Resilience Assessment of Bunkering Operations for A LNG Fuelled Ship

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In the present paper, a methodological framework to move from risk assessment to resilience assessment is described. In order to demonstrate the practical capability of the outlined methodology reference is made to a LNG (Liquefied Natural Gas) bunker activity for a cruise ship. The focal point to assess the resilience of a system is the identification of precursor events, which refers to early detection of "weak" signals from the system during the operations. In order to identify the precursors, a large amount of data analytics is needed. By data processing, validation and analysis, it is possible to predict the behaviour of the system, thus catching the guide-words for a resilient performance. Starting from the operative steps of LNG bunker activity in the maritime field, various coupled Data Driven BNs can be built, which involve the probability of operational perturbations, and their updates based on the hard and soft evidences during the operation. Ship propulsion by LNG as a possible fuel (with dual fuel engines installed on board) implies to deepen safety issues that might be involved in the LNG bunkering operations. Not so many investigations are available in literature at present and the paper is aimed to frame the most significant critical aspects about this topic.

Keywords: Resilience Engineering, Data Driven Models, Dynamic Risk Management, LNG ship propulsion, Bayesian Networks, Decision Support System.

1. Introduction

Resilience assessment integrates a set of key concepts to provide an innovative way of thinking about, and practicing, safety management. Resilience is fundamentally a system property. It refers to the magnitude of change or disturbance that a system can experience without shifting into an alternate state that has different structural and functional properties. The application of this powerful concept is very versatile and it represents a very interesting opportunity to discuss about safety performances of a very complex system, i.e. when safety as a performance is the outcome of a successful interaction among different elements and sub-systems. Under this perspective safety can be defined as a emergent property where resilience is the key enabling property. The increasing interest in the resilience assessment is to be understood in the deep change of paradigm from the prescriptive approach to the performance based one.

The risk assessment is a very useful approach in support of this change but at the same time it is not exhaustive to capture also the possible "failure" in the interface/interaction among the several single components of a complex system beside their specific failures. One of the reasons for the superior attention to resilience is the recent increased capability of data measurement /storage and relevant treatment for developing knowledge. Resilience thinking embraces learning, diversity and how to adapt to a wide range of complex challenges. The resilience approach to safety management is focused and driven by the case studies tackling a variety of critical infrastructures and it is built upon the so called "big data". There is no single accepted set of components of resilience, so, the framework proposed in the

Proceedings of the 30th European Safety and Reliability Conference and
the 15th Probabilistic Safety Assessment and Management Conference.
Edited by Piero Baraldi, Francesco Di Maio and Enrico Zio

ISBN: 981-973-0000-00-0 :: doi: 10.3850/981-973-0000-00-0_output

present paper, which is strictly related to the state-of-art of scientific literature, represents a robust approach to a systemic vision of safety management. What above described in terms of shift of safety paradigm is perfectly applicable to ship design and production especially for very complex units like passengers ships. The kind of continuous innovation trend together with the increasing importance of ship performances as emergent properties constitutes a very interesting field of applications to get a further insight into the issue. Actually, the application case here investigated is relevant to a cruise ship, since it represents a very interesting topic when dealing with environmental and accident hazards (Vairo et al. 2017). The proposed study specifically focuses on the peculiar issue of LNG refuelling. In any case it can be considered a good example in order to propose a complete approach based on the methodology description and on the metrics identification.

2. A new safety paradigm

The evolution of the safety paradigm from safety-I to safety-II implies safety defined as the ability to succeed in a context of varying conditions (Hollnagel, Woods, and Leveson 2006). The change of mind-set is epochal: the practical implication is the need to understand and describe the systems everyday functional performance and its variability as well. Focusing on what goes right, rather than on what goes wrong, shifts the focus from 'avoiding that something goes wrong' to 'ensuring that everything goes right' (Hollnagel 2014). The target implied in Safety-II is to make things go right but with the essential acknowledgment that performance variability is ineluctable: therefore it is necessary as well to find ways to monitor and control this variability (Hollnagel 2016).
The change of paradigm derives from the evidence that the complexity of systems (especially when also the socio-organizational levels are included) is continuously increasing together with the economic pressure.

Traditional safety analysis and a risk assessment might not be appropriate anymore since the complexity of systems implies a significant difficulty to consider all the situations where something can go wrong (Hollnagel 2017). In this regard, resilience is considered an important capability needed by the 21st century systems (Ordoukhanian and Madni 2019).
In the latest decades the term resilience has overflown from the material science (ability of a material to absorb energy when it is deformed elastically, and release that energy upon unloading) to other different fields like ecology, psychology, infrastructures and complex systems in general.
It should be remarked that environmental risk assessment within the wide framework of Seveso Directive is an appealing research area, still under development, and bringing out novel topics to be thoroughly discussed and faced by advanced tools (Sikorova et al. 2017).
Resilience has been defined in literature as "the ability of the systems to adapt to changing conditions in order to maintain a system property" (Leveson et al. 2006). In other words "a system is resilient if it can adjust its functioning prior to, during, or following events (changes, disturbances, and opportunities), and thereby sustain required operations under both expected and unexpected conditions (Hollnagel 2014).
However quantitative metrics of resilience are not well established and further investigations about approaches and techniques are needed (Lloyd's 2015, Beach et al. 2018).
In this paper a methodology based on data analytics will be proposed and applied in the context of a LNG refuelling operation for a ship.

3. The methodology for the resilience assessment

Hollnagel (Hollnagel 2017) proposed the following four needs for resilient performance:

- The ability to respond
- The ability to monitor
- The ability to learn
- The ability to anticipate

The quantitative risk assessment process is crucial for an effective control of major accident hazard but, as thoroughly discussed in Vairo et al. 2019, is affected by several limitations, essentially connected to its inherent static nature. Newly developed frameworks, including dynamic ones, were recently developed and applied to improve the effectiveness of accident investigations, e.g. Fabiano et al. 2016.
A main weakness is also represented by the large error bands associated with data for the likelihood of equipment, e.g. the likelihood of leaks different size spills from pipes, valves etc. obtained from various published sources.
The focal point to assess the resilience of a system is the identification of precursor events, which refers to early detection of "weak" signals from the system during the operations (Jain et al. 2018).
In order to identify the precursor events and thus maintain stability by applying appropriate adjustments, the analysis of a large amount of data is needed. By the data analysis, it is possible to predict the behaviour of the system, thus catching the resilient performance according to the above mentioned 4 guide-words.
During the last decade the so-called data-driven models are becoming more and more widespread. These models rely upon the methods of computational intelligence and machine learning, and thus assume the presence of a considerable amount of

data describing the modelled system's physics.
Data-driven modelling can thus be considered as an appropriate approach to resilience assessment that would complement the "knowledge-driven" models describing physical behavior.
The Bayesian approach has been proven to be a robust probability reasoning method under uncertainty, providing a tool for incorporating the evidences during operations. It can perform a forward and backward inference, and can be used to conduct operational reliability analysis in complex systems (Vairo et al. 2019, Kalantarnia, Khan, and Hawboldt 2008).
Starting from the operative steps of LNG bunker activity in the maritime field, various coupled BNs can be built, which involve the probability of operational perturbations, and their updates based on the hard and soft evidences during the operation.
Ship propulsion by LNG as a possible fuel (with dual fuel engines installed on board) is becoming more and more widespread, especially in the cruise ships market. This innovative solution implies to deepen safety issues that might be involved in the LNG bunkering operations.
When dealing with flammable HazMat, potential loss of containment must be considered of primary importance in relation with storage tanks and piping, where in case of accident the dominant scenario is pool fire (Palazzi et al. 2017). However, the probability of a scenario evolution can be affected by large uncertainties in its evaluation, mainly connected to the possibility of immediate, or delayed ignition.
Not so many investigations are available in literature at present and the paper is aimed to frame the most significant critical aspects of such probability evaluation.
The logic diagram for the proposed resilience assessment framework, in terms of stepwise procedure, is shown in Fig. 1.

3.1. *Identification of precursors*

The main point of the proposed resilience assessment is the identification of precursors.
This stage can be performed by coupling two powerful techniques:

- Probabilistic modelling
- Bayesian modelling

The first stage of the process is to catch the probabilities of precursor events occurrences. The starting point is a safety assessment of the system, by a FTA (Fault Tree Analysis), and then a change from the "frequency based" perspective to the "Bayesian" perspective.
The three main steps are:

(i) Establish a belief about the data, including prior and likelihood functions.
(ii) Use the data and probability, in accordance with our belief of the data, to update our model, check that our model agrees with the original data.
(iii) Update our view of the data, based on our model.

In order to follow the above mentioned step, the tools used in the present work are Markov Chain – MonteCarlo (MCMC) and Bayesian Networks (BNs).
MCMC is a class of techniques for sampling from a probability distribution and can be used to estimate the distribution of parameters given a set of observations.
So, it is possible to estimate the parameters of a logistic function that represents the precursors occurrence patterns:

$$P(precursor \mid t, \alpha, \beta) = \frac{1}{1 + e^{\beta t + \alpha}} \quad (1)$$

We used the PyMC3 implementation of the Metropolis-Hastings (MCMC-MH) algorithm to compute the distribution space of α and β, thus deriving the most likely logistic model.
The precursors are identified starting from the frequencies in FTA. Between the "safe" state and the "failure" state, one intermediate state is inserted, which probabilities are derived from the Metropolis-Hastings algorithm.
The idea behind Bayesian thinking is to keep updating the beliefs as more evidence is provided.
In the philosophy of decision making, Bayesian inference is closely related to the Bayesian view on probability: it manipulates priors, evidence, and likelihood to compute the posterior, according to the Bayes theorem:

$$P(\theta \mid D) = \frac{P(D \mid \theta)\, P(\theta)}{P(D)} \quad (2)$$

Where:

- P(θ | D) is the posterior
- P(D | θ) is the likelihood
- P(θ) is the prior
- P(D) is the evidence

In other words, we would like to find the most likely distribution of θ, the parameters of the model explaining the data, D.
MCMC allows us to draw samples from a distribution, even if we can't compute it. It can be used to sample from the posterior distribution (what we wish to know) over relevant parameters. It has seen much success in many applications where the need is to compute the distribution of parameters given a set of observations and some prior belief.
Metropolis-Hastings is a specific implementation of MCMC.
This technique requires a simple distribution called the proposal Q(θ' | θ) to help draw samples

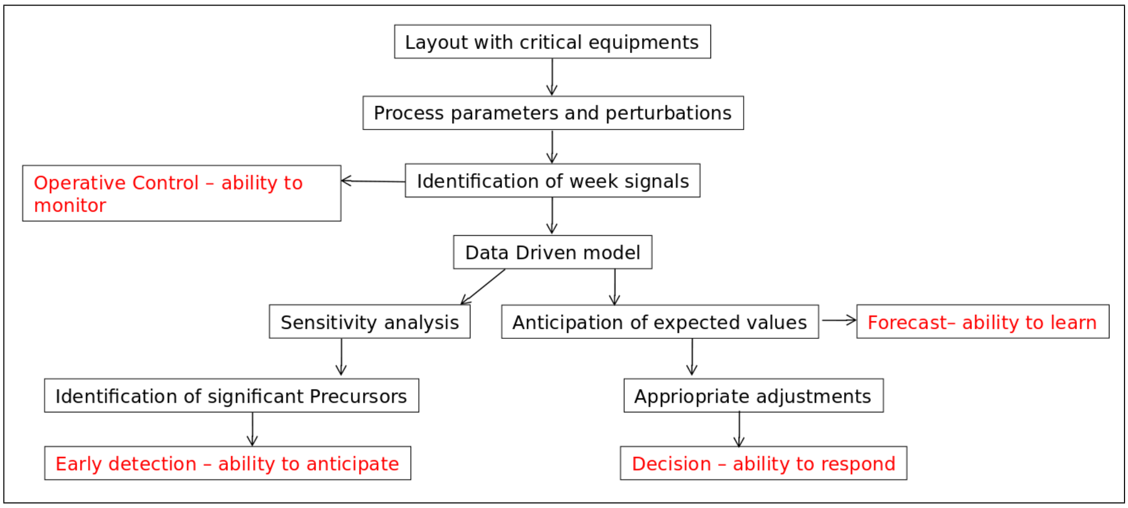

Fig. 1. Resilience assessment framework.

from an intractable posterior distribution P(Θ=θ | D).
Metropolis-Hastings uses Q to randomly walk in the distribution space, accepting or rejecting jumps to new positions based on how likely the sample is. The Markov Chain part (the random walk) is needed because failures are memory-less processes.
To decide if θ' is to be accepted or rejected, the following ratio must be computed for each new proposed θ':

$$\frac{\prod_i^n f(d_i \mid \Theta = \theta')P(\theta')}{\prod_i^n f(d_i \mid \Theta = \theta)P(\theta)} \tag{3}$$

Where f is the above mentioned proportional function. The rule for acceptance is:

P(accept) = (3) if (3) $<$ 1
1 otherwise

This means that if a θ' is more likely than the current θ, then we always accept θ'. If it is less likely than the current θ, then we might accept it or reject it randomly with decreasing probability, the less likely it is (Salvatier, Wiecki, and Fonnesbeck 2016).

4. Applicative case study: LNG bunkering

In the latest decades, important rules addressing ships environmental impact, with specific focus on the exhaust gas effect on air pollution, (MARPOL, Annex VI) where developed and issued by the International maritime Organization (IMO).
At present the use of LNG as fuel is among the most successful solutions in order to comply with the MARPOL requirements. This is in fact the preferred solution for new buildings, especially in the field of cruise ships. Present solutions adopt a dual fuel engine able to use both oil and gas. Engines that are designed for and use LNG won't need to also install scrubber systems or pay high prices for low sulphur fuel.
LNG is natural gas cooled to approximately -260°F (-162.7°C). This enables the gas to be easy to store and transport to various locations.
The most notable benefits and advantages of using LNG is cleaner emissions and lower cost.
In its liquefied state, LNG is odourless, colourless, non-toxic, and non-corrosive.
LNG releases no sulphur, 99% less particulate emissions, 85% less NOx emissions, and 25% less greenhouse gas emissions.
As a consequence, LNG can be regarded as an inherent cleaner fuel allowing to obtain a sharp reduction of critical pollutant emissions (Vairo et al. 2014).
A main issue implied by the adoption of LNG as fuel is the lack of bunkering (fuelling) facilities available yet, so getting an LNG-powered ship refuelled be problematic.
Though there are plans for more fuelling depots to be established for LNG ships, some worries are related to the possible threat this plant and their operational activity might originate: several administration and port authorities are addressing the safety issues the refuelling operations might imply for citizens and coastal environments.
Basically the possible solutions now under development in Europe and worldwide are (EMSA 2018):

(i) Truck-to-Ship - TTS
(ii) Ship-to-Ship - STS
(iii) Terminal (Port)-to-Ship -PTS

For the purpose of this paper, the resilience assessment will be carried out for the case of shore to ship refuelling and a schematic layout is depicted in figure 2 (rif. DNV-GL 2015):

The basic steps of the bunkering process are summarized as follows, derived with some simplification from EMSA 2018:

- precooling of the line (landside), cargo pump included;
- actions to avoid ground fault arcing;
- loading arms are usually used for bunker hose connection;
- the hose is put in place;
- inert gas are used to remove oxygen and moisture from the piping of the receiving ship;
- then the receiving system is purged from the residual nitrogen using the natural gas remained in the LNG tank on board the ship;
- closure of the onshore side valve;
- closure of the ship side valve;
- liquid line stripping;
- bunker line inerting;
- disconnection of the bunkering hose.

For the purpose of this paper a specific attention will be given to the liquid transfer phase, with focus on:

- analysis during the actual bunkering phase
- analysis during the immediate post bunkering phase with the pressure increment

The whole resilience assessment can be very large; in order to understand the validity of the proposed methodology the investigation will be limited to the leakage hazard originated in the part of the system between the two flanges of the connecting hose, technically indicated as “LNG transfer system” (ISO 2018).

4.1. *FTA and BNs*

The developed FTA related to leakage hazard originated in the LNG transfer system is shown in the figures 3, 4, 5 and 6.

The probabilities of failures of the single component are taken from literature (Lees 2012).
Between the safe state and the failure state, one intermediate state is inserted, in order to identify the precursors.
The estimation of precursors distribution is performed by means of MCMC-MH algorithm.

4.2. *Precursors and Probabilistic Bayesian Reasoning*

A conventional fault tree has a converging structure that describes how a group of root events can lead to a top event. This logical structure enables causality reasoning between root events and top event; it allows performing both forward and backward analysis.
For quantitative reasoning, however, only statistical and static information is available. To calculate the probability of occurrence of a top event, the probabilities of the root events have to be either estimated from statistical data or specified by expert knowledge. Furthermore, the basic events are assumed to be statistically independent each other (Yu, Khan, and Veitch 2017). The limitations of FTAs can be easily overcome using the Bayesian probabilistic approach by applying the MCMC-MH algorithm.
The FTAs can be dynamized by considering the root failures frequency as prior probabilities, and then performing the MCMC-MH simulation.
The posterior probabilities are estimated making reference to the solution of the FTAs, as depicted in Figures 7, 8, 9.

Figures 10, 11 and 12 show the values of leakage probability in each iteration, observing only 5% of the original population (i.e. the ”evidences”).

5. Key resilience considerations

From the simulations described above, we are able to anticipate root failures (and consequently to avoid leakages) by analysing the data coming from the operations.
The failure state is anticipated by the intermediate state.
Table 1 summarizes the expected probabilities for the states of the root components (expressed in terms of Maximum Likelihood Estimation), obtained by the Bayesian analysis:

Information could lead to identify the weak signals in the whole system.
Recalling the four needs for resilient performance, we have:

- The ability to respond.
  the system is able to identify the precursors occurrences during the operations.
- The ability to monitor.
  The system is able to analyse data coming from the plant.
- The ability to learn.
  The Bayes theorem is the chosen machine learning algorithm. The training dataset is constantly updated by the evidences.
- The ability to anticipate.
  The opportunity of identifying the precursor events, allows to anticipate any leakages, and to avoid them, by taking possible countermeasures.

The probabilistic nature of the perturbations, and thus of their associated outcomes, necessitates a probabilistic scoring system for resilience. Furthermore, the multitude of plausible scenarios, each one with associated probability distribution, necessarily limit any scoring system to specific

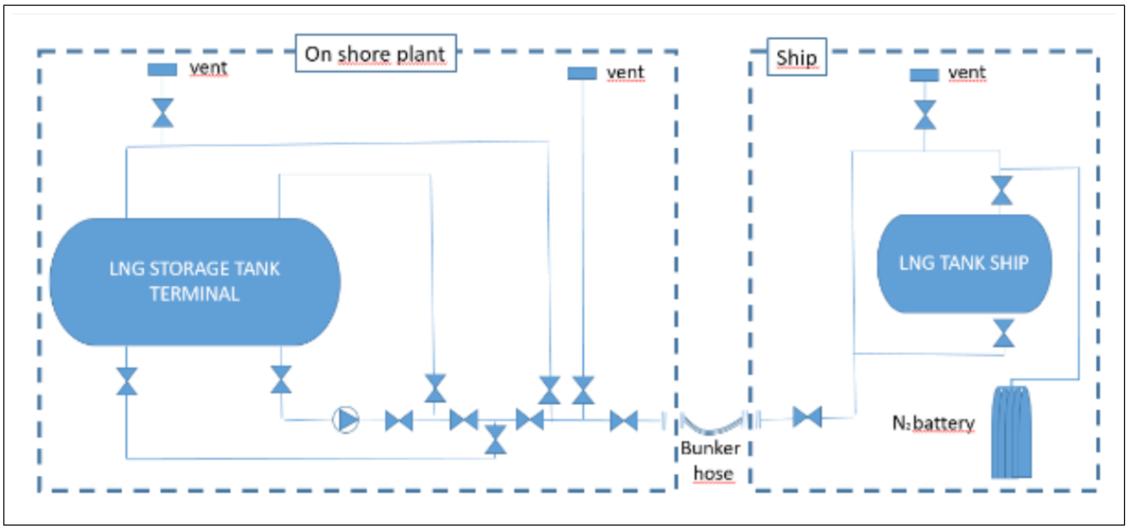

Fig. 2. Representative layout of a shore to ship LNG refuelling plant.

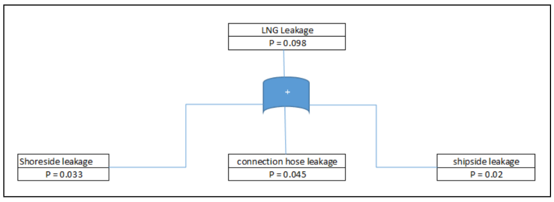

Fig. 3. General FT.

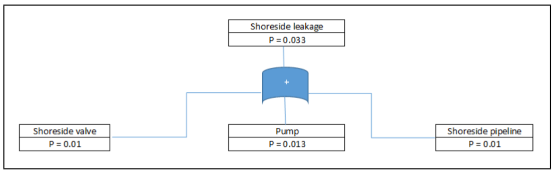

Fig. 4. Shoreside FT.

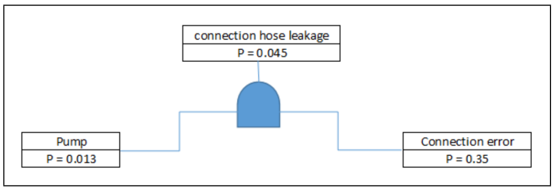

Fig. 5. Connection FT.

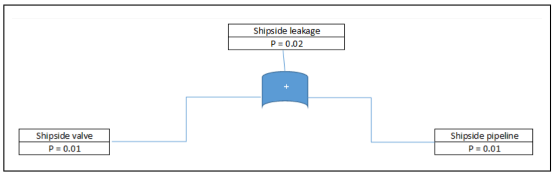

Fig. 6. Shipside FT.

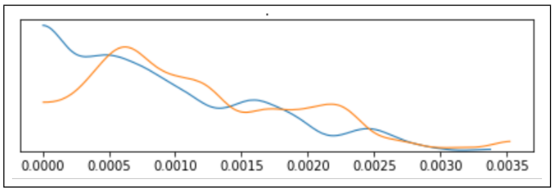

Fig. 7. Posterior pdf of leakage on the shoreside plant.

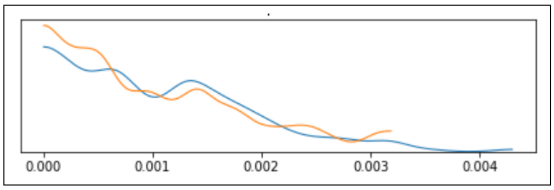

Fig. 8. Posterior pdf of leakage on the shipside plant.

classes of representative perturbation, without prejudice to the possibility of inserting new ones derived from the system application in the field.
The resilience of the whole system can thus be expressed as an indication of how close the system performance is to the precursors. What is needed is to insert the time variable in the simulation, in order to know how the state of the plant is changing in time.
That could be done applying a Bayesian survival model, to perform a survival analysis using Gaussian random walks. So it is possible to represent the resilience score with a parameter varying between 1 (system safe) and 0 (system failure). The value of the resilience parameter can be updated with the state coming from the previous men-

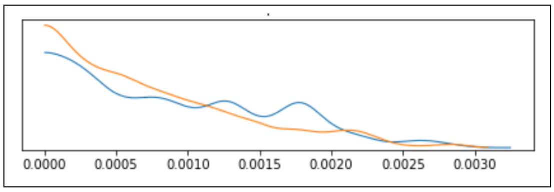

Fig. 9. Posterior pdf of leakage on the connection hose.

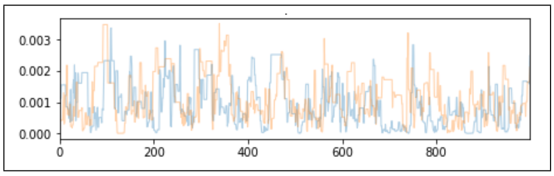

Fig. 10. Probability of leakage on the shoreside plant in each iteration.

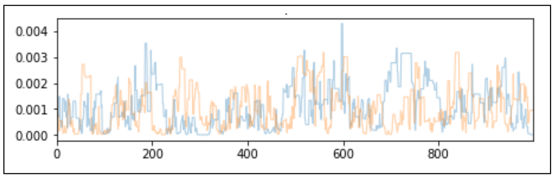

Fig. 11. Probability of leakage on the shipside plant in each iteration.

tioned random walks.
Each step of the overall resilience score takes into account the CDF (Cumulative Distribution Function) of the different states probability.
Figure 13 represents how the resilience score (as defined above) is changing during the operation, when different perturbative situations appear.

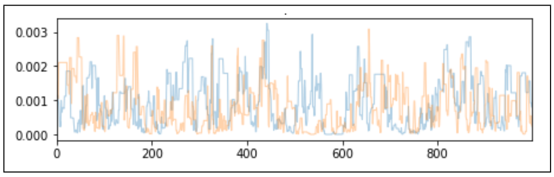

Fig. 12. Probability of leakage on the connection hose in each iteration.

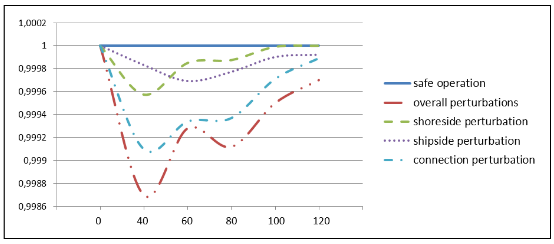

Fig. 13. Resilience score in different perturbative situations.

Table 1. Expected probabilities of occurrences of possible states in the root components.

Root component	Expected probability (MLE)
Shoreside valve	
safe	0.197
intermediate	0.784
failure	0.029
Pump	
safe	0.162
intermediate	0.803
failure	0.035
Shoreside pipeline	
safe	0.321
intermediate	0.612
failure	0.067
Hose	
safe	0.087
intermediate	0.854
fail	0.059
Shipside valve	
safe	0.197
intermediate	0.784
failure	0.029
Shipside pipeline	
safe	0.321
intermediate	0.612
failure	0.067

6. Conclusions

The idea behind the resilience analysis is that safety is an emerging property of the system. This work has shown how it is possible to evaluate the system's resilience through dynamic analysis, connected with what is happening in the plant at that precise moment operation in progress.
The approach used in this work, based on Bayesian statistical modeling and probabilistic machine learning, which focuses on advanced Markov chain Monte Carlo and variational fitting algorithms, has proven to be a useful and flexible tool to study, analyse and verify the achievement of the four basic needs of the resilience paradigm. The proposed score metric can represent a valid indicator to define how much the perturbations of system and subsystems can be absorbed without leading to failure.
Moreover, performing a resilience assessment, can help decision makers and planners to pursue

environmental and safety objectives more effectively.
As far as the specific application case, in relation with the plausibility of assumed input data, it seems that the LNG bunkering operation of a ship is characterized by satisfactory resilience property.
Further development of this versatile and robust approach could entail the environmental parameters as well, investigating their influence on the resilience assessment.

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