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Dynamic reliability model for subsea pipeline risk assessment due to third-party interference

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ABSTRACT

The accidents of subsea pipelines due to third-party interference often result in catastrophic impacts, therefore, risk assessment has progressively become substantial to ensure the safety and reliability of the systems. However, the current risk analysis approaches are unable to minimize the uncertainties in the analysis due to the high demands of the qualitative inputs. The Bayesian network approach is believed to be able to provide answers to such a problem. The main advantage of this technique is that it allows the inference model and predictive analysis for constructing the current and future performance of the system based on the observed evidence. These can be achieved by introducing the subsea pipeline's accident history and operational data in the model for developing the conditional probability distribution of each variable in the analysis. This paper proposes a dynamic reliability model for subsea pipeline risk assessment due to third-party interference based on the Bayesian approach. This technique is combined with fault tree and the finite element models for producing a reliable risk assessment framework for subsea pipelines. It is expected that the proposed model will be able to minimize the number of qualitative inputs in the analysis and also provides dynamic results for estimating the risk level of the subsea pipeline throughout its service life.

1. Introduction

Subsea pipeline risk assessment has now become increasingly important to guarantee the safety and reliability of the system throughout its service life (Kawsar et al., 2015; Khan et al., 2021). The likelihood and consequence of a subsea pipeline failure must be evaluated in order to assess the risks from several threats, such as corrosion, third-party damages and mechanical failures. The pipeline failure due to these threats could have devastating effects on human safety, environment and economy. However, it is hard to predict failure probabilities in advance, which makes it harder for operators to maintain their pipelines in safe operation (DNV, 2017).

Risk assessment presents several difficulties in its development, such as the limitation of available information on the likelihood of failure threats and the particular consequences of failure (Shan et al., 2018). This could lead to making several assumptions and using expert opinions in the model and analysis, which might result in greater uncertainty in the outcomes. Advanced logic-based approaches, such as dynamic fault tree (Aslansefat et al., 2020), Petri net (Guo et al., 2016), and Bayesian network, are contemporary models used for dynamic risk assessment of safety critical infrastructure. An efficient pipeline risk assessment should be able to characterize and calculate the risk associated with a pipeline. Unfortunately, the calculation of risk requires knowledge about the probability of failure and the consequence of failure. Both of which are difficult to estimate, and in practice, the system under analysis cannot be characterized precisely. Moreover, numerical or objective data are often inadequate, uncertain, and sometimes unavailable to perform calculations (Sulaiman, 2017).

Failure threats in subsea pipelines are hard to inspect, but the parameters influencing them are easier to observe. Bayesian networks are developed to manage and overcome data uncertainties in the prediction of corroded pipeline performance. The dynamic risk is considered by introducing the time function into the model variables (Aulia et al., 2019). Applying the dynamic Bayesian reliability model to an industrial case study produced a realistic result of the pipeline estimated risk level, which was similar to the risk assessment result specified by the Operator (Aulia et al., 2021). Given the high amount of uncertainties that will most probably be involved in risk analysis Pesinis and Tee (2018) have indicated that Bayesian networks can provide a possible modelling and predictive approach to forecast the pipeline performance. It is an effective method for reasoning under uncertainty, using well-established theoretical principles of probability as the basis for inference analysis and to overcome the uncertainty. Bayesian networks can also be expanded to consider a system's dynamic behaviour by introducing temporary network dependencies (Chang et al., 2019).

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In recent years, several studies have proposed relevant analysis methods in the field of subsea pipeline risk assessment (Bai and Bai, 2014; Li et al., 2019). Bai and Bai (2014) suggested the probability and consequences of the failure of subsea pipelines from different types of impact and investigated the prediction of risk and acceptance criteria to establish an optimal plan for inspection. Kawsar et al. (2015) implemented a QRA model of application by conducting numerical simulations with finite element analysis based on statistical sampling and probabilistic assessment of transverse accidental loading on submarine offshore transmission lines.

Maintenance operations of subsea pipelines are generally carried out under challenging working conditions and subjected to a series of factors such as human error, harsh environment and equipment failure (Li et al., 2019). Risk analysis during maintenance operations is required to improve the completion probability of operations, and to avoid unexpected incidents. Some research works mainly focus on assessing the integrity of the systems (Aljaroudi et al., 2015; Barihaa et al., 2016), however, these studies do not use risk as a decision supporting tool. Silva and Soares (2016) assessed the risk level of a pipeline system encompassing the pipelines as individual elements and their contribution to the subsea production system. A semi-quantitative risk assessment tool is used to evaluate the pipeline failure probability and the severity of the failure.

Pipeline leak accidents with disastrous consequences are rare, and insufficient data are available for probability estimation of such an event (Yang et al., 2015). In general, available information from different sources is gathered to address insufficient data. This process introduces data uncertainty in risk analysis. Li et al. (2019) propose a new methodology implemented with hierarchical Bayesian network (BN) to assess the risk of subsea pipelines leak. On the other hand, conventional methods would induce a biased result in probability estimation of the rare event with insufficient data. Quantitative risk assessment of such events is consistently a challenging task due to data scarcity.

Third-party interference is one of the significant causes resulting in subsea pipelines failure (Li et al., 2018; Okodi et al., 2021). According to European Gas Pipeline Incident Data Group (Horalek, 2015), 35% accidents of subsea pipelines are induced by third-party interferences. The current risk assessment methods for this failure threat are still relied on the qualitative factors, such as background and experience of experts, on most of the analysis and cannot practically address the complexity of the risk factors (Guo et al., 2018).

The main objective of this paper is to propose a dynamic reliability framework for assessing the subsea pipeline risk estimation due to third-party interferences. The fault-tree analysis is utilised to propose an initial idea of the subsea pipeline failure mechanism. Then, the proposed model is transformed into a dynamic Bayesian network to indicate the dependencies between each variable, and also to introduce the time variable in the model. Several qualitative inputs in the analysis are minimised by utilising the functional interpolating method proposed by (Mkrtchyan et al., 2016), leading to reduced uncertainty factors in the model. Finite element analysis is also used to determine the pipeline impact forces due to the failure threats. The risk estimates obtained with this model are compared with a practical industrial code-based assessment for validation purposes. Furthermore, the dynamic model is also utilised to estimate the risk estimation of the subsea pipeline throughout its design life using predictive inference. This inference analysis is expected to forecast the value of any node based on history and/or present data. With regard to pipeline life extension assessment, the model can also be expanded to cover the upcoming time slices beyond its design life, allowing to estimate the pipeline risk level during its extended life.

2. Pipeline risk assessment

Generally, risk assessments consist of an estimation of the failure frequency and an assessment of the accident consequences. The frequency of occurrence and the consequence of failure may be either:

(1) calculated when there is sufficient data (quantitative approach);
(2) estimated on the basis of engineering judgment or expert opinion (qualitative approach);
(3) combination of both approaches (semi-quantitative approach).

The occurrence frequency is then ranked from 1 (i.e. low frequency) to 5 (i.e. high frequency), and the consequence is ranked from 1 (i.e. low, non-critical) to 5 (i.e. high, significant impact).

Reference DNV (2017) categorises the subsea pipeline's failures into different damage categories, i.e. minor (D1), moderate (D2) and major (D3). The frequency ranking and consequence ranking are established for each of the relevant damage categories, thus giving the risk for each damage category. The explanation for each damage categories is as follow.

(1) Minor damage (D1): Damage neither requiring repair nor resulting in any release of hydrocarbons. Smaller dents in the steel pipe wall, e.g. up to 5% of the diameter, will not normally have any immediate influence of the operation of the lines.
(2) Moderate damage (D2): Damage requiring repair, but not leading to the release of hydrocarbons. Dent sizes restricting internal inspection (e.g. over 5% of the diameter for steel pipelines) will usually require repair. Ingress of seawater can lead to corrosion failures. However, the repair may be deferred for some time, and the pipeline or umbilical may be operational, provided that the structural integrity is confirmed.
(3) Major damage (D3): Damage leading to release of hydrocarbons or water, etc. If the pipe wall is punctured or the pipeline ruptures, the pipeline operation must be stopped immediately and the line repaired. The damaged section must be removed and replaced.
(4) In case of damage leading to release (D3), the following classification of releases are used:
(5) No release (R0).
(6) Small release (R1): The pipeline may release small amounts of content until detected either by a pressure drop or visually.
(7) Major release (R2): Release from ruptured pipelines. The full rupture will lead to a total release of the volume of the pipeline and will continue until the pipeline is isolated.

The subsea pipeline risk is then evaluated by plotting the established frequency and consequence in a risk matrix. In a risk matrix, the ALARP (as-low-as-reasonably-practicable) region identifies an area where the risk is acceptable; however, further reduction of the risk should be pursued with cost-benefit evaluation. In order to compare the frequency and consequences with the risk of any of the relevant hazards, an individual ranking is proposed by DNV (2017), as presented in Table 1.

There are several techniques which are widely utilised to identify failure causes and their effects and to estimate the associated probabilities in risk assessment, i.e. fault tree analysis (FTA), hazard and operability (HAZOP) study and failure mode and effect analysis (FMEA). Fault tree analysis is a widely known risk evaluation instrument that takes unwanted occurrences or flaws and reflects them in a tree-like framework through a straightforward logic and graphic design method (Kabir, 2017). A fault tree is built to identify and explicitly demonstrate all prospective causes (basic events) to result in the unwanted event (top event). The causal probabilities are linked through logical gates (OR, AND). These logical gates depict the connection between events of output and input. The objective of qualitative analysis in an FTA is to achieve minimum cut sets. If all the minimum cut sets and basic event probabilities were acquired, the likelihood of top event failure would be achieved. On the other hand, the constraint of fault trees is that they presume independence among the basic events, which is not usually a valid hypothesis. Furthermore, the basic event probabilities are most likely assigned utilising qualitative inputs, hence, it results in a higher degree of uncertainties in the analysis.

A HAZOP study is a structured and systematic approach to identifying any potential system hazards (Taylor, 2017). HAZOP is based on a

Table 1
Risk ranking and measurements (Adapted and modified from DNVGL, 2017)

Variables		State description	Proposed ranking	Measurement
Frequency of failure		Annual frequency	1	$< 10^{-5}$
			2	10^{-5}–10^{-4}
			3	10^{-4}–10^{-3}
			4	10^{-3}–10^{-2}
			5	$> 10^{-2}$
Consequences of failure	Human safety	Human endangered	1	No person(s) are injured
			3	Serious injury, one fatality
			5	More than one fatality
	Environmental	Amount of release	1	0 Tonnes
			2	< 1,000 Tonnes
			3	1,000–10,000 Tonnes
			4	10,000–100,000 Tonnes
			5	> 100,000 Tonnes
	Economic loss	Production delay	1	0 days
			2	< 1 month
			3	1–3 months
			4	3–12 months
			5	> 12 months

hypothesis that risk events are triggered by operational or design purpose deviations. It is a team approach involving multidisciplinary professionals for collective brainstorming to stimulate a variety of opinions on the subject based on a list of guidelines. There are some disadvantages in using HAZOP for risk assessment, such as low certainty due to the qualitative inputs and high demands on the knowledge and experience of the participants.

Failure mode and effects analysis (FMEA) is a structured approach to discovering potential failures that may exist within the design of a product or process (Lo et al., 2019). Those initiating events with similar obstacles can be put in the same group in the FMEA-based risk assessment approach. Analyses will be simplified by concentrating on the significant group instead of redundant events. FMEA analysis can be classified as a subset of a HAZOP study. FMEA's purpose is to allow a concentrated system or process evaluation to define potential threats and their potential effect on performance outcomes. The disadvantages of the assessment are that each event is treated as a different occurrence and no consideration is given to the interactions between events (Sulaiman, 2017).

There are several techniques and tools for analysing the safety and reliability of a system dynamically, by estimating its failure threats, frequencies and consequences. The artificial neural network (ANN) technique is a powerful method which is capable to learn information from samples, and is usually considered analogous to the human brain (Xu et al., 2017). ANNs possess the ability to implicitly detect complex non-linear relationships between independent and dependent variables, and predict accurate solutions for any undefined inputs in many research fields. El-Abbasy et al. (2014) presented a study of ANN to develop condition prediction models for oil and gas pipelines. The main advantage of ANN in their study was related to the capability of learning from specific predefined patterns. The learning capacity might include classification, prediction, and control of any specific task. Furthermore, ANNs were used to predict the corrosion rate based on the parameters of corrosion defects obtained from in-line inspection data (Ok et al., 2007), and applied to predict the ultimate tensile strength of the API X70 steels after thermomechanical treatment (Khalaj and Khalaj, 2016). Although the prediction results obtained from ANN models have acceptable accuracy, the uncertainties in the measurement of hidden variables in the networks are often neglected (Wen et al., 2019).

Petri Net is a popular mathematical and graphical modelling tool for minimising the uncertain, vague and random characteristics of risk factors on a system. Chang et al. (2018) claimed that the Petri Net model can conform to human thinking and cognitive style and has a good parallel processing capability for analysing the system risk. The Petri Net model can also be combined with fuzzy logic approach to further risk evaluation (Guo et al., 2016; Li et al., 2019). Guo et al. (2016) presented a Fuzzy Petri Net model combined with fuzzy reasoning algorithm for the risk evaluation of long-distance oil and gas transportation pipelines. The proposed model was claimed to be able to improve the traditional fault tree analysis approach by conducting further quantitative analysis and found the weak links of the system precisely. The other popular technique for modelling the probabilistic analysis is Bayesian network (BN). Kabir and Papadopoulos (2019) compared the Petri Net and Bayesian Network based models when used as model-to-model transformation approaches, considering a simple dynamic fault tree (DFT). It was seen from the result, from a graphical point of view, that the Petri Net model of the DFT was relatively more complex than the Bayesian Network model of the DFT. More specifically, while the Bayesian Network model had 23 nodes, the Petri Net model had 40 nodes. The Bayesian Network model had 23 arcs and the Petri Net model had 78 arcs and 34 transitions. In addition, in terms of parameter setting, the Petri Net model needs to set the firing rates of 13 timed transitions. On the other hand, Bayesian Networks need to set the conditional probability table (CPT) for analysis, and in this case, there are 17,574 values that needed to set in the conditional probability tables. Out of these values, 17,496 values are deterministic, i.e., either 0 or 1, hence set automatically. Therefore, there were 78 probabilistic values for 13 root nodes corresponding to 13 basic events of the DFT which were set manually. In a Petri Net model, a transient analysis is performed for generating 174,345 states. DFTs of larger systems can be much larger and more complex, leading to graphically complex and computationally demanding Petri Net models. In terms of results, the Bayesian Network and the Petri Net-based methods estimated the top event probability of the DFT as 0.0293 and 0.0290, respectively. This shows that the results given by the two models are comparable. A qualitative comparison between five soft computing techniques, i.e. decision tree, fuzzy rule, artificial neural network, Bayesian network and cognitive maps, was given in Ismail et al. (2011). It can be seen that Bayesian networks are the most suitable technique for the pipeline performance probability analysis.

Several studies have been conducted on the utilisation of the Bayesian network for analysing the risk on the pipeline. Li et al. (2019) demonstrated the application of Bayesian network in risk analysis of submarine oil and gas pipeline. The hazard identification and escalation process of pipeline leakage were modelled using the bow-tie approach. A Bayesian network model was developed due to the limitation of bow-tie in conditional dependency analyses and common cause failures. The proposed approach was claimed as an efficient tool in risk analysis on leakage failure of the pipeline. However, the conditional probability tables in this analysis were developed using the qualitative inputs, which may result in uncertainties and biases on the outputs. Further review of dynamic BNs is given in Section 3.2.

An efficient subsea pipeline risk assessment should be able to characterize and determine the risk associated with the pipeline, and examine the likelihood and consequences of the failure threats. However, the current approaches are lacking the ability to minimise the uncertainties in the analysis due to the high demands of the qualitative inputs. Therefore, this study will focus to overcome these uncertainties by developing dynamic reliability analysis, based on historical and actual pipeline data, to examine the probabilities of the frequency and consequences in the risk assessment. A Bayesian Network approach is believed to be able to provide answers to such a problem and this will be further explained in the next section.

3. High-level research framework

Fig. 1 shows the high-level research framework proposed in this study. It contains five stages, i.e. failure mechanism identification, conditional probability development, impact force analysis, frequency and consequence analysis, and risk ranking measurement. There are three tools which will be utilised to conduct the analysis, such as traditional fault tree analysis for initial causal network development, finite element analysis for impact force analysis and dynamic Bayesian network for constructing the conditional probability distribution and analysing the dynamic model for the whole risk assessment process. Each of the above tools are explained in the following sections.

3.1. Fault tree analysis-based workflow

Fault tree analysis is utilised to construct an initial model of the subsea pipeline failure mechanism. It consists of three main steps, i.e. potential threats identification, failure mechanism analysis and related factors identification. The tree development starts from identifying the top event that is selected by the user for a specific interest and the tree developed will identify the root cause. Several sources are used throughout in building the fault tree model, such as related research papers (Chang et al., 2019; Peng et al., 2016; Liang et al., 2012; Cheliyan and Bhattacharyya, 2018), technical literature and project experiences.

3.2. Dynamic Bayesian networks-based workflow

Dynamic Bayesian Networks (DBN) are a continuous enhancement of static Bayesian networks for modelling dynamic systems through the analysis of time variations (Hu et al., 2015). While the static Bayesian network indicates the cumulative probability distribution over a collection of time-independent random variables, the dynamic Bayesian network is a multi-dimensional depiction of a random process. The DBNs enable the interpretation of the present, the reconstruction of the past and the forecasting of the future, mostly due to the inference algorithms' computational complexity (time is considered as a discrete variable) (Zarei et al., 2017). In this paper, dynamic Bayesian networks are used to analyse the probability distribution of the failure frequencies and consequences in the risk assessment. Moreover, dynamic models are used to introduce time-variance in the analysis for predicting the future risk ranking estimation. The main advantages of the dynamic Bayesian network are that they allow inference analysis based on observed evidence and give options to model the future performance of the system (Nguyen and Bai, 2018).

The dynamic workflow from Fig. 1 considers the time-dependent variables related to failure threats in a systematic way. It minimises the qualitative inputs from experts in the CPT development by creating a more effective and efficient expert questionnaire, leading to a reduced degree of uncertainties in the analysis. The proposed framework is distributed among three levels. These are level 1: causal network development; level 2: conditional probability distribution development, and level 3: dynamic probability analysis. Details of the dynamic Bayesian analysis steps are presented in Aulia et al. (2021).

For the initial step, once the failure mechanism models have been constructed by the fault tree analysis, the models are converted to a dynamic Bayesian causal network to determine the causality of each variable, and their impact on the system. Time dependant variables are also defined in order to assign the time slice nodes into the network model. Several sources are utilized throughout in building the causal network to determine the state measurement and in assigning prior probabilities to variables where data is not available, i.e. from literature, project experiences, and expert opinion (Li et al., 2019). These prior probabilities will be updated when new observed evidences become available, and new results will also be extracted accordingly.

The next step is to develop the conditional probability distribution of the causal network. This stage is divided into three cases (Aulia et al., 2021). The first case is applicable when there are no available project databases, so the expert domain will be utilised. The second case is rele-

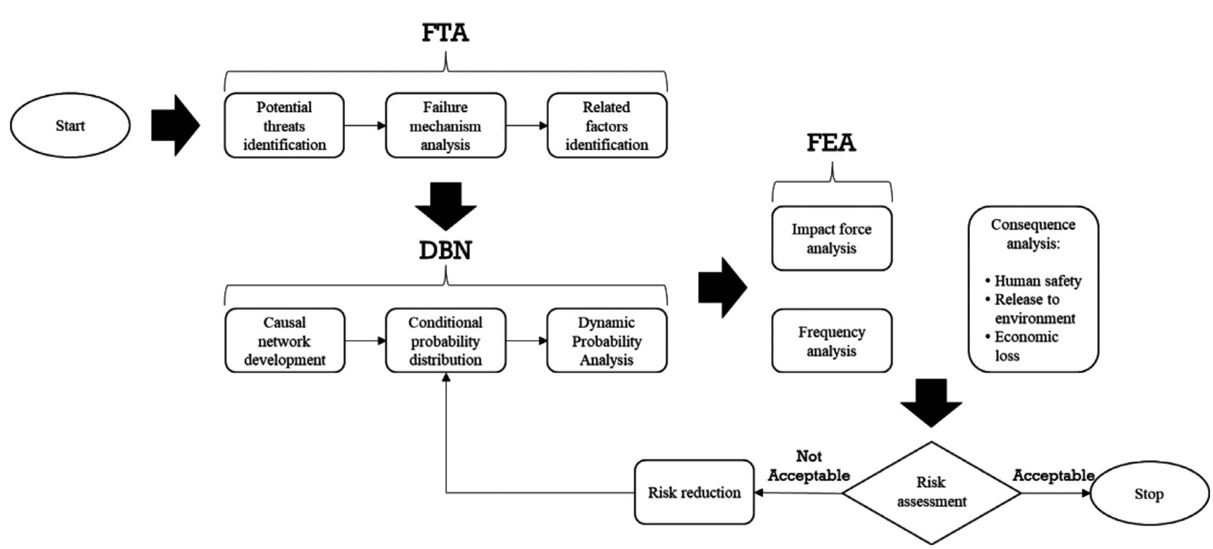

Fig. 1. Proposed five-stage research framework for pipeline risk assessment.

vant when the database containing pipelines' historical data is available to fill all variables such as pipeline design data, inspection history report, operational data and incident report. Finally, the third case is a combination of the first and second case techniques, which will be utilised when the project database information is limited, and expert opinions are used to fill the missing data. In this study, the third scenario will be used due to data availability for the conditional probability table development.

The last step is to analyse the time-dependant probability model using a dynamic Bayesian network. As the DBNs are applied to construct future probability distribution, the performance of the pipelines which are threatened by the failures can be predicted as a function of time. Current operational data, such as temperature, pressure and content, and also third-party data, such as latest ship traffic data near the pipeline, installation schedules, and platform lifting activities, are considered as evidence or observed data to update the conditional probability distribution and dynamic model for failure probability prediction. The future probability conditions of the top event are predicted using the prediction inference calculation of the DBN. Prediction inference can be utilised for all variables in the analysis as long as those variables have history and/or current observation data. Therefore, the Bayesian network's prior probabilities will always be updated when new data or evidence becomes available.

Dynamic Bayesian analyses are also employed in the risk matrix predictive analysis. The dynamic models provide a set of risk level probabilities throughout the pipeline service life, and it can also be expanded to analyse the estimated risk level during the pipeline life extension phase. If the estimated risk is above the relevant acceptance criterion, then risk reduction can be achieved by reducing the frequency of the event, reducing the consequence of the event, or a combination of both. The dynamic models allow the long-term effectivity assessment of several preventive and corrective actions taken to minimise the risk.

3.3. Finite element analysis methodology

The finite element approach is utilised in this study to analyse the damaging impact on the pipeline due to the forces of failure threat. The dropped object weight is represented by concentrated force, and is applied on a straight pipeline at an angle of 90° to the seabed to simulate the effects of the dropped object, as presented in Fig. 2. The force value is increased until the equivalent stress at the hit point is equal to the maximum allowable stress for each damage category. This is taken to be the point at which leakage can occur, considering the maximum weight from the dropped object, the specified minimum yield strength (SMYS) and specified minimum tensile strength (SMTS) of the pipeline. The damage categories from several sources (DNV, 2017; ASME, 2017; Alkazraji, 2008) are adopted and modified for conservatism purposes, as listed in Table 2.

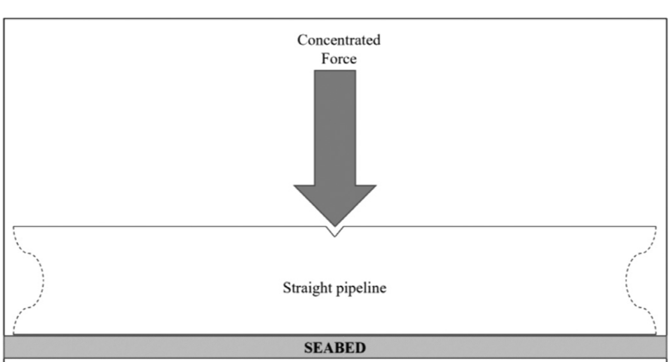

Fig. 2. Simulation of dropped object on the pipeline.

Table 2
Damage category for stress analysis.

Damage category	Maximum allowable stress
Moderate	0.9 x SMYS
Major	1 x SMYS
Serious	1 x SMTS
Catastrophic	1.1 x SMTS
Disastrous	> 1.1 x SMTS

These damage categories will be considered as the pipeline impact force variable states for the Bayesian conditional probability development. The frequency of the potential dropped object for each floater will be gathered to populate the conditional probability table.

The stress analysis is performed in accordance with (ASME, 2017) using AutoPIPE software Version 12.01.00.09. AutoPIPE is a finite element analysis program used to analyse piping and structural systems subjected to static and dynamic loading. The program contains a comprehensive library of material properties and piping components including pipes, bends, flanges and supports. The program takes into account the non-linear behaviour of the restraints due to gap and/or friction and models the buoyancy effect in subsea pipelines. The following sections detail the development of the model, the design load conditions and stress analysis.

3.3.1. Model development

In this study, pipeline elements are modelled as 3D straight pipe beam elements connected at nodes. An anchor is required in the model and in this analysis, it is located at the end of the pipeline section. For conservatism purposes, the seabed is modelled as rigid supports below the pipeline, and a sharp-edge load perpendicular to the seabed is applied to give the worst impact to the pipeline (DNV, 2017). The presence of water is represented by buoyancy load requiring water surface elevation and the specific gravity of the water. The wave is included by inserting its height and associated period and profile of current velocity at five different elevations is also included in the model.

The software works on the basis of a global coordinate system that can be located at any point along with the model. Nodes are established at important locations such as anchors, support locations and to define the length of the pipeline elements. The wave and currents loads are applied along with the global directions.

Boundary conditions are specified at any of the nodes to restrain translation or rotation of a particular node in any of the three global (or local) coordinate directions. The following describes the boundary conditions used for the supports in the model.

(1) V-Stop: the supports that restrain vertical downward movements of the pipeline.
(2) Anchor: the supports that restrain all translations and rotations at any node of the system and are used to model the pipeline ends, which are fixed in all degrees of freedom. The model ends at the restrained section of the pipeline is constrained for all translations and rotations.

Some of the software features which has been used in this study are described below.

(1) Coatings: external coatings (concrete & corrosion coating) are considered as part of the overall structural model of the pipeline. The pipe weight is computed directly by the program. Since only one coating is allowed to be input by AutoPIPE, external coatings that consist of several different layers of coatings are calculated for one composite coating density.
(2) Fluid Properties: both internal and external fluid properties influence the pipeline. Internal pressure is applied and results in both circumferential and longitudinal stresses. The specific gravity of the pipe contents can be specified in order to calculate its weight.

(3) Buoyancy: by specifying the water level with respect to the vertical global axis from the model origin and the specific gravity of seawater the buoyancy loads are simulated and considered for the analysis.
(4) Current and Waves: this feature facilitates to simulate the wave and current loads to be used in the stress analysis.

3.3.2. Load cases

The basic functional and environmental load cases are considered in this study. The functional loads are pipeline weight (gravity load), internal temperature and pressure, whilst the environmental loads are waves and currents from four global directions. The proposed load case combinations are as follows.

Load Case 1: Functional (GT1P1)
Load Case 2: Functional + Environmental (GT1P1+U1)
Load Case 3: Functional + Environmental (GT1P1+U2)
Load Case 4: Functional + Environmental (GT1P1+U3)
Load Case 5: Functional + Environmental (GT1P1+U4)

Where:

G: Gravity load (considering the pipe and coating / insulation weight)
T1: Fluid temperature
P1: Pressure (internal and external)
U1: Wave and current loads applied along + X axis (pipeline longitudinal "+" direction)
U2: Wave and current loads applied along + Y axis (pipeline lateral "+" direction)
U3: Wave and current loads applied along - X axis (pipeline longitudinal "-" direction)
U4: Wave and current loads applied along - Y axis (pipeline lateral "-" direction)

3.3.3. Stress analysis

Pipeline stress due to dropped object impact analysis has been carried out in accordance with (ASME, 2017). The hoop, longitudinal and combined stresses are verified against the allowable stresses by means of code compliance automatically by the program as per the design code. The stress analysis is performed to limit the stresses within allowable limit. In this study, it is assumed that the material remains elastic beyond the pipeline SMYS, therefore the failure load will be conservative. For the purpose of this assessment, the analysis is sufficient to determine whether or not the pipeline is at risk from this hazard.

4. Failure mechanism development

In this study, third party interference is considered as the main pipeline failure threat. Fig. 3 shows the proposed fault tree of the threat. It can be seen that there are 13 basic events in the system, with 4 intermediate events and 1 top event. Five types of floaters are considered in this model, i.e. commercial ships, fishing vessels, military vessels, installation vessels and rig/platform. The passing frequencies and potential dropped objects from these floaters are assigned as the basic events under the OR gates. Several accident preventive actions are also introduced in this fault tree such as vessel passing and dropped object preventions and the pipeline protection system. Probability of object hitting the pipeline and high impact force from the dropped object are examined to generate the pipeline failure probability as the top event. Details of each event can be seen in Table 3.

5. Causal network development

Bayesian networks are utilised to construct the causal network development based on the initial failure mechanism model from the fault tree, as can be seen in Fig. 4. It can be seen that thirteen basic events from the fault tree diagram have been reduced into six basic events in this Bayesian causal network. This is because the passing frequency and potential dropped objects from five floaters can be combined due to their dependencies. In addition, six variables are assigned to temporal clones, shown in shaded circles, to represent the condition of the events from the last operational activities or previous projects. The pipeline failure variable is divided into four small networks to determine the frequency and consequence of failure variable probabilities for each of the damage classifications. These damage classifications are taken from (DNV, 2017) as previously mentioned in Section 2, and it is assigned to the frequency and consequence of failure variables according to its relevance, such as:

Frequency of failure: D1, D2, D3, R0, R1, R1
Consequence of failure;

Human safety: R2
Environmental: R1, R2
Economic loss: D1, D2, D3, R0, R1, R2

6. Dynamic probabilistic modelling

Dynamic Bayesian networks are utilised to analyse the probabilistic modelling for the pipeline risk assessment. This technique is capable of minimising the uncertainties in the model and reducing the number of qualitative inputs in the analysis. Details of the dynamic Bayesian network methodology are presented in Section 3. The following sections present the applications of the technique, such as constructing the conditional probability table, analysing the predictive inference and introducing the technique into the pipeline impact force analysis.

6.1. Conditional probability table development

The conditional probability tables are constructed using the functional interpolation technique suggested by Mkrtchyan et al. (2016) to minimize the amount of qualitative inputs in the assessment. Five experts with professional knowledge and extensive pipeline engineering experience are invited to complete the questionnaire. Their answers are projected to provide a realistic measurement of the conditional probability distribution. This qualitative method is most probable to result in random distributions of probability due to varying backgrounds and experience of the experts. Due to lack of clear guidance from the literature, such uncertainties could be better depicted by a Gaussian distribution, as presented in this section.

Table 4 shows an example of expert questionnaire scores for commercial vessel passing frequency (CV_t) given its temporal clone (commercial vessel passing frequency from the previous time slice, CV_{t-1}), where t is the event's time slices. These scores are only considered as a numerical example to test the proposed approach. Dynamic Bayesian calculation shown in Eq. (1) has been used to analyse the conditional probability between these two nodes, where $P(CV_{i,t-1})$ are the parent nodes of $P(CV_{i,t})$ from the previous time-slice, i is the sum start value index and n is the upper range of i.

$$P\left(\mathrm{CV}_t|\mathrm{CV}_{t-1}\right) = \sum_{i=1}^{n} P\left(\mathrm{CV}_{i,t}\middle|P\left(\mathrm{CV}_{i,t-1}\right)\right) \tag{1}$$

A questionnaire state of 1 to 5 proposed by Baraldi et al. (2015) is used for the score measurement (1 for "very low", 2 for "low", 3 for "medium", 4 for "high" and 5 for "very high"), and the experts only needed to fill the positive state 1 (very low) and the negative state 5 (very high). The mean value of state 1 is 1.20 and the standard deviation is 0.45, whilst the mean value and standard deviation of state 5 are 4.40 and 0.55 respectively. These average scores are converted to probability values using the Gaussian distribution and the columns in between these positive and negative states are filled using the probability interpolating method, as can be seen in Fig. 5. These probability values will be used to populate the CPT of the dynamic Bayesian network model.

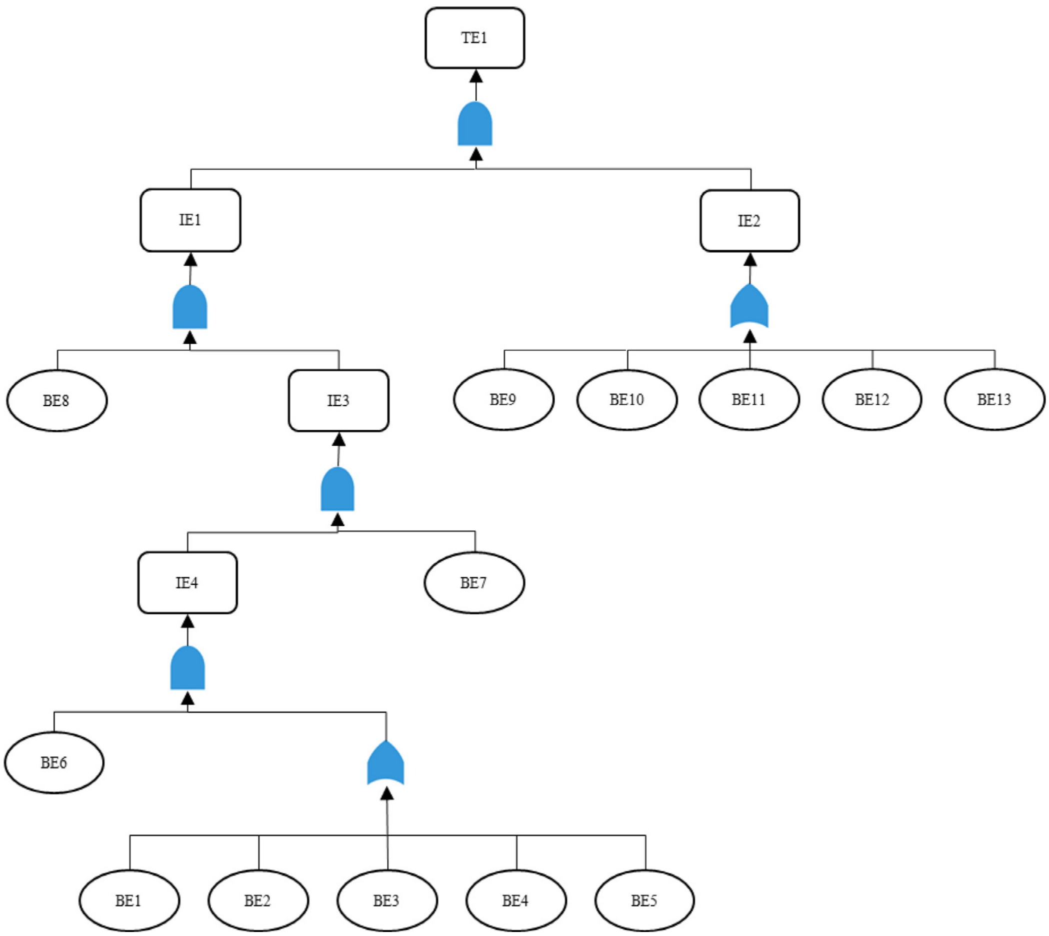

Fig. 3. Fault tree diagram for pipeline failure due to third-party interference.

Table 3
Fault tree events' descriptions.

Event codes	Details	Descriptions
TE1	Top event	Pipeline failure
IE1	Intermediate event 1	Object hits the pipeline
IE2	Intermediate event 2	High impact force from the object
IE3	Intermediate event 3	Dropped/dragged object
IE4	Intermediate event 4	Floaters pass the pipeline route
BE1	Basic event 1	Commercial ships very high passing frequency
BE2	Basic event 2	Fishing vessels very high passing frequency
BE3	Basic event 3	Military vessels very high passing frequency
BE4	Basic event 4	Installation vessels very high passing frequency
BE5	Basic event 5	Rig/platform near the pipeline
BE6	Basic event 6	No vessel passing preventive actions
BE7	Basic event 7	No dropped/dragged object preventive actions
BE8	Basic event 8	No pipeline protections
BE9	Basic event 9	Potential dropped object from commercial ships
BE10	Basic event 10	Potential dropped object from fishing vessels
BE11	Basic event 11	Potential dropped object from military vessels
BE12	Basic event 12	Potential dropped object from installation vessels
BE13	Basic event 13	Potential dropped object from rig/platform

Table 4
Expert questionnaire scores for commercial vessel passing given its temporal clone.

State no.	Parent node Name	State	Child node	Expert 1 score	Expert 2 score	Expert 3 score	Expert 4 score	Expert 5 score
1	CV_{t-1} (temporal clone)	Very low (VL)	CV_t	1	1	1	2	1
5	CV_{t-1} (temporal clone)	Very high (VH)	CV_t	4	5	5	4	4

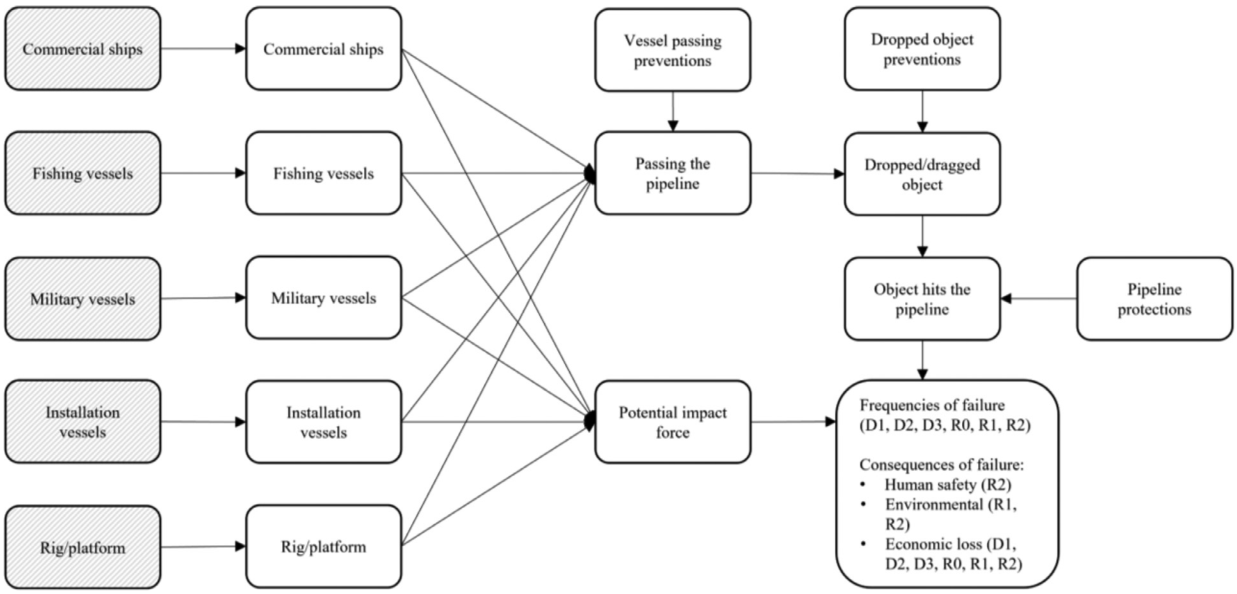

Fig. 4. Dynamic causal network for pipeline failure due to third-party interference.

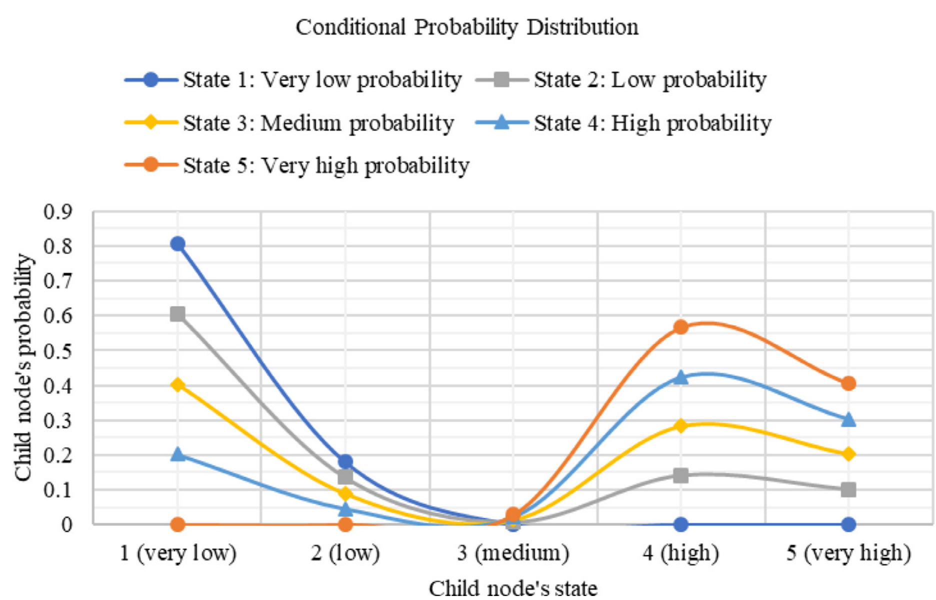

Fig. 5. Conditional probability distribution of commercial vessel passing frequency (child node) given its temporal clone (parent node).

6.2. Predictive inference analysis

In this level, the time series is introduced into the analysis using DBNs. Pipeline operational data and third-party activity reports are considered as evidence data to update the conditional probability distribution and dynamic model for failure probability prediction. An example of the DBN model of the commercial vessel passing frequency (CV_t) as the parent node, given its temporal clone from previous time slice (CV_{t-1}) and its effect on pipeline impact force (IF_t) as the child node is shown in Fig. 6. The detailed probabilistic prediction analysis methodology is presented in Section 3.2.

The future probability conditions of a variable commercial vessel passing frequency are predicted using the prediction inference calculation of the DBN. Prediction inference can be utilised for all variables in the analysis as long as those variables have history and/or current observation data (Maldonado et al., 2019). Therefore, the Bayesian network prior probabilities will always be updated when new data or evidence becomes available.

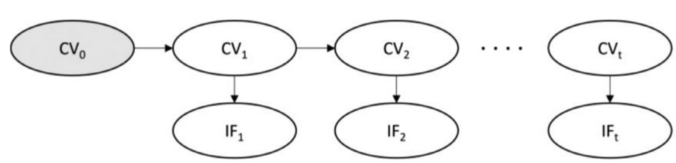

Fig. 6. Bayesian network commercial vessel passing frequency given its temporal clone from previous time slice.

6.3. Pipeline impact force analysis

The pipeline impact forces due to dropped objects are analysed using the combination of finite element modelling and the dynamic probabilistic analysis. As mentioned in Section 3.3, the finite element analysis in this paper is performed using Autopipe software. Pipeline and environmental data are presented in Table 5, and the loading parameters used in the model are a pipeline in operational condition with un-corroded

Table 5
Pipeline and environmental data.

Type of data		Value/remark
Pipeline data	Outside diameter	273.05 mm
	Wall thickness	12.70 mm
	Material grade	API 5L X65
	SMYS	448 MPa
	SMTS	530 MPa
	Concrete weight coating thickness	28 mm
	Design life	25 years
	Operational pressure	30.89 MPa
	Operational temperature	143 °C
	Content density	83.20 kg/m^3
Environmental data	Mean Sea Level	1.49 m
	Wave height 100-year	5.7 m
	Wave period 100-year	7.4 s
	Current velocity 100-year	0.47 m/s

wall thickness, and 100-year maximum wave and current return period. A concentrated force is applied on a straight pipeline and increased until the equivalent stress at the hit point is equal to the damage criteria. The conservative damage categories which have been mentioned in Section 3.3 are used for the analysis, and the maximum stress ratios (ratio between actual stress and maximum allowable stress) are appeared at the dropped object hit point, as can be seen in Fig. 7. The governed case for this maximum actual stress is from the combined stress (hoop, longitudinal and torsional stresses). Global coordinate system is used in the model as presented in Fig. 7, i.e. X as pipeline longitudinal axis, Y as pipeline lateral axis and Z as pipeline vertical axis. The code "Axx" assigned along the pipeline in this figure are the node numbers for anchors, supports below the pipeline (seabed) and the dropped object hit point.

The maximum potential forces for each damage category have been determined, and these forces are converted to weights measurement, as can be seen in Table 6. The measured weights for each damage criteria are specified as the state measurement for the conditional probability table development.

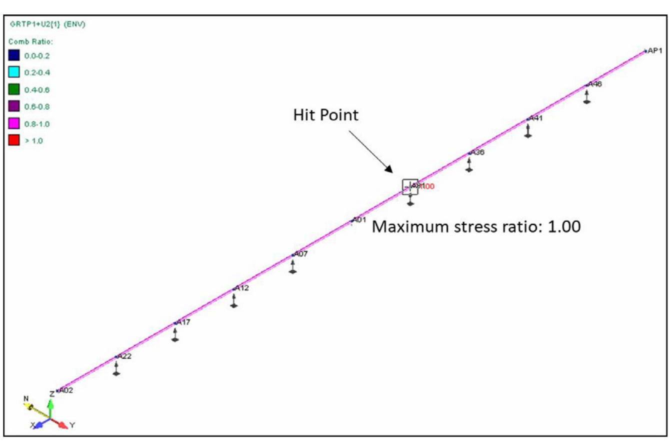

Fig. 7. Pipeline stress result from Autopipe.

Table 6
Maximum forces for each damage category.

Damage category	Maximum force (N)	Maximum weight (Tonnes)
Moderate	5,500	0.56
Serious	15,000	1.53
Major	32,000	3.26
Catastrophic	42,000	4.28
Disastrous	> 42,000	>4.28

For the probabilistic modelling, the conditional probability table for the pipeline impact force is populated by gathering the floater's potential dropped object data. There are ten gathered data points for each type of floaters as can be seen in Table 7. These data are considered as the frequency probability of dropped object on the pipeline and combined as the conditional probability table for each damage criteria specified previously. The detailed methodology of conditional probability table development based on frequency data is presented in (Aulia et al., 2021).

7. Case study

The application of the proposed model to an industrial case study is presented in this section. The pipeline and environmental data from Table 5, and third-party data from Table 8 are included in the analysis as the observed evidence for updating the prior probabilities in the conditional probability table of the dynamic Bayesian network shown in Fig. 4. The potential dropped object categorisation in Table 8 is taken from DNV (2017). The pipeline is still in the construction phase and the service life is 25 years. With this information, the estimated risk probabilities were computed using the proposed dynamic Bayesian model. Further fundamental details of the dynamic risk and reliability modelling are available in Aulia (2019).

7.1. Frequency and consequences probabilistic analysis

Relevant damage classification for each frequency and consequence variables are assigned according to the causal network development method presented in Section 6. Details of each network can be seen in this section. The assigned risk ranking was given in Table 1.

Fig. 8 shows the frequency of failure causal network, based on the overall network shown in Fig. 4. All damage classifications (D1, D2, D3, R0, R1 and R2) are included in the network as they are related to the frequency of failure variable. The analysis result based on the case study pipeline data is shown in Table 9. It can be seen that the most probable states for D1, D2, D3, R0, R1 and R2 are state 1 (very low), state 2 (low), state 3 (medium), state 1 (very low), state 2 (low) and state 3 (medium) respectively.

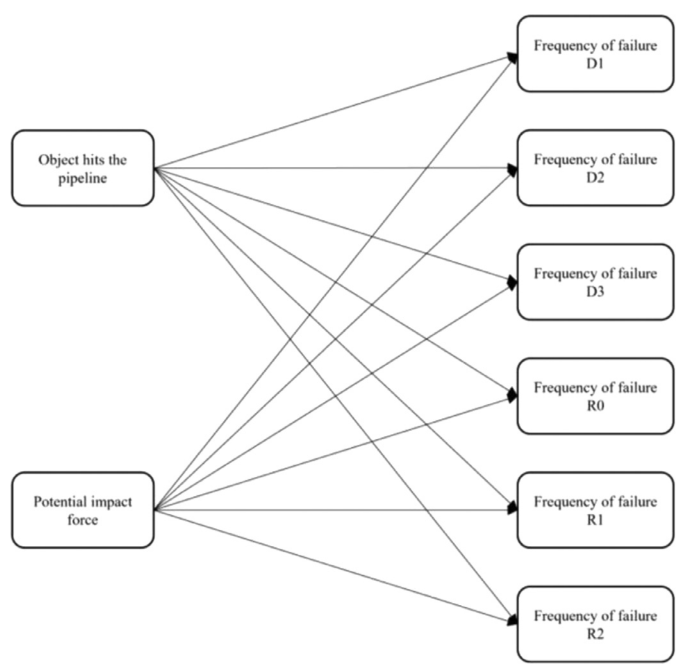

Fig. 8. Causal network for pipeline frequency of failure due to third-party interference.

Table 7
Potential dropped object weight classification for each floater.

Floater's type	No. of sample	No. of potential dropped object weight classification				
		Moderate	Serious	Major	Catastrophic	Disastrous
Commercial ships	10	0	2	8	0	10
Fishing vessels	10	9	10	1	8	2
Military vessels	10	0	3	7	0	10
Installation vessels	10	2	13	3	2	10
Rig/platform	10	21	35	23	15	10

Table 8
Third-party data for application to an industrial case study.

Type of ship/vessel	Passing frequency per year	Potential dropped object categories of ship/vessel					
		Flat/long shaped			Box/round shaped		
		< 2 Tes	2 - 8 Tes	> 8 Tes	< 2 Tes	2 - 8 Tes	> 8 Tes
Commercial ships	104	a	a	a	a	a	a
Fishing vessels	1,460	a			a	a	
Military vessels	730	a	a	a	a	a	a
Installation vessels	360	a	a	a	a	a	a
Type of structure	**No. of structures near the pipeline**	**Potential dropped object categories of structure**					
		Flat/long shaped			Box/round shaped		
		< 2 Tes	2 - 8 Tes	> 8 Tes	< 2 Tes	2 - 8 Tes	> 8 Tes
Rig/platform	1	a	a	a	a	a	a

Table 9
Probability analysis result for pipeline frequency of failure due to third-party interference.

Damage classification	States' probability (%)				
	1	2	3	4	5
D1	90.56	9.44	0.00	0.00	0.00
D2	28.75	65.38	3.98	1.89	0.00
D3	6.51	42.71	46.90	1.88	2.00
R0	65.38	20.74	10.57	2.34	0.97
R1	33.51	58.84	4.51	1.02	2.12
R2	7.02	39.31	47.57	1.74	4.37

Table 10
Probability analysis result for human safety consequence of failure due to third-party interference.

Damage classification	States' probability (%)		
	1	3	5
R2	98.65	1.05	0.30

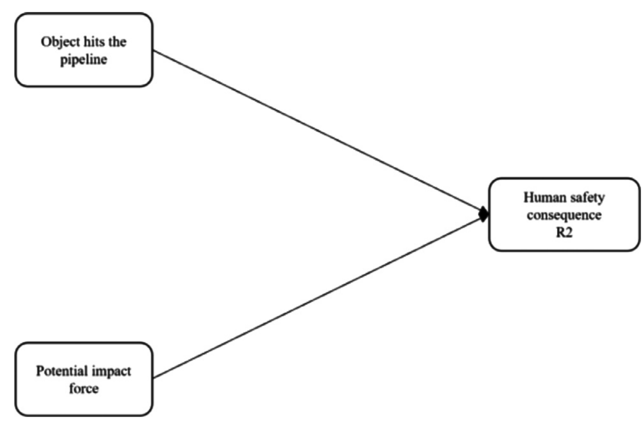

Fig. 9. Causal network for human safety consequence of failure due to third-party interference.

For the human safety consequence, there is usually very little human activity in the vicinity of pipelines. Pipeline releases at the platform approach or near subsea structures may have consequences for 1st party personnel on a platform or rig. In the pipeline mid-line zone, releases can endanger 3rd party personnel. Only major release scenarios (i.e. category R2) from pipelines transporting gas can endanger personnel. A gas cloud nearby the platform or the rig can be ignited resulting in a ball of fire or an explosion. Ignition will only occur if the gas above the sea surface is of flammable concentration and possible ignition sources are present within this cloud. Fig. 9 shows the human safety consequence causal network, and the analysis result based on the case study pipeline data is shown in Table 10. It can be concluded that the probability of the damage classification R2 for the human safety consequence in this case study is very low.

For the environmental consequences, Fig. 10 shows that the consequence should be established both for minor and for major release

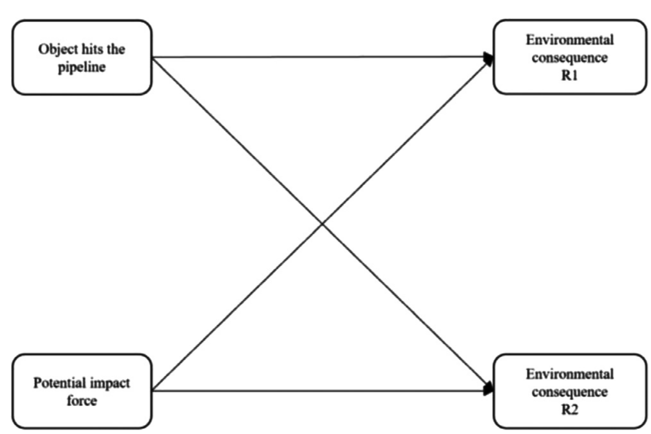

Fig. 10. Causal network for environmental consequence of failure due to third-party interference.

Table 11
Probability analysis result for environmental consequence of failure due to third-party interference.

Damage classification	States' probability (%)				
	1	2	3	4	5
R1	88.02	11.98	0.00	0.00	0.00
R2	0.00	88.80	8.75	2.01	0.44

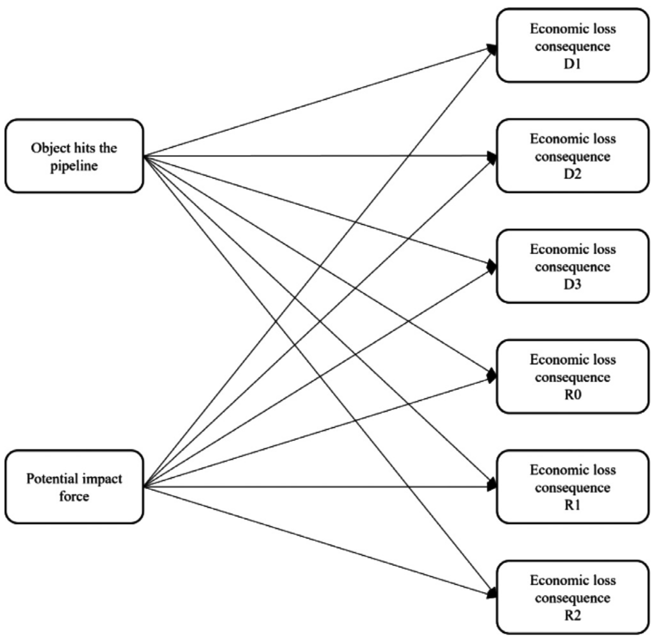

Fig. 11. Causal network for economic loss consequence of failure due to third-party interference.

scenarios (i.e. R1 and R2). The environmental consequence of any leakage from damaged pipelines should consider polluting impacts on ecosystems in the water. The analysis result based on the case study pipeline data is shown in Table 11. It can be seen that in this case study, the probability of environmental consequence for damage classifications of R1 and R2 are state 1 (very low) and state 2 (low) respectively.

The economic loss consequence of any damage to pipelines can be classified with respect to the delay in production from a pipeline. This consequence is related to all damage categories, i.e. DI, D2, D3, R0, R1 and R2, and its causal network is presented in Fig. 11. The cost of production delay normally exceeds the actual cost of repairing the damage. The analysis result based on the case study pipeline data is shown in Table 12. It can be seen that the probability of economic loss consequence for all damage classifications are state 1 (very low) except for the damage classification of R2 which is in the state 2 (low).

Table 12
Probability analysis result for economic loss consequence of failure due to third-party interference.

Damage classification	States' probability (%)				
	1	2	3	4	5
D1	90.56	9.44	0.00	0.00	0.00
D2	65.38	28.75	3.98	1.89	0.00
D3	46.90	42.71	6.51	1.88	2.00
R0	65.38	20.74	10.57	2.34	0.97
R1	58.84	33.51	4.51	1.02	2.12
R2	39.31	47.57	7.02	1.74	4.37

7.2. Dynamic risk assessment

The final risk assessment consists of coupling the relevant frequency rankings with the consequence rankings and then comparing the result against the acceptance criteria. Figs. 12–14 show the risk ranking results for human safety, environmental and economic loss consequences respectively. All the damage categories for each consequence are in acceptable level except damage category R2 of economic loss consequence which is in the ALARP region (shown in light shaded box). This is still categorised as an acceptable risk, however further reduction of the risk should be pursued with cost-benefit evaluation (DNV, 2017).

Examples of dynamic risk assessment results for environmental consequence R1 and R2 are presented in Figs. 15 and 16 respectively. The analyses result show that the estimated risk result for damage category R1 at the beginning of the pipeline's service life is in moderate level. However, the dynamic model predicts that the estimated risk in this level will gradually decrease throughout the year, while the major risk level is getting higher during its service life. In addition, damage category R2 also shows similar behaviour but at a different risk level. The highest risk level in the pipeline's early life is at the major level, however, it will also gradually decrease throughout the service year, and the serious risk level is steadily increased. The fluctuated movement of these probabilities are happened because there are five time-dependant basic nodes in the dynamic Bayesian network shown in Fig. 4 with their condi-

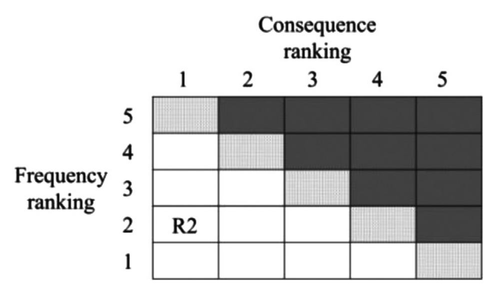

Fig. 12. Risk matrix for human safety consequence of failure due to third-party interference.

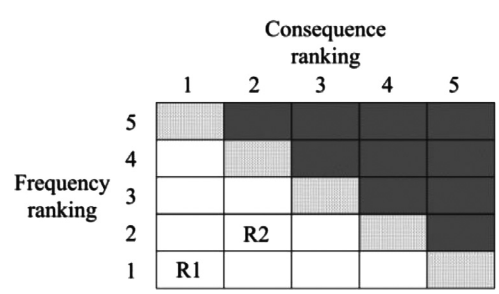

Fig. 13. Risk matrix for environmental consequence of failure due to third-party interference.

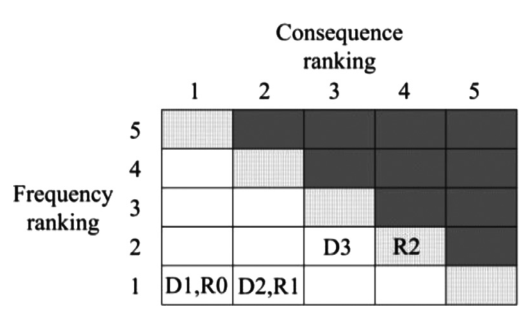

Fig. 14. Risk matrix for economic loss consequence of failure due to third-party interference.

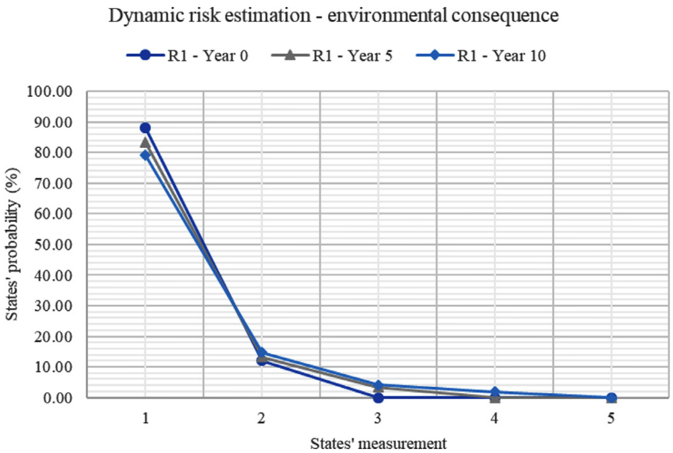

Fig. 15. Dynamic risk assessment for environmental consequence – R1.

tional probability distribution for each child node given the parent node (from previous time slice). The dynamic analysis is performed the predictive analysis based on these time-dependant conditional probability distribution and produced the dynamic risk results shown in Figs. 15 and 16.

The estimated risk result at the beginning of the pipeline's service life is similar to the risk result produced by the pipeline's Operator as presented in Table 13, however, the DBN-based result provides a set of risk level probabilities throughout the pipeline's service life. The DBN model can also be expanded for analysing the estimated risk level probabilities during the pipeline life extension phase, allowing the future trend prediction of the pipeline failure risk due to third-party damage.

In each project, the risk should be kept as low as reasonably practicable. This means that some low-cost risk reduction measures should be introduced even if the risk is considered to be acceptable. In this case study, dropped object factor seems to be the most significant cause of the pipeline failure as presented in Table 12. The risk reduction for this factor can be achieved by:

(1) reducing the frequency of the event; this can be done by limiting the lifting operations and the type of objects lifted in the pipeline zone, and by introducing safety distance and safe areas in this certain zone.
(2) reducing the consequence of the event; this can be done by increasing the pipeline protection level and stopping the production in pipeline during installation activity.
(3) combination of the above.

Frequency reduction measures shall be prioritised before consequence reduction measures. If the risk level is not acceptable, then mitigation measures should be taken to reduce the risk. The length of the pipeline to be protected should be so that the overall risk of both the protected and the unprotected parts are acceptable.

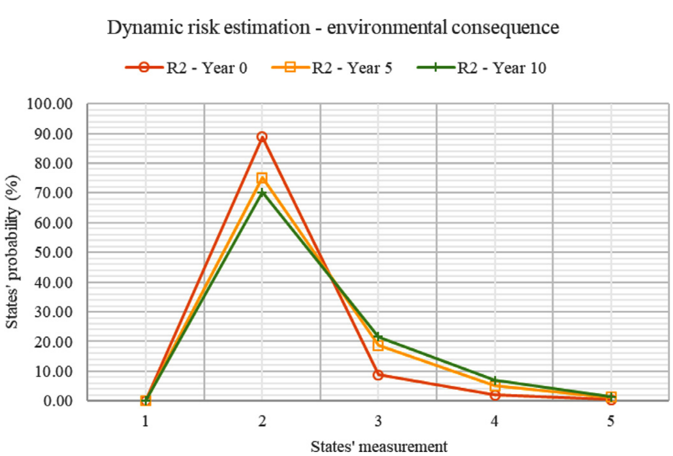

Fig. 16. Dynamic risk assessment for environmental consequence – R2.

8. Conclusions

A dynamic reliability framework is proposed in this paper for analysing the pipeline risk assessment due to third-party interference. The framework is established using three tools, i.e. fault tree analysis, dynamic Bayesian network and finite element analysis. Fault tree analysis is utilised to develop an initial model of the pipeline failure mechanism due to the third-party interference, then the model is upgraded to a dynamic causal model using the Bayesian network to indicate the variable dependencies and to include time variant characteristics in the analysis. The pipeline impact forces due to failure threats are simulated using a finite element model, and the conditional probability distribution is developed based on the stress results. The dynamic Bayesian network is also employed in the risk matrix predictive analysis. The dynamic models provide a set of risk level probabilities throughout the pipeline's service life, and it can also be expanded for analysing the estimated risk level during the pipeline life extension phase. The complete risk assessment framework is presented in Fig. 1.

Based on the dynamic Bayesian network shown in Fig. 4, the pipeline failure as the top event has been divided into four small networks for defining the risk assessment variables, i.e. frequency of failure, and consequence of failure for human safety, environmental and economic loss. Damage categories are defined for each variable according to their relevancies. There are eight basic events assigned to the model, and five of them are considered as time-dependant variables, hence, there are five temporal clones introduced in the analysis to represent those variables from the previous time slices. The state probabilities for the pipeline impact force variable are assigned based on the finite element analysis results and the floaters' potential dropped object data. From the dynamic risk assessment results, it can be seen that the estimated risks for each consequence variable are in reasonable range and comparable with risk result produced by the pipeline's Operator. In addition, the DBN-based outcome offers a set of risk level probabilities throughout the pipeline's service life and during the life-extension period, as presented in Figs. 15 and 16.

It was found that the advantages of the DBN-based risk assessment approach are significant, such as minimising number of qualitative inputs in the analysis, resulting expandable model to cover the upcoming time slices. It allows to estimate the pipeline risk level during its extended life, and enables the model to be updated when new data or

Table 13
Consequence of failure ranking comparison between Operator and DBN-based assessment results.

Pipeline		Damage category	Operator's result		DBN result	
Outside diameter	Wall thickness		Consequence of failure ranking	Most significant cause	Consequence of failure ranking	Most significant cause
273.05 mm	12.70 mm	R1	1	Dropped object	1	Installation vessel activity (dropped object)
		R2	2	Dropped object	2	Installation vessel activity (dropped object)

evidence become available, hence it can be categorised as self-learning tool. For further study, it would be intriguing to develop an advanced machine learning-based framework for third-party interference risk predictive analysis, leading to a complete set of subsea pipeline dynamic reliability assessment.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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