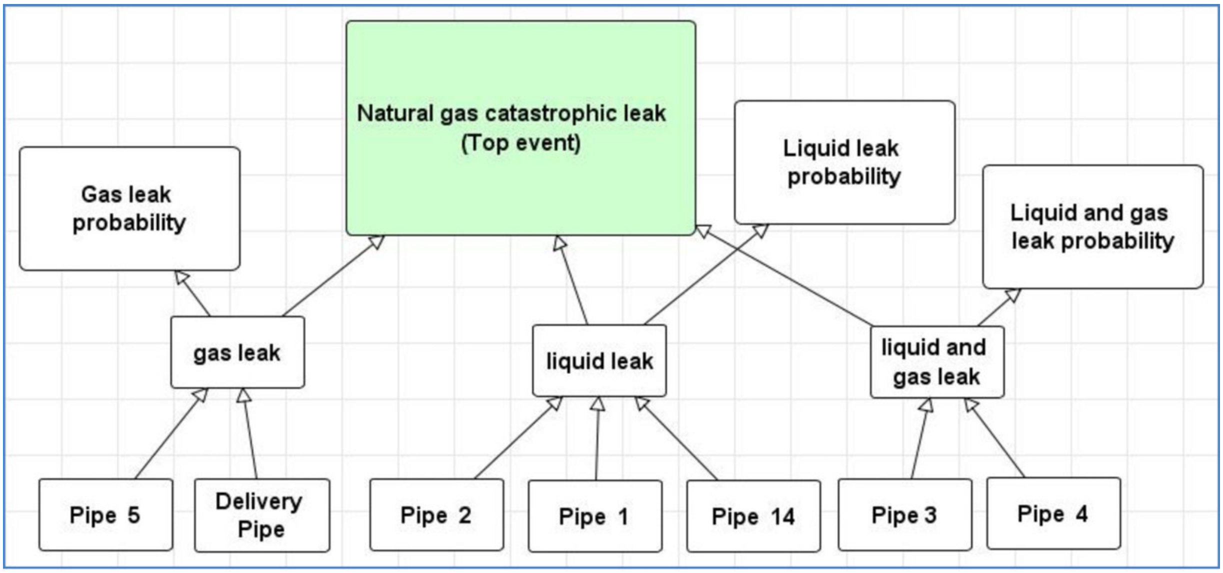

Fig. 10. BN representing a natural gas catastrophic leak (corresponding to FT from Fig. 6).

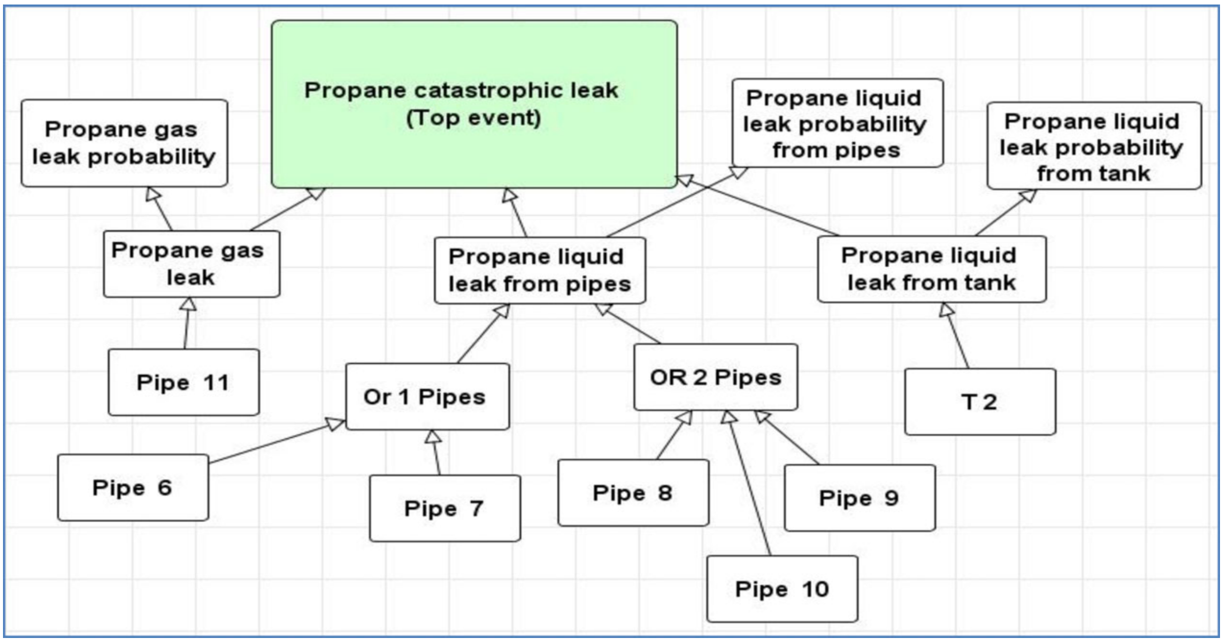

Fig. 11. BN representing a propane catastrophic leak (corresponding to FT from Fig. 7).

the primary hazards associated with propane are the same. When LNG mixes with water or comes in contact with a warmer surface, it forms a white vapor that dissipates in air, leaving no lasting residue. LNG vapors might burn when released into the atmosphere, but they do not release enough energy to create overpressures, or forces, associated with explosions. Propane behaves similarly when mixed with water.

To evaluate the consequence analysis, the commercial tool PHASTRISK v6.54[42] was used. PHAST is one of the best-validated consequence codes, with several validations for each implemented model.[6] The program models all the events, in

Table II. Failure Rates

Component	Failure Rate (λ; hour^{-1})
Ac1, Ac2	3.000×10^{-8}
P1, P2, P3	2.000×10^{-8}
P4, P5	3.800×10^{-7}
C	1.000×10^{-8}
Filters 1, 2, 3, 4	4.155×10^{-7}
T2	3.120×10^{-10}
HE2	1.000×10^{-7}
HE3	4.500×10^{-7}
HE1	1.500×10^{-7}
Pipes 1, 2, 3, 4, 5, 12,13, 14	6.700×10^{-9}[a]
Pipes 6, 7, 8, 9, 10, 11	2.237×10^{-8}[a]
V1, V2, V3, V6, V8, V9, V10, V11, V12, V13	3.180×10^{-7}
Delivery pipe	6.267×10^{-9}
V4, V5, V7	3.900×10^{-8}

[a]The unit used for the failure rate of the pipes is (m.hour)$^{-1}$.

Table III. Local Dependencies

State of Insulation	Failure Rate (λ; hour^{-1})
I_1	HE_1
Ok	1.500×10^{-7}
Fault	1.900×10^{-7}
I_2	HE_2
Ok	1.000×10^{-7}
Fault	1.500×10^{-7}
I_3	HE_3
Ok	4.500×10^{-7}
Fault	5.000×10^{-7}

Table IV. Leak Probabilities

	Undesired Event	Probability of Occurrence/Year
Natural Gas	Medium leak of gas	5.92×10^{-6}
	Medium leak of liquid	1.28×10^{-4}
	Medium leak of liquid and gas	3.55×10^{-5}
	Catastrophic leak of gas	1.68×10^{-7}
	Catastrophic leak of liquid	2.00×10^{-7}
	Catastrophic leak of liquid and gas	1.34×10^{-7}
Propane	Medium leak of gas	3.25×10^{-5}
	Medium leak of liquid	1.11×10^{-4}
	Medium leak of liquid and gas	5.73×10^{-5}
	Catastrophic leak of gas	2.18×10^{-8}
	Catastrophic leak of liquid from pipes	1.09×10^{-7}
	Catastrophic leak of liquid from storage tank	3.00×10^{-8}

which there is no immediate ignition, as a combination of spillage (leak), pool formation and evaporation, dispersion cloud to LFL, flash fire back to source, and finally pool fire.

Following the scenario sequence, the first step is the modeling of the leakage, which is performed using the discharge model.[7,8] In this study, two submodels were used: the orifice model (medium leaks) and the instantaneous model (catastrophic ruptures). The orifice model simulates a continuous release through an orifice and predicts the discharge rate and the discharge duration, considering the available inventory. The instantaneous model simulates the release of the entire inventory, resulting from a catastrophic rupture and comprising the content substance expansion from initial to atmospheric conditions.

The second step is the modeling of the pool formation and evaporation to predict the pool diameter as a function of time, length of the evaporation process, and the maximum quantity of vapor generated. There are different models to examine the pool formation and evaporation, such as the models presented by Weber,[9] Woodward,[10] and Witlox.[11] The PVAP (pool vaporization) model is implemented in the software PHAST used in this study. This model simulates the formation and dispersion of the liquid pool released on the ground or into water and provides an estimation of the evaporation rate from the pool, considering the flow of heat conducted from the surface (soil or water), convection through the air, radiation, and the dissolution of the liquid from the pool when formed over water. Initially, the temperature of the pool is assumed to be equal to the released liquid, and during each time step, the thermal balance of the pool is evaluated through an estimation of its vaporization, dimension, and temperature. Unlike the GASP and LPOOL models of Webber[9] and Woodward,[10] respectively, the PVAP model considers a minimum thickness for the pool, which limits its dispersion. The data obtained in this step are used in the next one to evaluate the cloud dispersion.

The cloud dispersion model estimates the evolution and the features of the cloud, such as concentration, temperature, velocity, and dimensions, as a function of time and position. In the case of flammable substances, this model facilitates the prediction of an area where a fire might occur and the quantity of flammable material in that area. Dispersion models are typically classified as models that

Table V. Weather Conditions

Period	Wind Speed (m/s)	Temperature (°C)	Class of Stability (Pasquill)	Relative Humidity	Wind Direction	Pressure (mb)
Day	4.7	26.5	D	76.9	SE	1008.0
Night	4.5	26.4	E	77.6	SE	1008.4

Source: Ramos *et al.*[41]

Table VI. Results of the Consequence Analysis of the Jet Fire Event

		Jet Fire			
		Day		Night	
	Undesired Event	12.5 kW/m^2	35 kW/m^2	12.5 kW/m^2	35 kW/m^2
Natural gas	Medium leak of gas	71.03	Not reached	70.74	Not reached
	Medium leak of liquid	142.63	108.72	143.56	109.49
	Medium leak of liquid and gas	71.03	Not reached	70.74	Not reached
	Catastrophic leak of gas	146.17	98.74	145.54	97.79
	Catastrophic leak of liquid	173.46	137.16	174.56	138.30
	Catastrophic leak of liquid and gas	146.17	98.74	145.54	97.79
Propane	Medium leak of gas	Not reached	Not reached	Not reached	Not reached
	Medium leak of liquid	69.57	Not reached	69.98	Not reached
	Medium leak of liquid and gas	68.07	Not reached	68.48	Not reached
	Catastrophic leak of gas	97.01	61.39	97.58	61.95
	Catastrophic leak of liquid from pipes	118.42	85.71	119.07	86.34

treat clouds with densities higher than the air density (as SLAB in TNO)[12] or models that treat clouds with densities equal or lower than the air density (as the Gaussian plume model also presented in TNO).[12] However, the UDM model (unified dispersion model)[13]is a generic integral model that simulates the dispersion of clouds with any density. Additionally, the UDM model can be used to simulate the dispersion of a cloud that results from an instantaneous, continuous, or a finite duration release with or without the presence of a jet and can be coupled with the PVAP model. This model is available in the PHAST software and was used to perform the analysis in this study.

If the concentration of the cloud reaches between the LFLs and UFLs and then encounters an ignition source, a flash fire or an explosion will occur. However, in the case of steady hydrocarbon clouds in an unconfined area, the speed of the flame propagation is between 5 and 30 m/s, which is not enough to cause overpressure. As presented in TNO,[12] in the case of flash fire, the area covered by the flammable cloud will be subject to a strong heat flux, resulting in a rate of fatalities equal to 100%; however, this rate of fatality is restricted to the area within the ignited gas cloud. Nevertheless, the flame can travel back to the spillage and cause a pool fire. Thus, it is necessary to determine the area covered by the flash fire to estimate the consequences to individuals.

To complete the consequence analysis (the fourth step of the methodology), the pool fire is modeled, which results from the burning of the vaporized material above the pool and not from the material in the pool. The pool formation and evaporation model estimates the pool dimensions that directly affect the flame dimensions and thus the thermal radiation emitted. The thermal effect is the principal mechanism of damage from a pool fire. TNO[12] compares the characteristics of a point source model and a surface emitter model and states that the former model presents a precise evaluation of distances greater than five times the pool diameter. For smaller distances, the surface emitter model must be used. The POLF model of Oke and Witlox,[14] which is a surface emitter model, predicts the heat flux, facilitating the evaluation of the area covered by the radiation effects, and it can be used to analyze the consequences of pool fires at any distance.

In parallel to these scenarios, in which there is no immediate ignition, is the jet fire, which occurs if

Table VII. Results of the Consequence Analysis of the Flash Fire Event

		Flash Fire (LFL)	
	Undesired Event	Day	Night
Natural gas	Medium leak of gas	63.80	61.26
	Medium leak of liquid	119.20	113.01
	Medium leak of liquid and gas	63.81	61.26
	Catastrophic leak of gas	112.10	107.31
	Catastrophic leak of liquid	139.62	136.44
	Catastrophic leak of liquid and gas	112.10	107.31
Propane	Medium leak of gas	15.30	15.03
	Medium leak of liquid	59.23	56.79
	Medium leak of liquid and gas	58.52	56.01
	Catastrophic leak of gas	74.13	72.21
	Catastrophic leak of liquid from pipes	88.14	80.46
	Catastrophic leak of liquid from storage tank	581.01	645.58

there is immediate ignition at the time of release. As with pool fires, the thermal effects are the primary mechanism of damage from a jet fire. To estimate the geometry and radiation of the flame, TNO[12] proposes the model presented by Chamberlain, which is the original cone model and was developed for near-vertical vapor-phase releases. Cook *et al.* modified this model to describe the shape of jets that contain liquid.[15] Moreover, Johnson proposed a model to represent horizontal vapor release, presented by Oke.[15]

4.4.1. Defining Parameters for the Consequence Analysis

The leakages considered in the quantitative analysis of the likelihood of the undesired events were divided in two types: medium leak, which assumes leaks equivalent to holes with diameters of 100 mm or less for natural gas pipes and 50 mm or less for propane pipes, and catastrophic leak, which assumes leaks equivalent to holes with diameters greater than 100 mm for natural gas pipes and holes greater than 50 mm for propane pipes (both will be treated as catastrophic ruptures of the pipeline) and the rupture of the propane storage tank.

The consequences analysis was performed considering that the regasification is conducted in the Suape Industrial District, which is the most complete center for industrial business and trade in northeastern of Brazil. The meteorological conditions considered for this study are consistent with those presented in Ramos *et al.*[41] (see Table V). The diurnal period corresponds to the conditions between 6:00 AM to 6:00 PM, and the nocturnal period corresponds to the conditions between 6:00 PM to 6:00 AM.

The FSRU considered in this application has a storage tank capacity equal to 145,000 m^3, divided among five tanks with 29,000 m^3, and the propane storage tank capacity is equal to 500 m^3. However, it was assumed that the emergency shutdown system would successfully interrupt the regasification system operation in case of any medium or catastrophic leakage in 30 seconds (15 seconds for leakage detection and 15 seconds for isolation of the failure) and shutdown the system. Therefore, the maximum LNG flow rate in the pipes is 1510 m^3/h, and the largest amount of LNG spill will be approximately 13 m^3. Similarly, the maximum propane flow rate in the pipes was assumed to be 480 m^3/h, and the largest amount of propane spill will be approximately 4 m^3. The composition of LNG was assumed as 100% methane.

4.4.2. Modeling Consequence Analysis

First, a single ignition outcome is considered, which is assumed to occur when the cloud attains the maximum ground-level footprint area that happens when the cloud reaches its LFL concentration limit. This assumption is consistent with the recommendation of TNO,[12,43] and the probability of death is 100% in the area bounded by the LFL. The same references suggest that the radiation effects are proportional to the distance assuming that for 12.5 kW/m^2, the probability of death is equal to 1%, and for 35 kW/m^2, the probability of death is 100%. Moreover, an immediate ignition at the discharge moment is considered.

The results of the consequences analysis, representing the distances (in meters) reached for each consequence consistent with the leak and period (day or night), are presented in Table VI (to immediate ignition), Table VII (to ignition at the time when the cloud reaches its LFL), and Table VIII (to ignition at the time when the pool has maximum radius).

The consequences analysis shows that, if an ignition occurs immediately after a leak, the radiation produced by jets fires might reach significant areas

Table VIII. Results of the Consequence Analysis of the Pool Fire Event

	Pool Fire			
	Day		Night	
Undesired Event	12.5 kW/m^2	35 kW/m^2	12.5 kW/m^2	35 kW/m^2
Catastrophic leak of liquid from propane tank	449.69	276.42	449.87	275.13

Table IX. Scenarios, Contribution to the Risk

	Undesired Event	Risk / Average Year	Risk Contribution (%)
Natural gas	Medium leak of gas	–	–
	Medium leak of liquid	1.03E-06	98.53
	Medium leak of liquid and gas	–	–
	Catastrophic leak of gas	1.38E-09	0.13
	Catastrophic leak of liquid	3.50E-09	0.33
	Catastrophic leak of liquid and gas	1.10E-09	0.10
Propane	Medium leak of gas	–	–
	Medium leak of liquid	–	–
	Medium leak of liquid and gas	-	-
	Catastrophic leak of gas	-	-
	Catastrophic leak of liquid	4.32E-10	0.04
	Catastrophic leak of liquid of the tank	9.04E-09	0.87
	Total	1.05E-06	100

around the release point. The radiation level equal to 12.5 kW/m^2 might reach 174 m (in this area the probability of death is equal to 1%), and the radiation equals to 35 kW/m^2 might reach 138 m, causing 100% fatalities in this area. In some of the scenarios shown in Table VI, it is possible to verify that the radiation level of 35 kW/m^2 is not reached because the jet fires formed in these scenarios are not capable of producing this level of radiation. Moreover, in propane scenarios, the effects of liquid leak and gas and liquid leaks are similar. This effect potentially reflects the fact that in both cases, only liquid leak is expected, and thus, the conditions of the leak are the same. However, the temperature is slightly higher in the liquid and gas leak scenario. A leak of two phases only occurs if there is malfunction of the system; thus, the difference between these cases is the probability of occurrence. Similar results were observed in natural gas scenarios between the gas leak and liquid and gas leak, in which only gas leak was expected.

As previously discussed, if there is no immediate ignition, a single ignition outcome is considered, which is assumed to occur at the time when the cloud reaches its LFL. In this case, flash fires and pool fires might result. Table VII shows that the distances achieved by flash fires caused by liquid leaks are larger than the distances obtained by flash fires resulting from gas leaks. The clouds formed by liquid leaks take longer to reach the LFL, as clouds with liquid fractions have much higher concentrations than those comprising only steam. In the case of natural gas and the catastrophic leak of liquid, the LFL of the cloud might reach 139 m from the leakage point, and in the case of a catastrophic rupture of the propane tank, the LFL might reach 645 m, revealing a significant area around the leakage point that can be impacted by a flash fire.

Finally, in the analyzed scenarios, the leakages are not sufficient to form a pool due to the vaporization of the entire material leaked before reaching the water, except for catastrophic leak of liquid from the propane tank, where the radiation level equals 35 kW/m^2 due to a pool fire that reached 276 m, causing 100% fatalities in this area.

4.5. Risk Evaluation

The commercial tool PhastRisk[(42)] was used to evaluate the risk, considering just fatalities and not injuries, which means that the individual risk will be the likelihood of an individual, at a given location, to experience fatal effects.

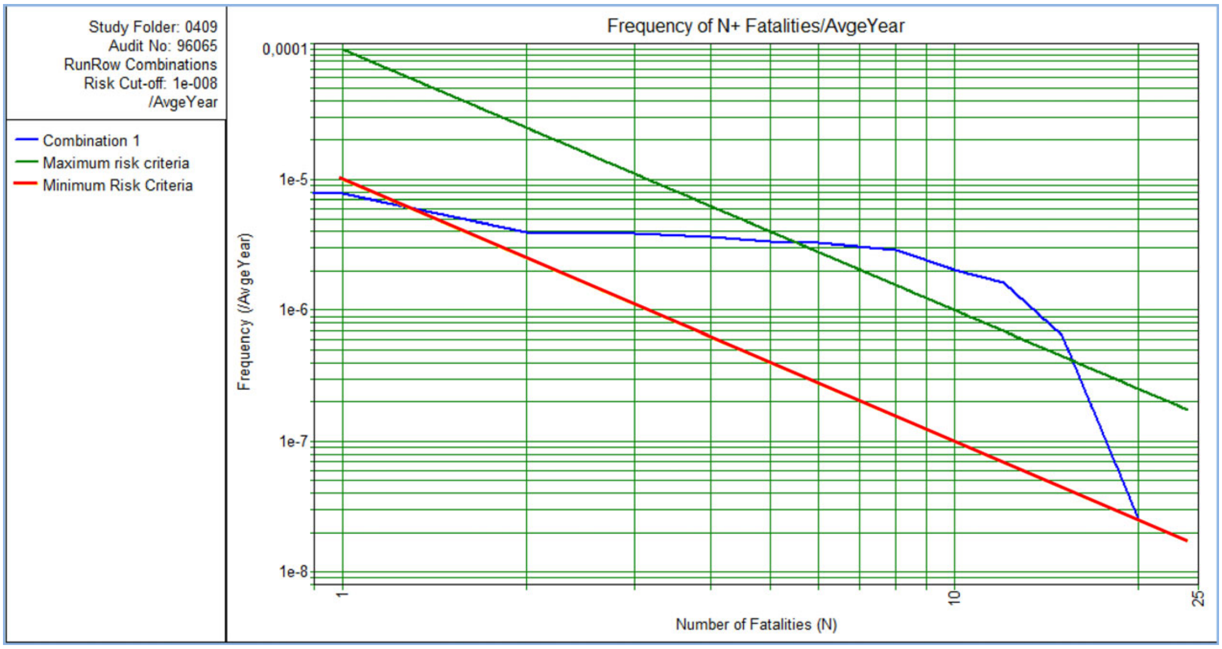

Fig. 12. *F-N* curve representing the societal risk of the system operation and the acceptable limits.

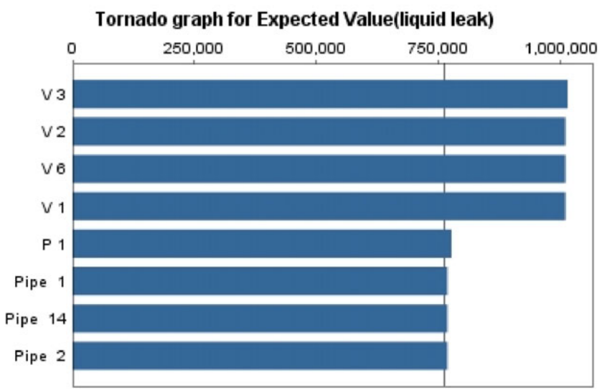

Fig. 13. Impact of the basic components in the expected time to occur of a medium leak of liquid of natural gas.

To evaluate the distribution of the risks in the local area, HSE's guidelines(44) on tolerability limits suggest the following criteria for individual risk:

- Maximum tolerable risk for workers: 1×10^{-3}/year;
- Maximum tolerable risk for the public: 1×10^{-4}/year;
- Broadly acceptable risk: 1×10^{-6}/year.

Determining the risk distribution around the floating unit is useful to reach a decision about its localization. The distance to reach an acceptable individual risk associated with the operation of the regasification system is approximately120 m.

The contribution that each event makes to the individual risk at specific locations might also be obtained. Table IX shows the contribution of each event to the risk at 120 m from the release point, indicating the events that have potential to cause the highest risk at a given localization point. At 120 m from the release point, the medium leak of liquid of natural gas is considered the event that most contributes to the total risk. Thus, the mitigation measures should focus on actions to minimize the risk associated with this event.

Considering that an FSRU might operate in several locations using an offshore terminal to connect to the delivery gas pipeline, it is assumed that this terminal is located far enough from the coast and the consequences do not reach the local population. Thus, the societal risk is evaluated considering the crew (22 persons) as the individuals who might be affected by the consequences of the undesired events.

The IMO(45) reports that the tolerable level of societal risk is usually lower than the tolerable level of individual risk. Therefore, considering a graph in which the abscissa represents the

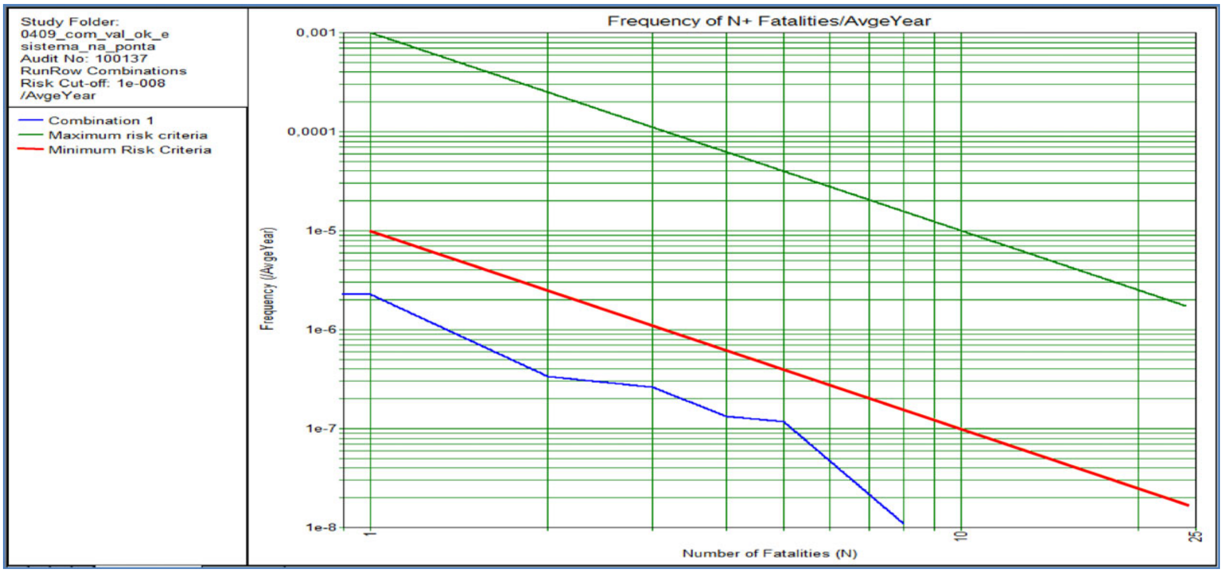

Fig. 14. *F-N* curve representing the societal risk of the system operation and the acceptable limits after mitigation measures.

number of fatalities (N) and the ordinate represents frequency (F) of N fatalities, it was assumed that the minimum risk criterion is limited by the line defined by points with coordinates ($1; 1 \times 10^{-5}$) and ($10; 1 \times 10^{-7}$), and the maximum risk criterion is limited by the line defined by points with coordinates ($1; 1 \times 10^{-4}$) and ($10; 1 \times 10^{-6}$). Fig. 12 shows the *F-N* curve, where the yellow line represents the minimum risk criteria, the green line represents the maximum risk criteria, and the blue line represents the societal risk of the regasification system operation (colors visible in online version). These results show that the societal risk is above the maximum risk criteria. Thus, the operation of the regasification system is unacceptable. Notably, the failure rates used to perform this study are from the available databases mentioned earlier(39,40) and refer to similar pieces of equipment, which are not exactly the same as those used in the system. Thus, it is necessary to obtain more data about the system to perform this analysis more reliably.

4.6. Mitigation Measures

The data concerning the contribution of each event to the individual risk at a specific point, as presented in Table IX, might facilitate the design of mitigation measures. This table shows that natural gas medium liquid leak is the event that contributes most to the individual risk at this point. Thus, it is expected that reducing the risk associated with this event will significantly reduce the total risk. The BN analysis can be used to verify which components contribute the most to this undesired event. It is possible to analyze the criticality of each system component through evaluations of their posterior probabilities using the relevant inference algorithm, considering the natural gas medium liquid leak as evidence.

Fig. 13 shows a visual perspective, where the length of the bars is a measure of the impact of each node on the target node (the natural gas medium leak of liquid). The first bar indicates the range between the lowest and highest values for the expected time for a natural gas medium liquid leak to occur given the expected time for a leak to occur in the V3 valve. The initial point of the bar (equal to zero) reflects the expected time for the natural gas medium liquid leak given the time expected for a leak to occur in the valve being near zero. The end point is the expected time of the natural gas medium liquid leak given that the expected time to leak in the valve significantly exceeds the mission time, which influences the expected time for the natural gas medium liquid leak. After this point, the expected time for the natural gas medium liquid leak stabilizes. Even if the valve's expected time increases, the expected time to natural gas medium liquid leak does not change. The second bar represents the expected values for the expected time for natural gas medium liquid leak conditioned on the expected time for valve V2. The subsequent bars are plotted using the same concept. The graph shows that the valves V1, V2, V3, and V6 are the components that contribute most to the undesired event.

To reduce the risk associated with this event, it is reasonable to consider reducing the failure rates of the most critical components. Thus, the BN can be used to verify changes in the frequency of the undesired event due to the improvement of the critical components. To perform this analysis, it is only necessary to include the evidence in the model. A scenario was created through an assumption that the valves (V1, V2, V3, and V6) fail only after the mission time, and the beliefs are subsequently recalculated given the evidence. Thus, the probability of occurrence of the undesired event decreases from 1.28 $\times$ 10^{-4} to 2.79 $\times$ 10^{-6} and, consequently, the risk of the undesired event is reduced from 1.03 $\times$ 10^{-6} to 2.30 $\times$ 10^{-8} and the risk at 120 m from the release point is reduced from 1.05 $\times$ 10^{-6} to 3.85 $\times$ 10^{-8}. This is the greatest possible reduction in the frequency of the undesired event "natural gas medium liquid leak" acting on these components. Assuming a mitigation measure that improves the reliability of the valves, in which the failure rate decreases from 3.18 $\times$ 10^{-7} to 3.18 $\times$ 10^{-8}, we can recalculate the risk; the individual risk at 120 m from the release point decreases from 1.05 $\times$ 10^{-6} to 1.18 $\times$ 10^{-7}.

The reallocation of the regasification system was proposed as an additional mitigation measure. Originally, it is allocated amidships. However, the relocation of the system to the bow of the vessel was proposed to reduce the effect of the undesired events on the crew, which is assumed uniformly distributed throughout the vessel. After the inclusion of these mitigation measures, the societal risk falls into the acceptable region, as shown in Fig. 14.

5. CONCLUSIONS AND FUTURE WORK

This article presented a methodology to perform a risk analysis using hybrid BN and demonstrated how BN can be useful in performing more comprehensive risk analysis and it was applied to the risk analysis of a regasification system of LNG onboard an FSRU. All the steps of the proposed methodology were evaluated; thus it was possible to estimate the probabilities of undesired events (using BN), to estimate the consequences of these events, and evaluate the risk.

As fault trees, BNs are useful to characterize the interactions between subsystems. However, BNs might also offer the inclusion of expert opinion and the use of continuous variables, uncertainties, and dependencies between the components under analysis. These options are significant for the examination of a system that does not have a large amount of statistical data, such as the FSRU regasification system. This analysis could not be accomplished using fault trees, as it does not facilitate the inclusion of local dependencies between insulators and the heat exchanger, the use of continuous variables to represent the TTF of all components and subsystems, the use of nonexponential distributions to represent the insulator TTF, and the diagnostic analysis to identify critical components that contribute to the most probable undesired event (the natural gas medium liquid leak).

The possibility of including continuous variables and dependencies between the components makes the model more realistic, thereby improving the analysis. To generate a more efficient analysis, it is essential to obtain more information about the system and equipment. Additionally, BN allows the study of the evidence propagation and the behavior system over time, which allows the analysis of different scenarios and of the conditional reliability by evaluating the posterior marginal probability distribution, as presented by Martins and Schleder[46] and by Schleder *et al.*[47]

The consequence analysis showed that both the leakages, LNG and propane, could cause undesired consequences, which might reach significant areas. The analysis performed in this study considered the leak in the regasification system of the FSRU, which are not large due to flow restrictions and the emergency shutdown system. However, it is important to consider in future studies the reliability of the emergency shutdown system, the total rupture of the LNG tanks that supply the system, and the cascade events that can cause the leakage of all the tanks in the FSRU. Similar events might cause consequences that will reach larger areas and subsequently cause more damage and fatalities.

The individual risk was estimated and the distribution of associated risk to the regasification system in the local area was verified, confirming that at a distance of approximately 120 m, the individual risk associated with the regasification system is acceptable at approximately 1 $\times$ 10^{-6}/year. However, the societal risk was not acceptable when compared to the considered criteria. Using the BN, the undesired event that contributes the most to the risk was identified. Thus, the BN analysis was used to define mitigation measures through the analysis of the contribution of each component to the occurrence of the undesired event. Once the critical components were identified, the reduction of the failure rate of the critical components (valves V1, V2, V3, and V6) and the reallocation of the regasification system were proposed for the reduction of societal risk. The analysis of only the undesired event that most contributed to the risk at a distance of 120 m might be improved using the BN diagnostic analysis of other undesired events, thereby contributing to the identification of additional mitigation measures.

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APPENDIX: NUMERICAL ACCURACY

As mentioned in Section 2.2, the method used to evaluate the probability of the leaks is not completely accurate; therefore, it is recommendable to verify the numerical accuracy. In order to exemplify the error estimation, the error for a simple case of warm spare was evaluated as in Marquez *et al.*[1]

Indeed, let us consider two components in a warm standby configuration, in which the main component has a Weibull failure distribution with a shape factor of $s = 1.5$ and a scale factor of $\beta = 1/1{,}500$, the standby component has also a Weibull failure distribution with a shape factor of $s = 1.5$ and a scale factor of $\beta = 1/1{,}500$ when in active mode and a shape factor of $s = 1.5$ and a scale factor of $\beta = 1/2{,}000$ when operating in standby mode.

Table A1 provides the values for the reliability at different times of operation calculated using numerical integration (performed using the software MATLAB) and the values provided for the BN model (obtained using AgenaRisk V5.6.0 with 100 iterations).

It is worth to note that the major error estimated for the reliability, in this example, is less than 2%. However, in scenarios where the value of the failure probability is critical, the BN error could be significantly larger. In these cases, it is essential to consider the error due to the estimation via the BN.

More information about the numerical accuracy of this procedure can be found in Marquez *et al.*,[1] where the comparison between numerical and BN results of eight examples is presented; in Chaur and Sou,[48] who perform a reliability analysis of hydropower system and compare the results obtained by the BN and the FT analysis; and in Neil *et al.*,[25] in which the accuracy of hybrid BN is discussed.

Table A1. Comparison Between Numerical and BN Results.

Time	Reliability BN	Reliability Numerical	Reliability BN Error (%)	Probability of Failure BN	Probability of Failure Numerical	Probability of Failure BN Error (%)
20	0.99997	0.9995	0.05	3.00E-05	5.00E-04	6.00
50	0.99988	0.9980	0.19	1.20E-04	2.00E-03	6.00
100	0.99937	0.9941	0.53	6.30E-04	5.90E-03	10.68
200	0.99638	0.9828	1.38	3.62E-03	1.72E-02	21.05
500	0.96456	0.9828	1.86	3.54E-02	1.72E-02	106.05

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