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Risk assessment of LNG importation terminals using the Bayesian–LOPA methodology

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ABSTRACT

In order to meet the fast growing LNG (Liquefied Natural Gas) demand, many LNG importation terminals are now in operation. Therefore, it is important to estimate potential risks of LNG terminals using LOPA (Layer of Protection Analysis), which can provide quantified results with less time and effort than other methods. For LOPA applications, failure data are essential to compute risk frequencies. However, available failure data from the LNG industry are sparse and often statistically unreliable. Therefore, Bayesian estimation, which can update generic failure data with plant-specific failure data, was used to compensate for insufficient LNG system failure data. This paper shows the need for the Bayesian–LOPA methodology, how to develop the method, and a case study to demonstrate application of the method. Finally, this paper proposes that the Bayesian–LOPA method is a powerful tool for risk assessment of not only the LNG industry but also in other industries, such as petrochemical, nuclear, and aerospace.

1. Introduction

LNG refers to natural gas converted into its liquid state by super cooling to −260 °F (−162.2 °C). LNG consists of 85–98% methane with heavier hydrocarbon components. Thus, LNG is highly flammable when it forms a 5 ∼ 15% volumetric concentration mixture with air at atmospheric conditions. LNG provides a cost-effective containment as well as transportation across great distances onshore and offshore at atmospheric pressure. Moreover, LNG is environmentally friendly because of its clean burning.

Because of these properties, LNG demand has been growing to diversify the energy portfolios and fulfill energy demand for LNG fuel for many applications, including heating, cooking, and power generation. Following the increasing demand for LNG, there are at least 100 currently active LNG facilities across the U.S., including importation terminals, peak shaving facilities, or baseload plants. In addition, there are also a number of proposed projects for LNG terminals in North America. In order to fulfill the increasing LNG demand, it is necessary to build and operate more LNG importation terminals to import LNG from other countries. Therefore, this paper will focus on LNG importation terminals. Even though LNG has several advantages, it may cause fire or explosion when it is discharged at undesired conditions. Especially in LNG importation terminals, large consequences may occur due to the huge amounts of LNG stored. Thus, although the LNG industry has had an excellent safety record over the past 40 years, risk related to LNG terminals may be increasing with the growing LNG industry. Consequently, risk-informed decisions founded on sound science are critical to control risks related to LNG terminals.

2. Why use a Bayesian–LOPA method?

In order to control risk, it is necessary to quantify the risk by applying risk assessment methodology. LOPA, as applied in this paper, provides a straightforward and systematic approach to obtain quantified risk results with less effort and time than other methods, especially quantitative risk assessment (QRA).

For the application of LOPA methodology, failure data of equipment and facilities are required to quantify the risk. However, the LNG industry has a relatively short operational history compared to other industries, such as the chemical industry, and there are only a few incident records. Therefore, available plant-specific failure data of LNG system are very sparse. The risk values estimated with these insufficient data may not show statistical stability or represent specific conditions of an LNG facility. Generic failure data from other industries such as the petrochemical and nuclear industries may be used for the LNG industry because they have sufficient and longer-term historical records. However, these data also may not provide appropriate risk results for the LNG

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Nomenclature

BOG	Boil off gas
BV	Block valve
EIReDA	European Industry Reliability Data Bank
HAZOP	Hazard and Operability Study
IPL	Independent protection layer, which is one of the safeguards that is capable of preventing an incident scenario from proceeding to undesired consequences
LNG	Liquefied natural gas
LOPA	Layer of protection analysis
MTBF	Mean time between failures
OREDA	Offshore reliability data
PFD	Probability of failure on demand
PHA	Process hazard analysis
PRV	Pressure relief valve
QRA	Quantitative risk assessment
TSV	Temperature safety valve

industry because the operational conditions and environment of LNG facilities are different from those of other industries.

Therefore, the Bayesian estimation can be used to obtain more reliable risk values. Bayesian logic, named after Thomas Bayes who found the theorem, can produce updated failure data using the prior information of generic data from other industries and the likelihood information of LNG plant-specific data. The updated data can reflect both statistical stability from the generic data and the specific conditions from the LNG plant data. In addition, Bayesian estimation includes variability and uncertainty information to result in Bayes' credibility or probability intervals, such as a 90% credible interval of updated data, even though LNG plant failure data are sparse. In other words, the weakness of failure data from LNG industry can be reduced or overcome by the use of Bayesian estimation. Therefore, the Bayesian–LOPA methodology, which was newly developed in this paper, was used to conduct risk assessments for an LNG terminal.

Table 1
Summarized conjugate relationships.

Class	Prior distribution	Likelihood function	Posterior distribution
Frequency of initiating event	Gamma	Poisson	Gamma
PFD of IPL	Beta	Binomial	Beta

3. Methodology development

LOPA is a simplified form of quantitative risk assessment that uses initiating event frequency, consequence severity, and the probability of failure on demand (PFD) of independent protection layers (IPLs) to estimate the risk of an incident scenario (Center for Chemical Process Safety, 2001). Typically, LOPA builds on the information developed during process hazard analysis (PHA) where techniques, such as HAZOP and What-If methods, are employed to develop incident scenarios. The purpose of LOPA is to estimate risk values for a facility so that risk decisions can be made based on tolerable risk criteria adopted by the facility. LOPA can also be used to rank the estimated risk values of identified incident scenarios to give priority to safety measures for higher risk scenarios and for critical equipment that contribute significantly to the risk levels.

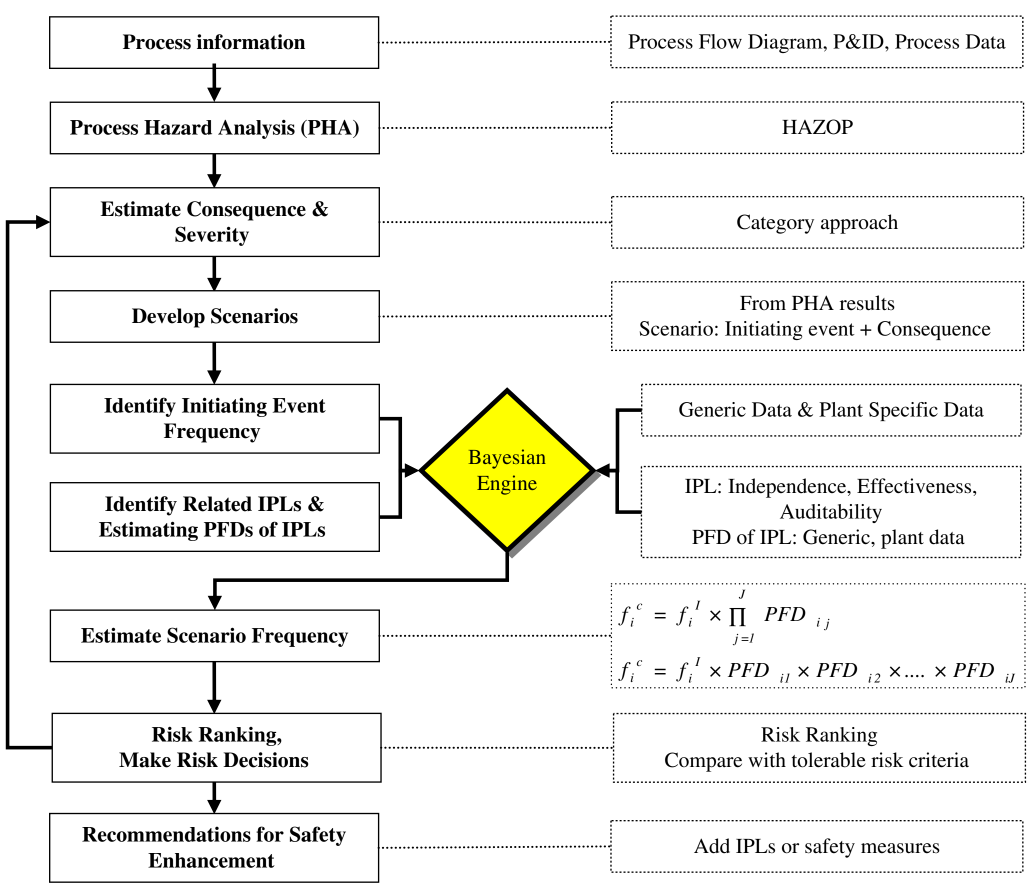

Fig. 1. Procedure for the Bayesian–LOPA method.

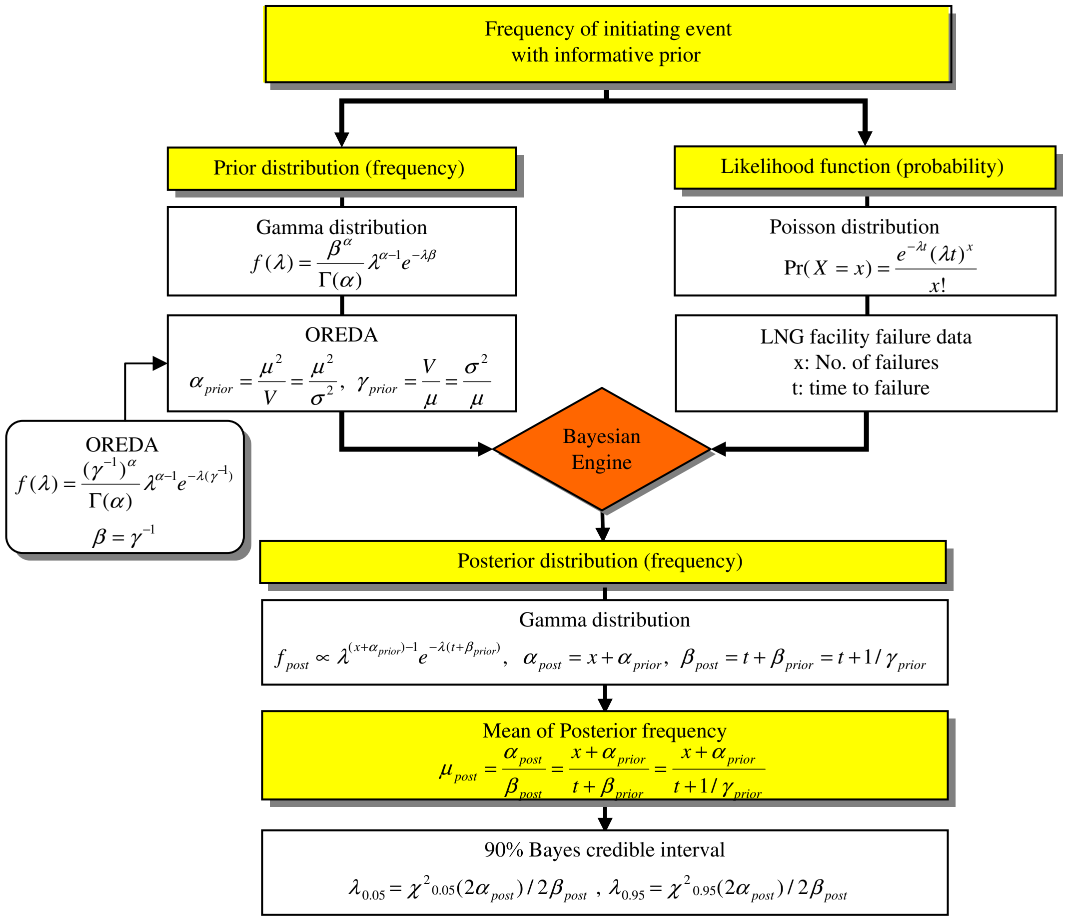

Fig. 2. Schematic diagram of Bayesian estimation for initiating events.

According to Wan (2001), Bayesian estimation is the basic tool to combine a prior judgment and experimental information, based on Bayes' theorem. Modarres (2006) presents the Bayes' theorem as developed from the concept of conditional probability. The generalized form of Bayes' theorem for discrete variables is

$$\Pr\langle Aj|E\rangle = \frac{\Pr(Aj)\cdot\Pr\langle E|Aj\rangle}{\sum_{i=1}^{n}\Pr(Ai)\cdot\Pr\langle E|Ai\rangle} \tag{1}$$

The right-hand side of Bayes' equation consists of $\Pr(Aj)$, *the prior probability*, and the remaining factor, *the relative likelihood*, is based on evidential observations or plant-specific data. $\Pr\langle Aj|E\rangle$, which is updated probability of event Aj, is called the *posterior probability* of event Aj given event E. The above equation means that probability data can be updated by combining the prior probability (from previous information) and the relative likelihood (from plant-specific data). Typically, the selection of the prior distribution is somewhat subjective, so a selection of a conjugate prior from the same family of distributions as the posterior can make the choice more objective for easier computation of the posterior parameters. For a PFD (failure probability), a beta distribution for a prior distribution with a binomial likelihood function results in a conjugate beta posterior distribution, as shown in Table 1. For a failure frequency, a gamma distribution for a prior distribution with a Poisson likelihood function results in a conjugate gamma posterior distribution.

The Bayesian–LOPA methodology is an advanced LOPA method, because it can yield more statistically reliable or concrete risk results in an LNG facility than normal LOPA methods. Fig. 1 shows the procedure of the Bayesian–LOPA method.

As a PHA method, a Hazard and Operability (HAZOP) study (Crowl & Louvar, 2002) will be used because it is one of the most systematic hazard identification methods. The HAZOP method requires process information such as Piping and Instrument Diagrams (P&IDs) and process flow diagrams, which include basic designs and minimum specifications adopted from industrial standards such as NFPA 59A (National Fire Protection Association, 2001) and EN 1473 (Committee of European Nations, 1997) for an LNG terminal. Results from a HAZOP study are used to make incident scenarios, which can be pairs of causes and consequences. The incident scenarios are screened according to severity by the category method, which is a qualitative way to classify consequences using engineering expert judgment.

Causes found in the HAZOP results may be initiating events of incident scenarios. After identifying an initiating event, its occurrence frequency should be obtained for a LOPA application. Based on Bayesian estimation, the frequency of an initiating event can be obtained by using a conjugate gamma distribution for the prior information and a Poisson distribution for the likelihood function as shown in Table 1 and Fig. 2. Offshore reliability data (OREDA) (SINTEF Industrial Management, 2002) can be used in this manner as prior information, because data were produced from a gamma distribution. Fig. 2 also shows some formulas for not only gamma and Poisson distributions, but also mean value and 90% credible interval of Bayesian updated posterior values. If there is no prior information, the Jeffreys non-informative prior (Sandia National Laboratories, 2003) may be used. For the plant-specific likelihood information, the LNG plant failure database (Johnson & Welker, 1981), which was established from 27 LNG facilities, is used. This

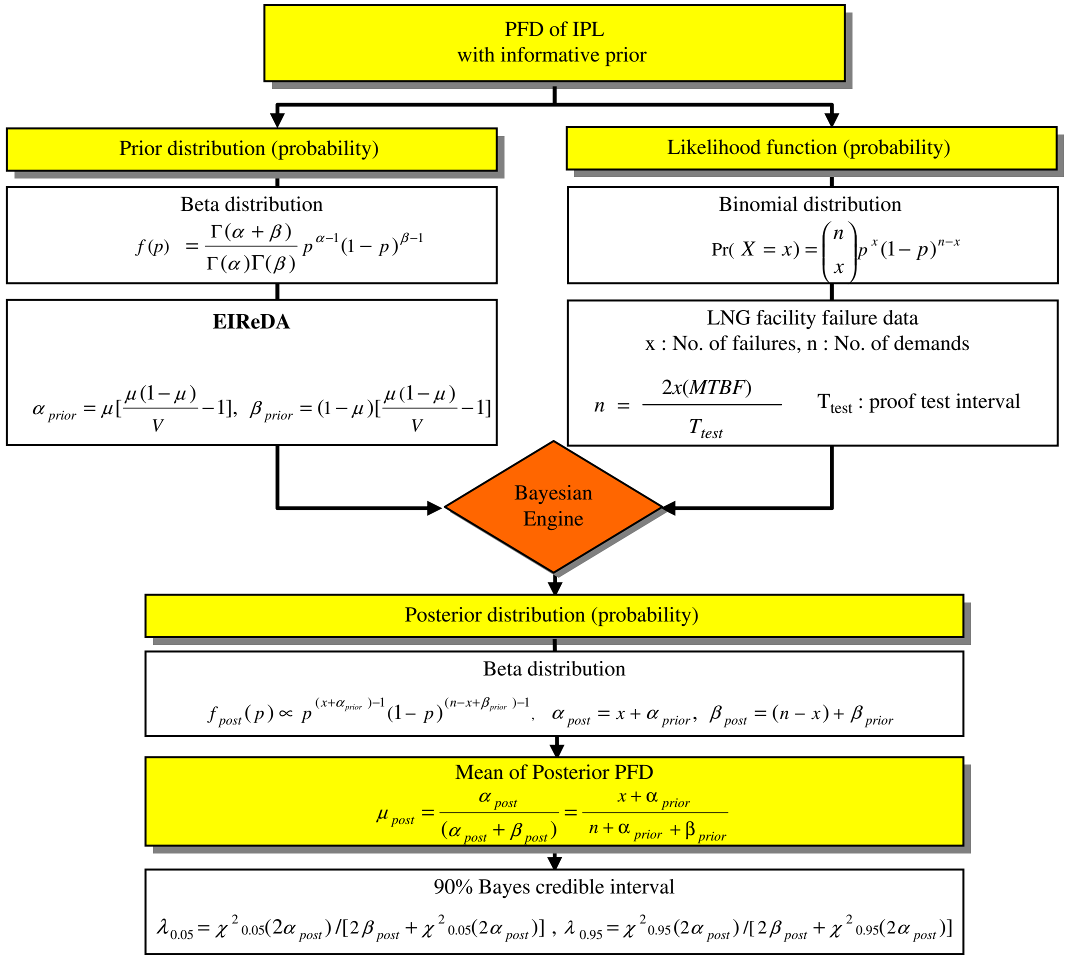

Fig. 3. Schematic diagram of Bayesian estimation for IPLs.

database provides operating hours, number of failures, and mean time between failures (MTBFs) of equipment or facilities.

After obtaining the frequency data of an initiating event, it is necessary to identify each independent protection layer (IPL), which can be found and chosen in the list of safeguards of each incident case in the HAZOP results. However, even though all IPLs can be safeguards, not all safeguards are IPLs, because IPLs must meet the three requirements: independence, effectiveness, and auditability. Thus, very careful consideration should be taken to designate a safeguard as an IPL. Following IPL identification, the PFD of each IPL should be obtained. Generally, this procedure is similar to the case of initiating events, but there are a few differences in the distributions and mathematical calculations. The PFDs of IPLs can be estimated using the conjugate beta prior distribution and binomial likelihood distribution, as shown in Fig. 3.

EIReDA (European Industry Reliability Data Bank) (Procaccia, Arsenis, & Sopyros, 1998) will be used for prior information, because it was prepared from a beta distribution. When EIReDA does not provide failure data, the newly developed frequency-PFD conversion method (Yun, 2007) may be used. LNG plant failure data will be represented by a binomial likelihood function. However, even though some types of failure data are available, the EIReDA database does not provide the number of demands, which is

Table 2
LOPA incident scenarios in an LNG terminal.

No.	Scenarios
1	LNG leakage from loading arms during unloading.
2	Pressure increase of unloading arm due to block valve failed closure during unloading.
3	HP pump cavitation and damage due to lower pressure of recondenser resulting from block valve failed closure. Leakage and fire.
4	Higher temperature in recondenser due to more boil off gas (BOG) input resulting from flow control valve spurious full open. Cavitation and pump damage leading to leakage.
5	Overpressure in tank due to rollover from stratification and possible damage in tank.
6	LNG level increases and leads to carryover into annular space of LNG, because operator lines up the wrong tank. Possible overpressure in tank.
7	Lower pressure in tank due to pump-out without BOG input resulting from block valve failed closure. Possible damage of tank.

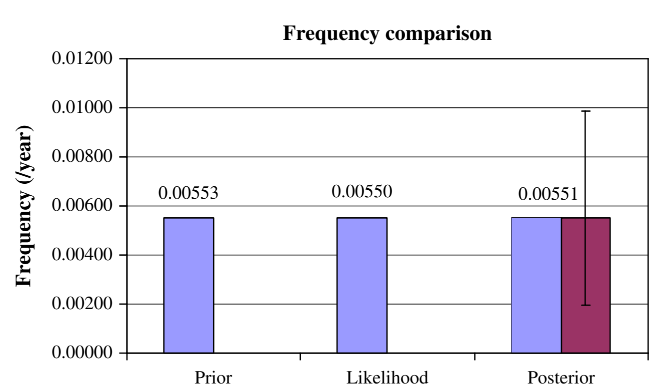

Fig. 4. Frequency of a spurious trip of a block valve closure by Bayesian estimation.

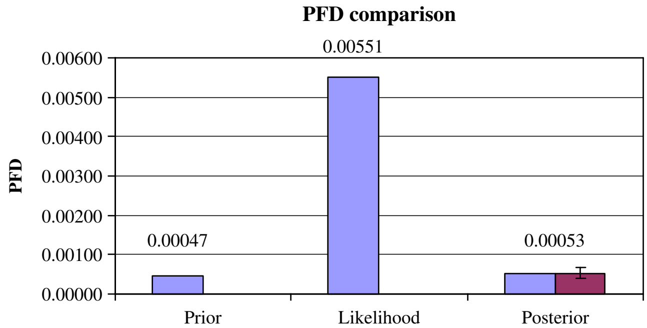

Fig. 5. PFDs of a TSV corresponding to Bayesian estimation.

needed together with the number of failures for the binomial distribution. The number of demands can be estimated, however, by correlation using the PFD estimating equation as shown in Fig. 3, provided periodic tests of equipment are performed that reveal the failures (Crowl & Louvar, 2002; Yun, 2007; Sandia National Laboratories, 2003).

The next step is to use a spreadsheet to calculate the frequency of an incident scenario from the equation given in the "Estimate scenario frequency" step of Fig. 1. In this paper, Microsoft EXCEL software is used.

The last step is to make risk decisions from comparison of an obtained scenario frequency to tolerable risk criteria, which may be specified by companies, industries, or government. The CCPS (Center for Chemical Process Safety, 2001) states that for human fatalities, the frequency criterion for tolerable risk is less than 1×10^{-4}/year. If the estimated frequency cannot meet the tolerable criteria, some recommendations that may include additional IPLs or more frequent proof tests must be given to reduce the incident frequency or mitigate the severity of consequence. As shown in Fig. 1, these steps will be repeated for every incident scenario. The frequencies of all incident scenarios will be estimated and then compared to each other to rank the risks among all scenarios with similar consequence severities. This risk ranking may be used also to develop strategies for maintenance or safety measures.

4. Case study results and validations

During the HAZOP study, seven incident scenarios were developed as shown in Table 2. As an example of a Bayesian–LOPA application, scenario 2 will be described briefly. For emergency shutdown, a block valve, BV-1, is installed to stop the flow of LNG in the LNG unloading pipeline. However, if the valve is closed inadvertently during the unloading procedure, the pressure within the unloading arms and pipelines will be increased to the level of the shut-off pressure of the ship pumps and may cause undesirable consequences in the arms or pipelines.

As an initiating event, the frequency of the spurious trip of a block valve closure can be estimated with the OREDA data and the LNG facility failure data using Bayesian estimation. OREDA provides the failure frequency of a spurious operation for a shut-off valve, so the OREDA frequency is used as prior information. The Bayesian estimated frequency data are given in Fig. 4, which shows that the posterior value of failure frequency is located between the prior and likelihood values. The posterior value is shown to be based on the historical prior and the current likelihood information using the Bayesian engine. That is to say, the posterior value reflects both long-term based historical experiences from the OREDA generic data and short-term based plant-specific conditions from the LNG facility failure data. It is important to be aware that as the sample size of likelihood information becomes larger, the posterior value becomes closer to the likelihood value than to the prior value, i.e., uncertainty is reduced. Thus, it is better to use larger sample data set of likelihood information to obtain more accurate updated posterior values. The vertical line of the posterior column indicates the 90% Bayesian credible frequency interval from 0.0019/year to 0.0099/year.

For this scenario, one IPL involving the temperature safety valve (TSV) may be considered. The PFD of a TSV can be estimated with the EIReDA data and the LNG facility failure data. EIReDA provides the PFD mean value and the values of α and β parameters of the beta distribution for the pressure relief valve (PRV). A TSV and PRV have a similar design configuration, so the PRV failure data are used also as prior information for the TSV. The LNG failure database provides the operating hours, number of failures, and MTBF of the cryogenic valves including the PSVs. The Bayesian estimated PFD of a TSV is shown in Fig. 5. The vertical line of the posterior column indicates the 90% Bayesian credible probability interval from 0.0004 to 0.0007.

Consequently, the mitigated failure frequency of scenario 2 can be estimated using the LOPA spreadsheet as shown in Table 3. For the risk determination, the estimated posterior risk value, 2.90E-6/year, can be compared to the tolerability criterion of less than 1.00E-4/year. Based on this comparison, the risk decision is that

Table 3
LOPA spreadsheet of incident scenario 2 (Bayesian updated results).

Scenario no. 2	Scenario title: pressure increase of unloading arm due to block valve failed closure during unloading		Node no.1
Date	Description	Probability	Frequency (per year)
Consequence description/category	Pressure increase of unloading arm		
Risk tolerance criteria (frequency)	Tolerable		<1.00E-04
Initiating event (frequency)	During unloading, block valve (BV-1) spurious trip close		5.51E-03
Frequency of unmitigated consequence			5.51E-03
Independent protection layers	A TSV along transfer line	5.26E-04	
Total PFD for all IPLs		5.26E-04	
Frequency of mitigated consequence (/year)			2.90E-06
Risk tolerance criteria met? (Yes/No)	Yes		
Actions required to meet risk tolerance criteria	1. A PSV may be installed before TSV, unless TSV can operate as a PSV in case of overpressure.		
Notes	1. Unloading arm and pipe was designed to bear the shut-off pressure of ship pump.		

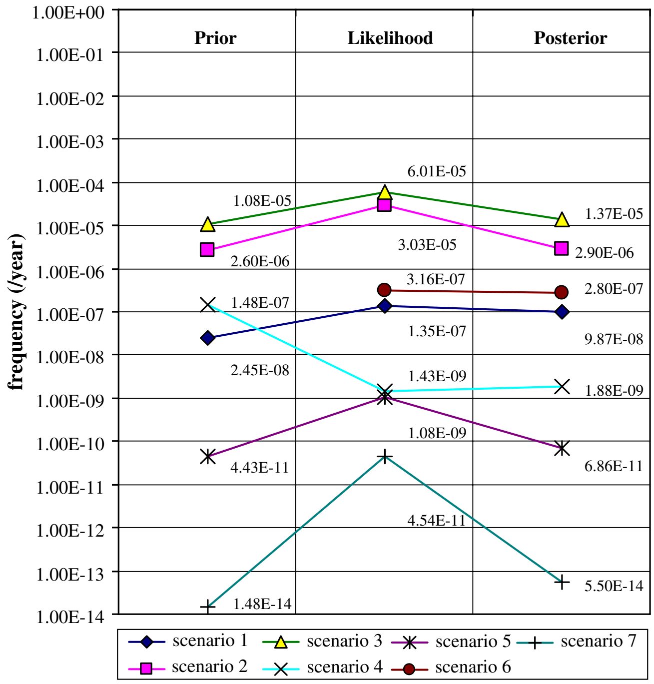

Fig. 6. Frequency values of seven incident scenarios.

scenario 2 is tolerable. Fig. 6 shows that the posterior failure frequency of scenario 2 is located between the prior and likelihood values.

Consequently, for all seven incident scenarios, it is proved that the Bayesian–LOPA method produces valid and well-updated risk values in terms of the fact that the posterior value of every initiating event or IPL is located between the prior and likelihood values. Fig. 6 provides seven risk value graphs that show prior, likelihood, and Bayesian posterior values to check the differences. Additionally, Fig. 6 shows the incident scenario risk ranking based on frequency, which can be used to decide the priority of additional safety measures.

5. Conclusions

As indicated by the good safety record of the LNG industries, it can be generally concluded that a LNG terminal has good safety protection to reduce the probability of upset events as shown in Fig. 6. However, careful caution should be taken that this conclusion is based only on the information that is available to the public, so the results or recommendations may not accurately represent a real LNG terminal. The newly developed Bayesian–LOPA methodology is a powerful tool for risk assessment in LNG importation terminals due to the sparse plant-specific data and the relatively short operational history. Similarly, the methodology can be applied in other industries including refineries, petrochemicals, nuclear plants, and space industries to obtain more reliable risk values. Moreover, it can be used with other frequency analysis estimation methods such as Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) to strengthen their results.

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