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Vessel traffic geometric probability approaches with AIS data in active shipping lane for subsea pipeline quantitative risk assessment against third-party impact

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Abstract. A subsea pipeline designed across active shipping lane prones to failure against external interferences such as anchorage activities, hence risk assessment is essential. It requires quantifying the geometric probability derived from ship traffic distribution based on Automatic Identification System (AIS) data. The actual probability density function from historical vessel traffic data is ideal, as for rapid assessment, conceptual study, when the AIS data is scarce or when the local vessels traffic are not utilised with AIS. Recommended practices suggest the probability distribution is assumed as a single peak Gaussian. This study compares several fitted Gaussian distributions and Monte Carlo simulation based on actual ship traffic data in main ship direction in an active shipping lane across a subsea pipeline. The results shows that a Gaussian distribution with five peaks is required to represent the ship traffic data, providing an error of 0.23%, while a single peak Gaussian distribution and the Monte Carlo simulation with one hundred million realisation provide an error of 1.32% and 0.79% respectively. Thus, it can be concluded that the multi-peak Gaussian distribution can represent the actual ship traffic distribution in the main direction, but it is less representative for ship traffic distribution in other direction. The geometric probability is utilised in a quantitative risk assessment (QRA) for subsea pipeline against vessel anchor dropping and dragging and vessel sinking.

Keywords: automatic identification system; Gaussian Distribution; marine traffic; Monte Carlo; QRA

1. Introduction

In parallel with the continuous development of new oil and gas fields, offshore facilities such as subsea pipelines and offshore platforms might be designed to operate in location with significant third-party hazard. For instance, this facilities are in heavy marine traffic such as international shipping lanes. Therefore, it is necessary to quantify the geometric probability due to ship traffics and perform risk assessment to determine the risk level and managing the risk.

Geometric probability in quantitative risk assessment (QRA) of subsea pipeline facilities requires ship traffic data, which are usually obtained from AIS data (Bartolini *et al.* 2018, Mulyadi *et al.* 2014a). A series of scatter ship traffic data in the AIS data need to be processed and analysed to determine the probability of passing vessels in the pipeline area. Vitali *et al.* (2012) and Marcjan *et*

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al. (2017) processed the ship traffic data into an actual ship distribution that describes the frequency of ship traffic per kilometre of pipe. This approach provides detailed and representative probability assessment because it uses actual data. However, the analysis using this method is limited for the pipeline within the scope of the data. Thus, if similar risk analysis is carried out for different pipelines, it is necessary to recalculate and reanalyse the actual ship distribution.

For rapid use, the actual ship distribution is fitted with specific analytical distribution which are the utilised to predict geometric probability for other pipeline locations. Huang *et al.* (2019), Mujeeb-Ahmed *et al.* (2018), and Wang *et al.* (2020) approached the actual ship distribution using the Gaussian distribution. This method is a commonly used, as it is recommended in DNVGL-RP-F107 (2017) that the Gaussian distribution can be used to model the ship distribution passing offshore facilities in a shipping lane. However, in relaity the ship distribution in a shipping lane does not always in the fitted following a Gaussian distribution. This gaussian distribution is not always able to describe the unique ship traffic patterns in any sea areas, therefore, it cannot generate accurate risk assessment (Yoo and Kim 2019). Hence, there is a possibility that calculation errors may occur, which will furthermore lead to less accurate results. Therefore, it is necessary to remodeled the actual ship distribution with appropriate distribution or simulation approaches.

Mulyadi *et al.* (2014b) developed another method to approach the ship distribution more accurately by dividing the pipeline into several segments and conducting a goodness-of-fit test with various types of distribution for each segment. The subsea pipeline was divided into nine segments and fitted by several types of distribution, including uniform, lognormal, log-Pearson 3, and Weibull distribution. Risk assessment by using this method will generate numerous statistical parameters and distributions, thus, might complicate the analysis mainly when applied to a relatively long pipeline. Therefore, for simplicity the ship distribution needs to be approached with one distribution equation.

A Monte Carlo probabilistic simulation are an alternative to calculating the geometric probability of passing vessels, as demonstrated by Huang *et al.* (2019). In their study, frequency analysis was conducted for ship position data to generate discrete probability data for each data interval. Then, a Monte Carlo simulation was conducted on the regression of the ship's distribution data to obtain the trajectory of the ship's movement to determine the probability of passing vessels. This approach utilises a random simulation on historical data, thus, it might will be an alternative approach if there is not enough time and resources to fit a distribution.

In this study, the ship distribution is analysed across the entire AIS data coverage area in Natuna Sea, so that the ship distribution can be utilised for risk analysis on adjacent pipelines within the shipping lane. The probability of ship distribution is calculated by comparing two methods to the actual ship distribution: the goodness-of-fit test of multi-peak Gaussian distribution and the Monte Carlo simulation. The obtained probability and ship distribution are used to assess the subsea pipeline failure risk. This study was conducted to explore a simpler and more accurate approach to vessel traffic geometric probability analysis which can be continuously utilised for further risk assessment on adjacent pipelines on the same shipping lane. This approaches will provide useful insight on how the geometric probability are determined for implementation in area with scarce AIS data.

2. Methodology

The methodology is summarised in Fig. 1. The analysis in this study began with the processing of AIS data by filtering and removing irrelevant data (e.g., moored vessel, navigation buoy, platform,

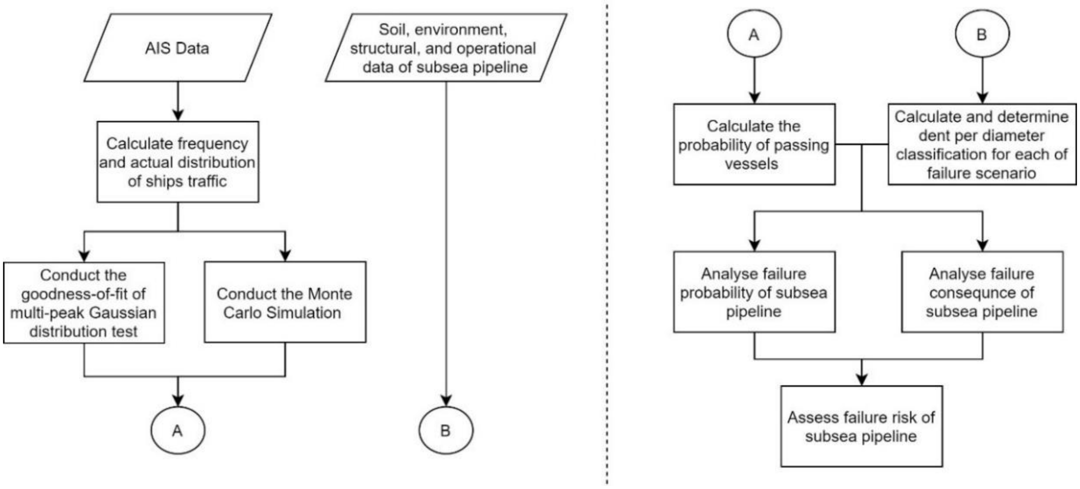

Fig. 1 Flowchart of research method

etc.) from the study and selecting a single data point from each ship data series to eliminate frequency repetition. Then, complete the ship dimension and tonnage data based on ship statistics (Trelleborg 2003). After all the data had been completed, each data was categorised into six direction categories, as illustrated in Fig. 3, and was analysed to generate the ship distribution data for each direction category. The actual ship distribution data for the dominant direction category was then modelled using a multi-peak Gaussian distribution goodness-of-fit test and a Monte Carlo simulation. Thus, the frequency and probability of passing vessels at the subsea pipeline area can be obtained. In parallel, a set of provided soil, environment, structural, and operational data is analysed to provide inputs for pipeline damaged analysis, resulting in dent per diameter and damage category for various failure scenarios. The probability of passing vessels and the corresponding dent per diameter values are then used as inputs in both probability of failure and consequence of failure assessments, which are then used to estimate the failure risk of subsea pipeline.

In accordance with DNVGL-RP-F107 (2017), a pipeline damage analysis was performed for each failure scenario based on pipeline parameters. There are many potential failure scenarios to be considered in a pipeline risk assessment. However, damage analysis in this study is focused on damage due to third-party impact in shipping activities such as dropped anchor, dragged anchor, and vessel sinking. In the pipeline damage analysis, calculations are performed to determine the class limits of pipeline damage based on the ratio of local deformation to the total diameter. Then, all data were categorised into each pipeline damage class: minor damage, moderate damage, major damage, and rupture. Failure probability analysis was performed by calculating the frequency and probability of failure for each class of pipeline damage based on the category of potential leaks i.e., no release, leakage, and rupture. Lastly, a risk assessment of subsea pipelines was performed based on the ranking of the probability and consequences of failure.

2.1 AIS Data

AIS (Automatic Identification System) enables a ship to communicate and exchange information

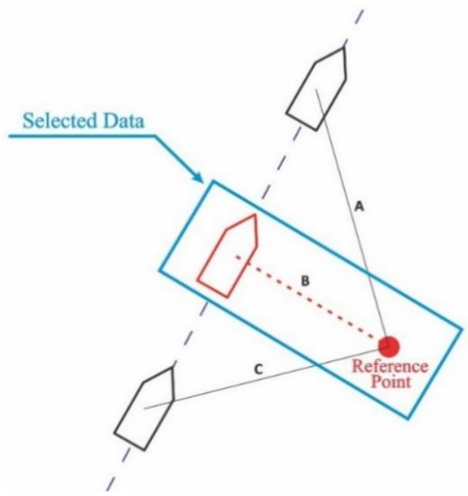

Fig. 2 Illustration of AIS data filter against its relative distance

with other ships and shore-based monitoring stations. By the end of 2004, the International Maritime Organization (IMO) obligated every ship with Gross Registered Tonnage (GRT) of more than 300 tons to utilise Autonomic Identification System (AIS) technology on board (Zhen *et al.* 2017). Hence, AIS technology is currently utilised by every ship, especially for large vessels operating on international shipping routes.

AIS data transmitted from the ship to the control station will be recorded into a database. The data received and transmitted include MMSI (Maritime Mobile Service Identity) number, dimensions and tonnage, location of the ship in the form of longitude and latitude, type of ship, speed and heading, time, destination, etc. Nonetheless, it is highly probable that data errors might occur due to deficiencies in recording tools and systems. Thus, before the AIS data can be used for further analysis, it is necessary to filter the data to remove data noise, duplicate data, inappropriate data and to fill in the missing data (Hu *et al.* 2021 and Svanberg *et al.* 2019).

Ships which are equipped with AIS will continuously transmit data at a predetermined time interval (Chung *et al.* 2019). Therefore, data repetition may occur if the ship is in the data coverage area for a long period of time. In this study, the movement of ships does not need to be accurately analysed one by one in order to assess the failure risk of subsea pipelines, yet only the number of ships that approach or pass through the pipeline area is required. Thus, a simpler data processing method is used, namely filtering the AIS data by selecting one ship data with the shortest relative distance to the reference point, as illustrated in Fig. 2. In a congested international shipping lane, ships will generally move in a straight line along the shipping lane corridor. Hence, one data out of a series of ship location data can be selected to represent its trajectory. While the reference point can refer to any important desired location, such as the location of a platform, the end of a pipeline, the center point of the data coverage area, etc. In this study, the reference point is the centre point of the AIS data coverage area so that the zero point of the ship distribution is right in the middle of the data coverage area.

Then, the AIS data are classified into several directional categories to determine the dominant direction of ship traffic and the number and position of minor shipping lanes within the data coverage

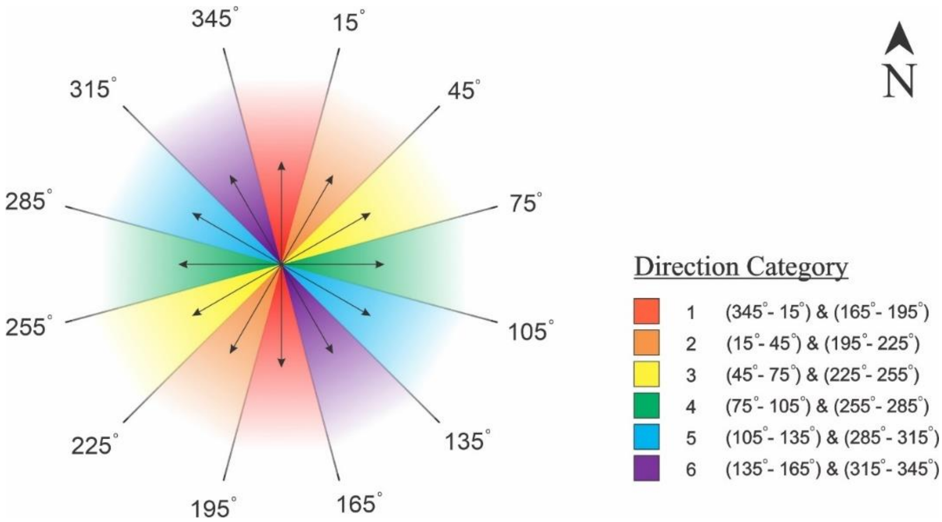

Fig. 1 Illustration of six direction category of ship traffic. The angles is measured from zero degree as true north

area. In this study, ship traffic directions are classified into six categories with an interval between categories of 30 degrees. The boundaries for each category are set at ±15% to the center of the direction category. Each direction category includes two opposite direction centers or has an angle difference of 180°, as illustrated in Fig. 3.

2.2 Pipeline damage analysis

In each failure scenario, the impact of pipeline damage will be analysed based on the size of the potential dent. Dent is a local deformation of a pipeline due to the impact of an object. The size of dent calculation for steel pipeline in this study refers to the DNVGL-RP-F107 (2017) standard as described in Eq. (1).

$$E = 16 \cdot \left(\frac{2\pi}{9}\right)^{\frac{1}{2}} \cdot m_{\mathrm{p}} \cdot \left(\frac{D}{t}\right)^{\frac{1}{2}} \cdot D \cdot \left(\frac{\delta}{D}\right)^{\frac{3}{2}} \tag{1}$$

where E is dissipated energy which has different values for each failure scenarios, m_{p} is the plastic moment capacity which equals to ¼ $\sigma_{\mathrm{y}} t^2$, σ_{y} is yield stress, D is outer diameter of the steel pipeline, t thickness of the pipeline, δ is dent.

In dropped anchor and vessel sinking scenario, the total impact energy represents the amount of kinetic energy received by the steel pipe after deducted by the absorbed energy due to the concrete protective layer as stated on DNVGL-RP-F107 (2017). Tawekal and De Velas (2019) studied damage analysis for subsea pipeline with concrete mattress protection due to dropped anchor activity. This study uses the same calculation method but is applied to an unburied pipeline without any additional protection.

Whereas in dragged anchor scenario, the total dissipated energy on subsea pipelines should be analysed using a finite element model to obtain more accurate and representative analysis results

Table 1 Failure consequence ranking results

Category	Consequence Rating
No Release	2
Leakage	3
Rupture	4

(DNV RP F-111, 2010), as also used by Tawekal *et al.* (2017). However, the calculation of the dissipated energy due to dragged anchor in this study uses conservative assumptions, where all the forces and displacements are converted into energy quantities as an input variable in the Eq. (1). It aims to obtain only a preliminary model of the local damage when the anchor just hits and is about to drag the subsea pipeline.

Dragged anchor scenario is a sequence of several possible events when an anchor is thrown by a moving ship. Therefore, the total dissipated energy due to dragged anchor activity consists of several kinds of energy, i.e., impact energy, pull over energy, hooking energy, and additional energy due to inertia of the anchor, where all amounts of energy for all events are calculated by referring to DNV RP F-111 (2010). Impact energy is calculated by assuming that a ship will generally move in the shipping lane at a maximum speed of 12 knots or 6.17 $\mathrm{m/s}$ (Spouge 1999). Pullover energy is the resultant vector of vertical and horizontal energy due to pipeline displacement. Hooking energy is the total of potential and kinetic energy to hook and lift the subsea pipeline when the anchor is wedged under the pipe. The last component that makes up the dissipated energy due to dragged anchor is the additional energy due to the inertia of a moving anchor. When the anchor strikes and drags the subsea pipeline, the hanging steel chain will provide additional load due to the inertia of the chain motion. The magnitude of the additional force is conservatively assumed to be equal to the weight of the entire hanging steel chain.

2.3 Consequence of failure analysis

According to the DNVGL RP-F107 (2017), the consequence of failure of an offshore oil and gas facility must be evaluated based on three factors: safety, the environment, and the economy (production delays). The pipeline used in this case study is an offshore gas distribution pipeline, which is located far from human activities. Therefore, the consequence assessment to worker safety and the environment is irrelevant. Thus, the consequence of failure analysis is conducted solely from an economic standpoint, based on the impact of pipeline damage (Aulia *et al.* 2021). Each category of the impact of pipeline damage can be reclassified according to the likelihood of leakage: no release, leakage, and rupture.

Replacement of a ruptured pipeline, from the cessation of operation to completion of the repair, is estimated to take about 13 weeks (Brown 1984). Thus, the pipeline with the potential for rupture is classified as CoF class 4 (DNVGL 2017). It is assumed that pipelines with more minor leaks require less repair time, so they are classified as CoF class 3. Meanwhile, pipelines that do not leak but undergo local deformation typically do not have a significant impact on the production process and operations. Nonetheless, the local deformation (dent) that occurs on the pipeline may reduce its strength, thereby posing a future risk of leakage (Macdonald *et al.* 2007). Therefore, even the deformed pipeline without leakage also needs to be repaired in accordance with the routine repair and maintenance schedule, so it falls under CoF class 2. Thus, it can be concluded that the consequences of subsea pipeline failure are as shown in Table 1.

2.4 Muti-Peak Gaussian distribution

Multi-peak Gaussian distribution is a combination of several normal distributions with different statistical parameters. The formulation of the multi-peak Gaussian distribution in this study was iterated not only with respect to the number of peaks but also to the position of each peak. Iteration of the goodness-of-fit test was continuously carried out until the desired maximum coefficient of determination was achieved. The multi-peak Gaussian distribution is expressed in the form of a probability density function as described in Eq. (2).

$$f(x) = y_0 + \frac{A_1}{w_1}\sqrt{\frac{2}{\pi}} \cdot e^{-\frac{2(x-xc_1)^2}{w_1^2}} + \cdots + \frac{A_i}{w_i}\sqrt{\frac{2}{\pi}} \cdot e^{-\frac{2(x-xc_i)^2}{w_i^2}} \tag{2}$$

where, y_0 is the offset factor, A_i is the amplitude of the ith Gaussian distribution, w_i is the deviation factor of the ith Gaussian distribution, xc_i is the average of the ith Gaussian distribution.

2.5 Monte Carlo simulation

In this study, Monte Carlo simulation is used to determine the probability of passing vessels by referring to the actual ship distribution data. Theoretically, the Monte Carlo simulation will generate a random number between 0 and 1 which represents the cumulative probability of the ship's distribution. The Monte Carlo simulation was carried out five times, with the number of realizations up to 100 million times each. The generated random value is then interpolated against the actual cumulative density function to generate the estimation of the ship's position. Each of the simulated ships' position data is then filtered against the subsea pipeline area to determine whether it passes through the pipeline area. The probability of passing vessels is a ratio between the number of ships that pass through the pipeline area and the total realisation data.

2.6 Probability of failure analysis

In this study, the probability of failure analysis was conducted in accordance with DNVGL-RP-F107 (2017) but with modified equation variables. The probability of failure can be calculated using Eq. (3).

$$P_{\mathrm{Fail}} = N \cdot P_1 \cdot P_2 \cdot P_3 \cdot P_4 \cdot CP \tag{3}$$

where, P_{Fail} is the probability of failure, N is the total frequency of passing vessel, P_1 is the probability of a vessel passing the pipeline area, P_2 is the probability of ship's category, P_3 is the probability of interference due to external activity, P_4 is the reduction factor of the probability of failure, and CP is the conditional probability (DNVGL-RP-F107 2017).

2.6.1 The probability of a vessel passing the pipeline area

The first component of the subsea pipeline probability of failure equation is the probability for ships passing through the pipeline area (P_1). In this study, P_1, states the probability of ships passing through the pipeline area. The P_1 value is calculated and approached using three methods: based on historical ship traffic data, integration of the multi-peak Gaussian distribution equation, and statistical analysis of the results of the Monte Carlo simulation.

2.6.2 The probability of the ship's category

The second factor that composes the probability of failure equation is the probability of the ship's category (P_2). In this study, P_2 states the probability of a ship being in a particular category. The ship's category is determined based on impact analysis on the limits of each pipeline damage category at 5%, 10%, 15%, and 20% dent to the pipeline diameter ratio.

2.6.3 The probability of interference due to external activity

The third factor that composes the probability of failure equation is the probability of interference due to external activity (P_3). In this study, P_3 states the probability of a failure scenario to cause a leak on the subsea pipeline. The value of P_3 is 1.16E-06 for the anchoring scenario and 1.67E-07 for the vessel sinking scenario (De Stefani and Carr 2011). However, for dragged anchor scenario, P_3 must be multiplied by a multiplier which denotes the ratio between drag distance and the anchor length.

2.6.4 Reduction factor

The fourth factor that composes the probability of failure equation is the reduction factor (P_4). In this study, P_4, states the magnitude of the reduction in the probability of failure due to preventive measures or mitigation of potential risks. The reduction factors used in this study are: the application of a navigation marine chart of 0.1 (De Stefani and Carr 2011), vessel traffic system (VTS) of 0.2 (Spouge 1999), and marine patrol of 0.14 (DNVGL 2017). Thus, the total value of P_4 used in this study is 2.8E-03.

3. Geometric probability assessment

3.1 Ship traffic frequency

The frequency of ship distribution data is calculated per kilometer for each category of ship direction. The ship traffic shown as sample data in this study from an active shipping lane in Natuna Sea, with its specific location will be described in Section 4. The actual frequencies from ship distribution analysis for each direction category as described in Fig. 3, for 5 years are shown in Fig. 5. Based on the frequencies bar chart of ship distribution, the direction category 2 is the dominant category with a maximum frequency at the center of the route is about 4500 ships. In comparison to the ship frequency in other direction categories, the value of ship distribution in category 2 is more significant and representative of the overall distribution. For clarity, the ship frequency data for all direction categories are converted into a probability density function, as shown in Fig. 4.

In contrast, the PDFs for all direction categories other than category 2 are completely unique, which means they do not follow any common distribution or are randomly distributed and seem to consist of several minor shipping lanes. However, although the PDFs for other categories seem more significant due to a higher peak value than category 2, Fig. 5 shows that the frequency for each category is not significant. It indicates that there are only a few ships that move in a back-and-forth motion.

Based on the box plots in Fig. 6, most of the ships in the direction category 2 operate within a limited area with much narrower boundaries than those in the other categories. It shows that ships in category 2 typically move in a particular channel, whereas ships in other categories are distributed uniformly or randomly. The mean value (shown by the dashed line) and the median value (shown

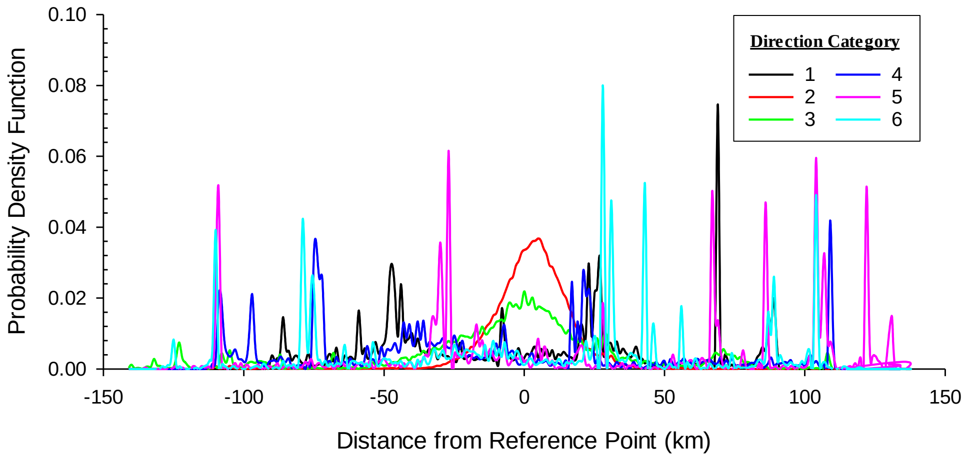

Fig. 4 PDF of ship distribution for each direction category as described in Fig. 3, for five years from June 2016 until May 2021

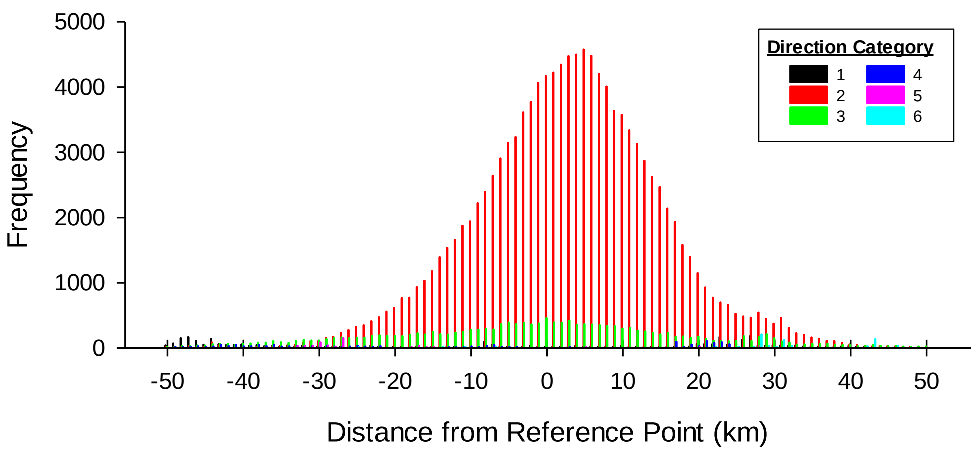

Fig. 5 Frequency of ship distribution for six direction category as described in Fig. 3, for five years data from June 2016 until May 2021

by the solid line) in the direction category 2 are located right in the middle and almost coincide. It shows that ships are distributed almost symmetrically to the left and right of the distribution. Therefore, as a limitation of this study, the probability of ship distribution will only be analysed in category 2 as the dominant direction category. Ship distributions in other categories are excluded to keep this study's focus on comparing the geometric probability analysis methods. However, the addition of probability of ship distribution from category 3 will be briefly compared to the category 2 in risk assessment at the end of Section 4. Furthermore, an assessment should be performed to ensure that the relevance of the ship distribution is not limited to the period of data.

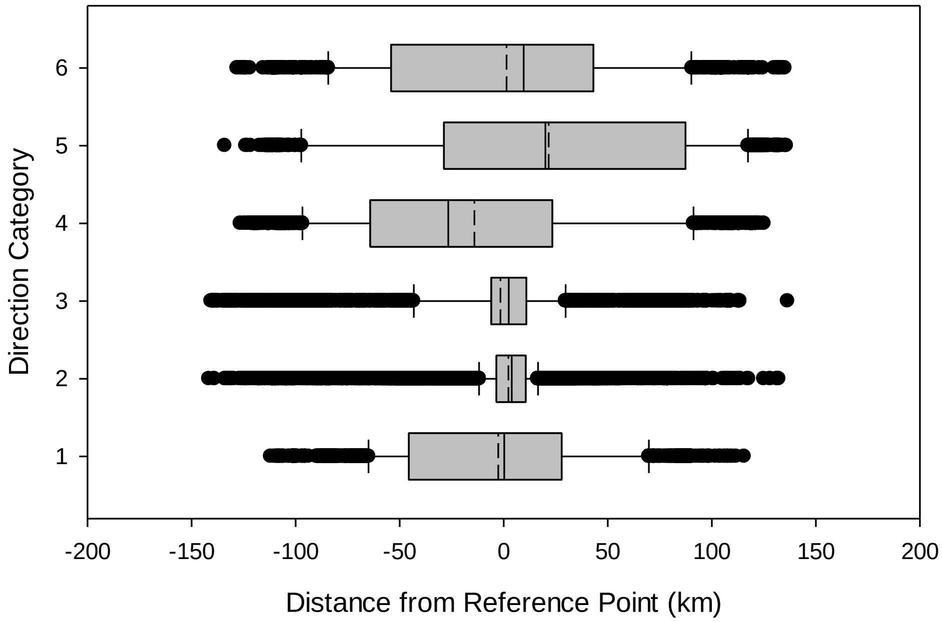

Fig. 6 Comparison of five years ship distribution for each direction category as described in Fig. 3, from June 2016 until May 2021

Based on the ship distribution data in category 2, a deeper analysis is performed by comparing the PDF graph of the distribution of ship data per year. It aims to verified the position and density of ship traffic on the shipping lane by analysing the annual patterns and trends of the distributions. The comparison of PDFs per year is shown in Fig. 7.

Based on the PDF comparison chart in Fig. 7, although the frequency of ship traffic varies from year to year, the PDF distribution of ship data in category 2 demonstrates a typically similar trend. In general, international shipping lanes are located between –50 km and 50 km, with the distribution peak occurring in the middle of the shipping lanes. Therefore, it can be concluded that five years of AIS data is sufficient to provide a representative analysis of the ship distribution in the actual shipping lane. Thus, the acquired ship distribution can be used to assess the risk of other adjacent offshore facilities which are dominated by the same shipping lane.

3.2 Goodness-of-fit test

The discrete ship distribution from AIS data will be approximated by a continuous multi-peak Gaussian distribution equation. To determine the number of peaks that can yield the most accurate results, it is necessary to conduct iterations on the number of peaks in the goodness-of-fit test until the coefficient of determination is close to one. In this study, the ship distribution is iterated from one peak to five peaks, as sampled for one and five peaks in Fig. 8.

The comparison graph in Fig. 8 shows that the five-peak Gaussian distribution is more accurate to the actual distribution than the Gaussian distribution with one peak. Although, in general, the one-

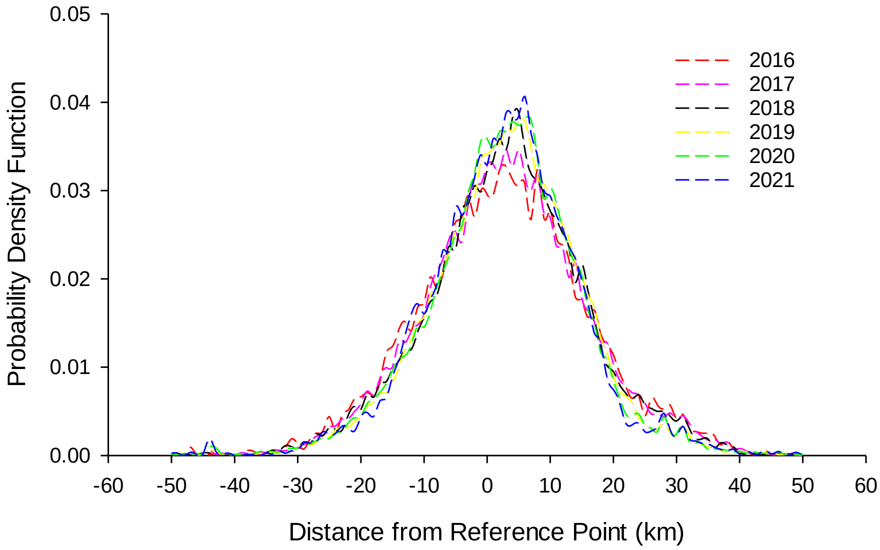

Fig. 7 Comparison of annual probability density function for direction category 2 from June 2016 until May 2021

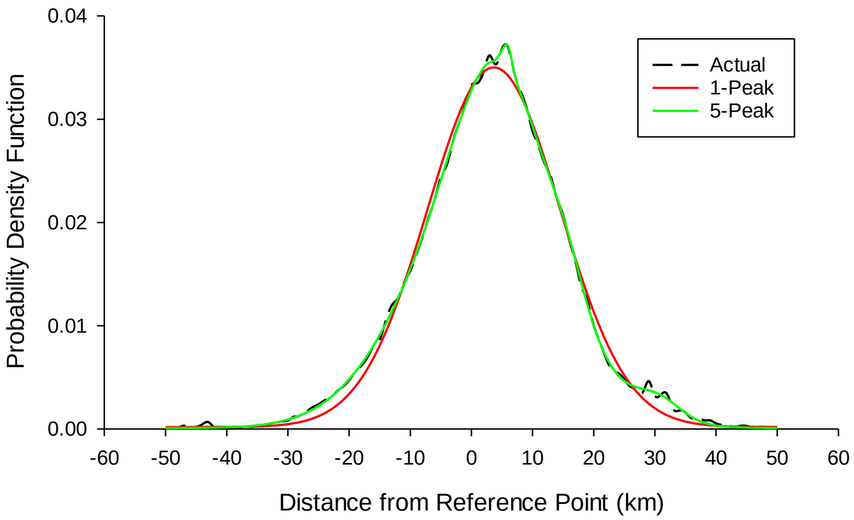

Fig. 8 Comparison of 1-peak and 5-peak Gaussian distribution against actual distribution

peak Gaussian distribution is close enough to the actual distribution, some segments cannot be approximated accurately. The objective of this study is to generate a general ship distribution for analysing the potential risk of offshore facilities throughout the entire coverage area. Therefore, the

Table 2 Coefficient of five-peak Gaussian distribution equation

Peak	Coefficient	Value	Peak	Coefficient	Value
1st Peak	A_1	0.6708	4th Peak	A_4	0.0230
	XC_1	1.6877		XC_4	15.6248
	W_1	24.8315		W_4	6.1409
2nd Peak	A_2	0.2594	5th Peak	A_5	0.0170
	XC_2	5.0162		XC_5	30.5926
	W_2	14.1974		W_5	7.2269
3rd Peak	A_3	0.0043	Offset	Y_0	0.0001
	XC_3	5.8590			
	W_3	1.5192			

ship distribution must be as accurate as possible to the actual distribution to reduce the possibility of calculation errors. The ship distribution used in this study is a five-peak Gaussian distribution with a coefficient of determination of 0.9995, and the coefficients that make up the distribution equation in Eq. (2) are shown in Table 2.

4. Case study

In this study, risk assessment was performed on one of the subsea pipelines in Natuna Sea as illustrated in Fig. 9. The colours on the map indicate the density of ship traffic in that area. Areas with little or no ship traffic are marked in blue, while areas with heavy traffic are marked in red. The examined pipeline is right at the centre of an international shipping lane and is in the red zone, which means that the subsea pipeline area is traversed by many ships.

The Natuna Sea is traversed by international shipping lanes that connect the two busiest container ports in the world, namely the Port of Singapore and the Port of Shanghai, and is directly connected to the busiest and most important international shipping lane, The Suez Canal Route, which passes through the Malacca Strait (Idris and Ramli 2018). The Natuna Sea is also one of the world's most important crude oil and LNG trade shipping lanes connecting Asia, Africa, and Australia. At least one-third of the world's oil and natural gas demands are distributed through this route (U.S. Energy Information Admisnistration 2013). Therefore, the ship traffic in this area is dominated by large vessels, which poses a potential threat to the existence of subsea pipeline facilities.

In this study, pipeline damage assessment was performed on subsea pipelines using the parameters as shown in Table 3. Pipeline damage analysis is conducted for each failure scenario to determine the anchor/ship mass at the limit of each pipeline damage class. The results of the pipeline damage analysis are shown in Table 4.

The probability of a ship passing through the pipeline area was determined using the calculation method described earlier. The results of the probability of ships passing through the pipeline area calculation are shown in Table 5.

Based on the results obtained from the calculation errors analysis, the five-peak Gaussian distribution is more accurate in modelling the actual ship distribution with a maximum error value of 0.23%. Although the normal distribution is close enough to the actual distribution, it turns out that it generates the highest error value among all other methods. Whereas the Monte Carlo simulation showed a higher error value than the five-peak Gaussian distribution because it was

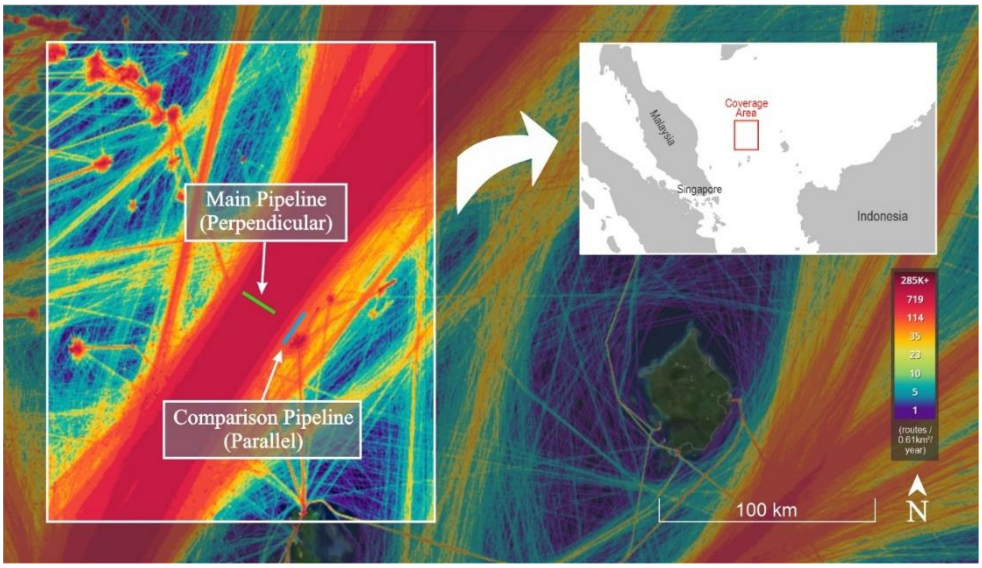

Fig. 9 Pipeline location map against international shipping lane

Table 3 Pipeline structural parameters

Parameter	Value	Unit
Content	Gas	-
Length	16	km
Diameter	219.075 (8.625)	mm (inch)
Wall thickness	9.53 (0.375)	mm (inch)
Specification of Material	CS API 5L X52 PSL2	-
SMYS	360	MPa
Steel density	7850	kg/m^3
Concrete coating thickness	40	mm
Anti-corrosion coating thickness	0.5	mm

Table 4 Damage category and ranges for each hazard

Damage Category		Dropped Anchor	Dragged Anchor	Vessel Sinking
Dent / Diameter (%)	Category	Anchor Mass (kg)	Anchor Mass (kg)	Ship Mass (Ton)
< 5	Minor Damage	< 8639	< 15424	< 35.68
5 – 10	Moderate Damage	8639 – 8679	15424 – 15524	35.68 – 36.01
10 – 15	Moderate Damage	8679 – 8730	15524 – 15653	36.01 – 36.44
15 – 20	Major Damage	8730 – 8791	15653 – 15806	36.44 – 36.95
> 20	Rupture	> 8791	> 15806	> 36.95

performed on interpolated discrete data. So, it can be concluded that the Monte Carlo simulation method gives a less relevant result. Therefore, the approach to model the actual ship distribution in this study uses a five-peak Gaussian distribution with variables that make up the distribution equation are shown in Table 6.

Based on the rating of consequence and probability of failure on the subsea pipeline, a failure

Table 1 Summary of the probability analysis of a ship passing through the pipeline area

Method	Probability	Error
Actual Distribution	0.49574	0.00%
Normal Distribution	0.48920	1.32%
Five-peak Gaussian Distribution	0.49462	0.23%
Monte Carlo Simulation	0.49181	0.79%

Table 2 Results of failure probability analysis on the examined subsea pipeline

Code	Probability	Rank	Code	Probability	Rank	Code	Probability	Rank
DpA-I	2.60E-05	2	DgA-I	6.68E-04	3	VS-I	2.54E-06	1
DpA-II	6.91E-06	1	DgA-II	5.27E-05	2	VS-II	1.33E-06	1
DpA-III	2.30E-05	2	DgA-III	1.84E-04	3	VS-III	4.57E-06	1

Note: DpA: dropped anchor, DgA: dragged anchor, VS: Vessel Sinking, I: no release, II: leakage, III: rupture

risk assessment can be carried out and then plotted into a risk matrix (Ponte 2021), as shown in Fig. 10. It can be seen that the potential risks tend to be in acceptable areas, except for the risk of rupture due to dropped anchor and dragged anchor are in the As Low As Reasonably Practicable (ALARP) areas. Therefore, it can be concluded that the examined pipeline is relatively safe and does not require any additional protection.

This study also includes a comparison analysis to validate the applicability of the five-peak Gaussian distribution application for calculating the geometric probability of vessel traffic in the dominant shipping lane. The comparison analysis was conducted on an adjacent subsea pipeline with a parallel configuration to the main shipping lane and the same structural parameters as the previously examined pipeline. This configuration was chosen because the dominance of the main shipping lane has the least impact when compared to the subsea pipeline with a perpendicular direction to the main shipping lane. The results of frequency analysis for each direction category are shown in Table 7.

It is shown in Table 7 that the dominant direction category on the comparison pipeline is no longer the direction category 2 but category 1, with a total frequency of 695 ships. A parallel configuration diminishes the significance of the main shipping lane on the subsea pipeline, even though the pipeline is still located within it. For the main pipeline, the frequency of passing vessels in direction category 2 is much more significant than in the other categories, thus makes it the dominant direction category. Unlike the main pipeline, the frequencies of vessel traffic in direction categories 1, 2, and 6 on the comparison pipeline show a similar result. Therefore, all the frequencies must be included in the geometric probability analysis with the actual distribution method, while the goodness-of-fit test of multi-peak Gaussian distribution still uses the five-peak Gaussian distribution, which has been determined previously in direction category 2. It aims to examine the applicability of the five-peak Gaussian distribution to approach the actual geometric probability.

The result of the comparison analysis of the probability of a vessel passing through the comparison pipeline area is shown in Table 8. It can be seen that the five-peak Gaussian distribution generated a high value of the calculation error of 58.3%. Therefore, it can be concluded that the five-peak Gaussian distribution is less representative for ship traffic analysis on a subsea pipeline with a parallel configuration to the main shipping lane, as shown in Fig. 9. Thus, in order to obtain more precise results, it is necessary to analyse the local ship distribution in the vicinity of the examined pipeline area.

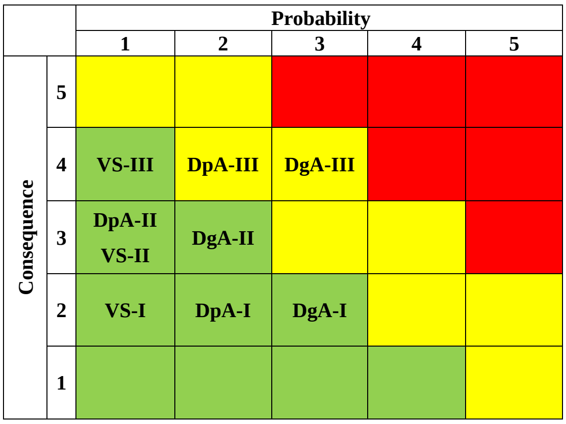

Fig. 10 Failure risk matrix of the examined subsea pipeline

Table 3 Comparison of passing vessel frequencies per direction category between the main and comparison pipeline

Pipeline	**Direction Category**						**Total**
	1	**2**	**3**	**4**	**5**	**6**	
Main Pipeline	333	61593	4232	61	0	155	66374
Comparison Pipeline	695	529	0	0	0	621	1854

Table 4 Summary of the probability analysis of a ship passing through the comparison pipeline area

Method	**Probability**	**Error**
Actual Frequency	0.01151	-
Five-peak Gaussian Distribution	0.00480	58.3%

Table 5 Summary of the probability analysis of a ship passing through the comparison pipeline area

Failure Scenario	**Direction Category 2**			**Direction Categories 2 & 3**		
	PoF	**PoF Score**	**Risk**	**PoF**	**PoF Score**	**Risk**
Dropped Anchor	2.42E-05	2	**Acceptable**	2.60E-05	2	**Acceptable**
	7.13E-06	1	**Acceptable**	7.67E-06	1	**Acceptable**
	2.38E-05	2	**ALARP**	2.55E-05	2	**ALARP**
Dragged Anchor	6.39E-04	3	**Acceptable**	6.87E-04	3	**Acceptable**
	5.58E-05	2	**Acceptable**	6.00E-05	2	**Acceptable**
	1.95E-04	3	**ALARP**	2.10E-04	3	**ALARP**
Vessel Sinking	2.33E-06	1	**Acceptable**	2.50E-06	1	**Acceptable**
	1.34E-06	1	**Acceptable**	1.44E-06	1	**Acceptable**
	4.60E-06	1	**Acceptable**	4.94E-06	1	**Acceptable**

Table 9 shows the comparison of risk analysis utilizing the dominant direction category 2 and if the less dominant category 3 is incorporated for main pipeline. It is clear that the addition of the less dominant category 3 increases the probability of failure slightly for each failure scenario. However, since PoF score does not change, the risk level remains the same.

5. Conclusions

This study presents the development of the geometric probability quantification methods as an approach to QRA of subsea pipeline facilities against external interferences based on AIS data. AIS data from marine traffic in Natuna Sea was processed by filtering and modeling the actual ship distribution throughout the entire coverage area so that the ship distribution can be used to analyse other adjacent subsea pipeline facilities in the same shipping lane. The actual ship distribution is always preferable for a more detailed and accurate analysis. However, sometimes there might be several limitations in acquiring reliable AIS data in every analysis. Therefore, it is necessary to assume the data behaviour as a specific distribution, especially for rapid simulation or conceptual study, as recommended in technical guidelines. The methods used and compared in this study are a goodness-of-fit test of multi-peak Gaussian distribution and a Monte Carlo simulation.

The results show that a Gaussian distribution with five peaks is required to accurately represent the actual data by providing an error of 0.23% compared with actual data. While the Monte Carlo simulation with a hundred million realisation provides a calculation error of 0.79%. The Monte Carlo simulation generated a less accurate result due to its limitation on approaching interpolated discrete data. The normal distribution approach, as is recommended in several technical guidelines, turns out to be less accurate than other methods by providing a calculation error of 1.32% because of its inability to accurately model the unique behaviour of the actual distribution. Therefore, it can be concluded that the multi-peak Gaussian distribution can represent the actual ship traffic distribution in the main lane direction. However, it becomes less representative when applied for ship traffic distribution in a parallel direction to the main lane direction of due to a different dominating direction category. Lastly, the performance of the geometric probability approach was assessed by utilising a quantitative risk assessment for a subsea pipeline against vessel anchor-dropping and dragging and vessel sinking. The results of the quantitative risk assessment show that most of the risks fall under the acceptable areas, except for the risk of rupture due to dropped anchor and dragged anchor, which fall under the ALARP areas. Thus, it can be concluded that the examined subsea pipeline does not require any additional protection.

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References

ABS (2013), “Rules for Building and Classing Steel Vessels Part 3 Chapter 5”, American Bureau of Shipping.

Aulia, R., Tan, H. and Sriramula, S. (2021), “Dynamic reliability model for subsea pipeline risk assessment due to third-party interference”, *J. Pipeline Sci. Eng.*, **1**(3), 277-289. https://doi.org/10.1016/j.jpse.2021.09.006.

Bartolini, L., Marchionni, L., Parrella, A. and Vitali, L. (2018), “Advanced FE modelling approach for pipeline hooking interaction of dragged anchors”, *Proceedings of the ASME 2018 37th International Conference on Ocean, Offshore and Arctic Engineering*, Madrid, Spain, June.

Brown, R.J. (1984), “Offshore Pipeline Repair Methods and Costs in Diapir Area, Alaska”, Zug Houston The Hague Singapore.

Chung, Y.N., Man, C.L., Juan, C.H. and Hsin, C.K. (2019), “Risk assessment and traffic behaviour evaluation of inbound ships in Keelung Harbour based on AIS data”, *J. Mar. Sci. Technol.*, 27. https://doi.org/10.6119/JMST.201908_27(4).0002.

De Stefani, V. and Carr, P. (2011), “A model to estimate the failure rates of offshore pipelines”, *Proceedings of the 2010 8th International Pipeline Conference*, Alberta, Canada, September.

DNV (2010), ‘DNV RP F-111 Interference Between Trawl Gear and Pipelines’. Det Norske Veritas.

DNVGL (2017), ‘DNVGL-RP-F107 Risk Assessment of Pipeline Protection’. Det Norske Veritas.

Hu, Z., Liu, Y., Li, Z. and Liu, Y. (2021), “Impact frequencies of subsea pipelines by anchoring and trawling based on AIS data”, *Proceedings of the 31st International Ocean and Polar Engineering Conference*, Rhodes, Greece, June.

Huang, J.C., Nieh, C.Y. and Kuo, H.C. (2019), “Risk assessment of ships maneuvering in an approaching channel based on AIS data”, *Ocean Eng.*, **173**, 399-414. https://doi.org/10.1016/j.oceaneng.2018.12.058.

Idris, H. and Ramli, M.F. (2018), “Southeast Asian region maritime connectivity and the potential development of the Northern Sea route for commercial shipping”, *JATI - J. Southeast Asian Studies*, **23**(2), 25-46. https://doi.org/10.22452/jati.vol23no2.2.

Macdonald, K.A., Cosham, A., Alexander, C.R. and Hopkins, P. (2007), “Assessing mechanical damage in offshore pipelines – Two case studies”, *Eng. Fail. Anal.*, **14**(8), 1667-1679. https://doi.org/10.1016/j.engfailanal.2006.11.074.

Marcjan, K., Dzikowski, R. and Bilewski, M. (2017), “Criteria of accidental damage by ships anchors of subsea gas pipeline in the Gdańsk bay area”, *TransNav, Int. J. Marine Navigation and Safety od Sea Transportation*, **11**(3), 441-446. https://doi.org/10.12716/1001.11.03.07.

Mujeeb-Ahmed, M.P., Seo, J.K. and Paik, J.K. (2018), “Probabilistic approach for collision risk analysis of powered vessel with offshore platforms”, *Ocean Eng.*, **151**, 206-221. https://doi.org/10.1016/j.oceaneng.2018.01.008.

Mulyadi, Y., Kobayashi, E., Wakabayashi, N., Pitana, T. and Wahyudi. (2014a), “Development of ship sinking frequency model over subsea pipeline for Madura Strait using AIS data”, *WMU J. Maritime Affairs*, **13**(1), 43-59. https://doi.org/10.1007/s13437-013-0049-2.

Mulyadi, Y., Kobayashi, E., Wakabayashi, N., Pitana, T., Wahyudi and Prasetyo, E. (2014b), “Estimation method for dragged anchor accident frequency on subsea pipelines in busy port areas”, *J. Japan Soc. Naval Archit. Ocean Engineers*, **20**, 173-183. https://doi.org/10.2534/jjasnaoe.20.173.

Ponte, G.P.D. (2021), *Risk Management in The Oil and Gas Industry*. Gulf Professional Publishing.

Spouge, J. (1999), *A Guide to Quantitative Risk Assessment for Offshore Installations*. CMPT Aberdeen, UK.

Svanberg, M., Santén, V., Hörteborn, A., Holm, H. and Finnsgård, C. (2019), “AIS in maritime research”, *Marine Policy*, **106**, 103520. https://doi.org/10.1016/j.marpol.2019.103520.

Tawekal, R.L., Allo, R.P.R. and Taufik, A. (2017), “Damage analysis of subsea pipeline due to anchor drag”, *Int. J. Appl. Eng. Res.*, **12**(5).

Tawekal, R.L. and De Velas, J. (2019), “Subsea pipeline protection design subjected to dropped anchor using concrete mattress”, *GEOMATE J.*, **17**(60), 251-258. https://doi.org/10.21660/2019.60.84652.

Trelleborg (2003), *Marine Fendering Systems: Ship Features & Tables*, Trelleborg.

U.S. Energy Information Admisnistration (2013), “The South China Sea is an important world energy trade route”, *U.S. Energy Information Admisnistration*. https://www.eia.gov/todayinenergy/detail.php?id=10671.

Vitali, L., Candiracci, F., Crea, C., Bruschi, R. and Rott, W. (2012), “Nord stream project - Pipeline safety against ship traffic related threats: Quantitative risk assessment approach”, *Proceedings of the 22nd International Offshore and Polar Engineering Conference*, Rhodes, Greece, June.

Wang, L., Li, Y., Wan, Z., Yang, Z., Wang, T., Guan, K. and Fu, L. (2020), "Use of AIS data for performance evaluation of ship traffic with speed control", *Ocean Eng.* **204**, 107259. https://doi.org/10.1016/j.oceaneng.2020.107259.

Woo, J., Kim, D. and Na, W.B. (2015), "Damage assessment of a tunnel-type structure to protect submarine power cables during anchor collisions", *Mar. Struct.*, **44**, 19-42. https://doi.org/10.1016/j.marstruc.2015.07.005.

Yoo, Y. and Kim, T.G. (2019), "An improved ship collision risk evaluation method for Korea maritime safety audit considering traffic flow characteristics", *J. Mar. Sci. Eng.*, **7**(12), 448. https://doi.org/10.3390/jmse7120448.

Zhen, R., Riveiro, M. and Jin, Y. (2017), "A novel analytic framework of real-time multi-vessel collision risk assessment for maritime traffic surveillance", *Ocean Eng.* **145**, 492-501. https://doi.org/10.1016/j.oceaneng.2017.09.015.

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