International Journal of Maritime Technology

Journal homepage: ijmt.ir

Risk Assessment of Dropped Objects on Corroded Submarine Pipelines Using Machine Learning Algorithms

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ARTICLE INFO

Article History:
Received: 23 Aug 2025
Last modification: 6 Apr 2026
Accepted: 11 Apr 2026
Available online: 13 Apr 2026

Article type:
Research Paper

Keywords:
Submarine pipeline,
dropped object,
Machine Learning (ML),
Monte Carlo Simulation (MCS),
Risk assessment,
pitting corrosion

ABSTRACT

This paper proposes a probabilistic model based on machine learning algorithms to estimate the risk associated with different levels of damage (per DNV-RP-F101) due to a dropped-object impact on subsea pipelines. The model is generalized by considering a wide range of pipeline geometric and mechanical specifications, corrosion conditions, and various possible impact scenarios. Multiple machine learning algorithms—including Linear Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine, and Gradient Boosting—were evaluated, with Random Forest demonstrating the highest accuracy. The analysis of how pipeline characteristics influence the probability of different damage levels provides a basis for decision-making on implementing preventive measures to reduce damage probability during the pipeline design stage.

ISSN: 2645-8136

DOI:

1. Introduction

Pipelines remain the most cost-effective and sustainable method for transporting oil and gas. For several decades, offshore fields have been prioritized for energy development through oil and gas extraction. In line with this development, submarine pipelines have been laid on a significant portion of the seabed. The development of marine pipelines, along with their expansion into deep water as exploration and extraction technologies advance, has elevated the risk and integrity assessment of these subsea structures to the top of the priority list for pipeline operators and owners. Given the complexity and high cost of managing and maintaining the integrity of subsea pipelines, studying and assessing potential risks to prevent pipeline damage is paramount.

The spread of pipeline networks and their interaction with maritime activities and navigation has elevated third-party threats to a significant level. Among the most critical third-party threats are damages resulting from anchoring, trawling, and dropped objects [1].

The inherent uncertainty associated with third-party threats and the need to predict structural responses and associated risk levels have driven research toward risk-based integrity assessment and, more comprehensively, Pipeline Integrity Management Systems (PIMS). Concurrently, advances in machine learning algorithms have enabled the formulation and study of uncertain phenomena using a logic-based approach and best-practice experience data.

According to a study by the Institute Concawe, Environmental Science for European Refining, on the causes of pipeline spills, as illustrated in the Figure. (1), third-party activities account for a substantial portion of threats [2]. The severity of this impact, coupled with its correlation with the corrosion threat on the one hand and the inherent uncertainty and probabilistic nature of these two factors on the other, necessitates investigating potential failure scenarios in pipelines exposed to dropped objects and corrosion during both the design and maintenance phases of operation.

The impact of dropped objects on subsea structures has been a subject of interest among researchers since the 1980s [3]–[5]. One of the earliest studies in this field was conducted by Aanesland [6], who numerically and experimentally investigated the trajectories and impact areas of drilling pipes accidentally released onto the seabed.

Kawsar et al. [7] have examined the safety of pipelines under potential impact scenarios using probabilistic and numerical modeling. In this study, the pipeline is considered adjacent to the platform, and, using the developed probabilistic model, the probability and frequency of impacts are provided and categorized by the effective length of the impacting object. Ultimately, the energy absorbed by the pipeline under various impact scenarios is calculated using the numerical finite element method and compared with the criteria mentioned in the DNV-RP-F107 standard [8].

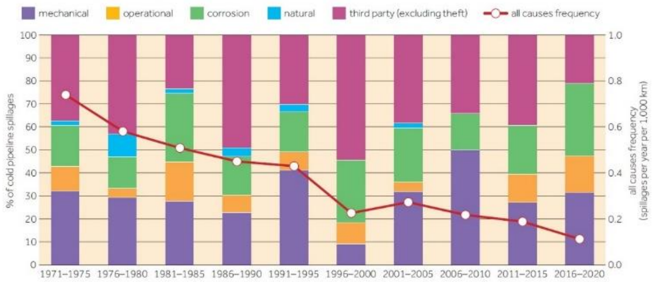

Figure. 1. Pipeline spillage frequencies by threats between 1971 and 2020 [2]

Edmollaii et al. [9] conducted a study to assess the reliability of pipelines under dropped-object impacts. The study employed a sensitivity analysis to examine the effect of various parameters on the reliability, including the object's mass, volume, projected area, drag coefficient, and mass coefficient. The results indicated that the impact area and drag coefficient were most sensitive to damage probability, while the mass and mass coefficient were least sensitive.

Zhou and Zhang [10] investigated the effects of significant, influential, and specific parameters on dimensionless deflection and impact limits, including internal pressure, eccentric distance, and deflection angle.

Jiang and Dong [11] propose a two-level quantitative risk assessment framework for submarine pipelines from dropped objects, integrating finite element analysis with probabilistic methods to evaluate nonlinear pipe-soil interactions and parameter uncertainties.

Numerous algorithms and software programs can significantly enhance the integrated management of pipelines. Park et al. [12], employing the Monte Carlo Simulation (MCS) and following the Canadian Standards Association (CSA) guidelines, developed a structural reliability-based model for underground pipelines. This model incorporates failure frequency data and equipment impact rates.

Aulia et al. [13] introduced a dynamic reliability model to assess subsea pipeline risks from third-party interference, using a Bayesian approach. The model was developed by integrating fault tree analysis with finite element modeling to improve risk evaluation reliability and reduce reliance on qualitative inputs.

Li et al. [14] developed a methodology to assess the risk of natural gas pipeline incidents caused by corrosion, incorporating uncertainty in incident escalation. This method can account for uncertainties in failure probability and in the consequences of pipeline leaks.

The quality and accuracy of the data used in pipeline integrity assessments significantly influence the reliability of calculations and the validity of results. Data is obtained experimentally or collected through models and mathematical calculations. An accurate, experimental dataset is necessary to validate the results. In Ossai's study [15], Monte Carlo simulations were used to forecast corrosion rates and assess the reliability of oil and gas pipelines. Historical data were utilized to generate random numbers for predicting corrosion rates, and the results were validated against data from 11 onshore oil and gas fields.

Durap and Balas [16] conducted a risk assessment of subsea pipelines that accounted for vertical and horizontal displacements induced by hydrodynamic forces. The Monte Carlo simulation was coupled with a three-dimensional hydrodynamic numerical model (Hydrotam-3D), developed initially by Balas and Özhan [17]. This integrated approach assessed interactions among the pipeline, soil, and environmental parameters, including wave-induced currents.

Tian et al. [18] investigated the influence of seabed conditions on the assessment of damage to subsea pipelines subjected to dropped-object threats using nonlinear explicit finite-element dynamic modeling. Additionally, Chen et al. [19] investigated dent-related depth and strain in sandwich pipes subjected to drop-object impact using finite-element numerical simulation, accounting for the effect of seabed flexibility. They also developed empirical formulas to predict the dent-related properties of sandwich pipes.

Developing machine learning algorithms and integrating them with numerical methods has been considered a powerful tool for assessing the failure risk of oil and gas pipelines caused by various threats. This method is a solution for the quantitative risk calculation of pipeline failures. The selection of probabilistic parameters for modeling the uncertainties inherent in phenomena related to various pipeline threats is among the topics researchers have focused on in recent years. Jiang and Dong [20] examined the impact of the nonlinear interaction between pipelines and soil, and the effect of pipeline burial depth, using the finite element method and machine learning algorithms. They proposed a relationship between the appropriate burial depth of pipelines and their failure probability, based on various acceptable design criteria.

Based on a review of studies on the use of machine learning algorithms to predict pipeline failures, this approach has been increasingly developed since 2019. Geometric specifications and pipeline route characteristics, fluid properties inside the pipeline, and data obtained from internal pipeline inspections are among the most important input parameters for machine learning-based pipeline failure prediction models [21].

This study investigates the efficacy of Machine Learning (ML) algorithms in evaluating the risk of dropped objects impacting offshore pipelines near platforms. The primary objective of this study is to develop a quantitative methodology for risk assessment of pipelines, accounting for uncertainties in geometry, age, material, and concrete coating thickness when subjected to potential third-party threats (e.g., drop-object impact).

For this purpose, a database has been created containing the geometric characteristics and material of the pipeline, as well as the probability of dent formation relative to the pipe diameter (in five levels defined by the DNV-RP-F107 standard [8]). This database was developed using a Monte Carlo Simulation program implemented in MATLAB. This simulation models a comprehensive range of potential impact scenarios involving the dropped object and the pipeline, accounting for factors such as mass, velocity, and impact conditions. This process is an effective tool for analyzing the accidental limit state of pipelines, which is one of the mandatory limit states stipulated in pipeline design standards. This analysis directly affects the pipeline's risk expenditure reduction over its lifecycle cost (LCC).

2. Methodology

Submarine pipelines face a significant risk from falling objects, underscoring the need to understand their potential impact. A dropped object is a possible accidental failure of a subsea pipeline, always caused by a crane operation. According to DNV GL-RP-F107, dropped-object failures are classified into three types, as shown in the Figure. (2). As indicated in the Figure, proportional to the damage caused, there is a probability of occurrence of consequences in terms of containment release. This relationship, proportional to the ratio of dent depth to diameter, is caused by the amount of impact energy absorbed by the pipe material, as the dent-absorbed energy, and is categorized and detailed in Table (1).

Considering smooth dent shape and knife-edge load applied perpendicular to the pipeline, Eq. (1) provides the dent-absorbed energy for steel pipelines as a function of the plastic capacity of wall-thickness, dent depth, and pipe diameter [8].

$$E_s = 13.369.M_p(D/t)^{\frac{1}{2}}.D.(\delta/D)^{\frac{3}{2}} \quad (1)$$

Where D = Diameter of the steel pipeline, t = Wall thickness, δ = Pipe deformation (dent depth), and $M_p = 0.25\,\sigma_y\,t^2$ is the plastic moment capacity of the pipe wall, wherein σ_y is the yield stress.

Table. 1. Impact capacity and damage classification of steel pipelines and risers [8].

Dent/ diameter (%)	*Impact energy*	*Damage level description*	*Conditional probability*					
			D1	D2	D3	R0	R1	R2
<5	Equation (1)	Minor damage	1.0	0	0	1.0	0	0
5-10	Equation (1)	Major damage Leakage anticipated	0.1	0.8	0.1	0.9	0.1	0
10-15	Equation (1)	Major damage. Leakage and rupture are anticipated.	0	0.75	0.25	0.75	0.2	0.05
15-20	Equation (1)	Major damage. Leakage and rupture anticipated	0	0.25	0.75	0.25	0.5	0.25
>20	Equation (1)	Rupture.	0	0.1	0.9	0.1	0.2	0.7

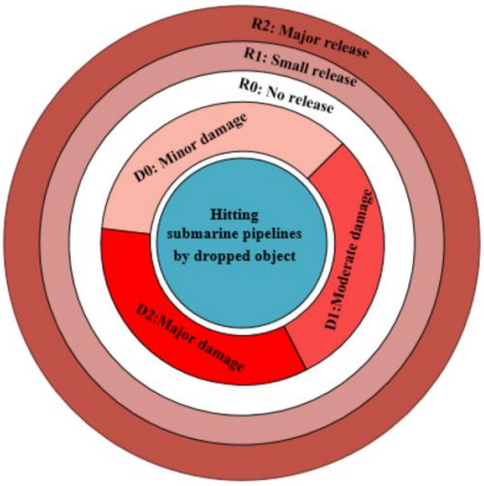

Figure. 2. Damage classification to submarine pipelines by the dropped object [9].

The deformation of the pipe structure, which leads to dent formation, is primarily triggered by the kinetic energy transferred from a dropped object, acting as the effective impact energy (E_E). The effective energy is calculated using Eq. (2), considering the terminal velocity of the dropped object, as determined by Eq. (3), and accounting for the equilibrium among gravitational, buoyant, drag, and added-mass forces.

$$E_E = \frac{1}{2}(m + m_a).v_T^2 \qquad (2)$$

$$(m - V.p_w).g = \frac{1}{2}.p_w.C_D.A_P.v_T^2 \qquad (3)$$

Where m = mass of the object, g = gravitation acceleration (9.81 m/s^2), V = volume of the object (the volume of the displaced water), ρ_w = water density, C_D = drag coefficient of the object, A_P = projected area of the object in the flow direction, v_T= terminal velocity through the water, $m_a = \rho_w \cdot C_a \cdot V$ is added mass, and C_a = added mass coefficient.

The effective impact energy resulting from the collision of an object with the pipeline is partially absorbed and damped by the concrete coating before being transferred and absorbed by the pipe structure.

Jensen's 1978 work presents equations (4 and 5) for determining the kinetic energy absorbed by concrete coatings under varying impact conditions [8]. These equations take into account parameters such as the penetration depth (x0, assumed equal to the coating depth and set to 45 mm at minimum), the object width (b), the crushing strength (Y), and the concrete-coated outside pipeline diameter (D_C).

$$E_k = Y.b.x_0 \qquad (4)$$

$$E_k = Y.b.\frac{4}{3}\sqrt{D_c.x_0^3} \qquad (5)$$

Typically, the crushing strength is 3-5 times the cube strength (range of 35 to 45 MPa) for conventional density concrete. For conservative estimation, the energy absorption by the polymer coating has been neglected in this study. Fig. 3 presents a schematic of the stages and components involved in the energy transfer process resulting from the impact of a dropped object on a pipeline near a platform.

The probabilistic characteristics of drop object events, along with the uncertainties inherent in material properties and the variations in pipeline thickness resulting from corrosion, create a demand for modeling that addresses a wide variety of scenarios specific to each pipeline.

By creating an extensive database of various pipeline types and their probable conditions, machine learning algorithms can be used to develop the relationship between the probability of occurrence of pipeline damage levels due to dropped object threat with material and structural features. For this purpose, a theoretical framework has been developed, as illustrated in Figure. (4), to assess the probability of damage levels in a corroded pipeline subjected to dropped object threat.

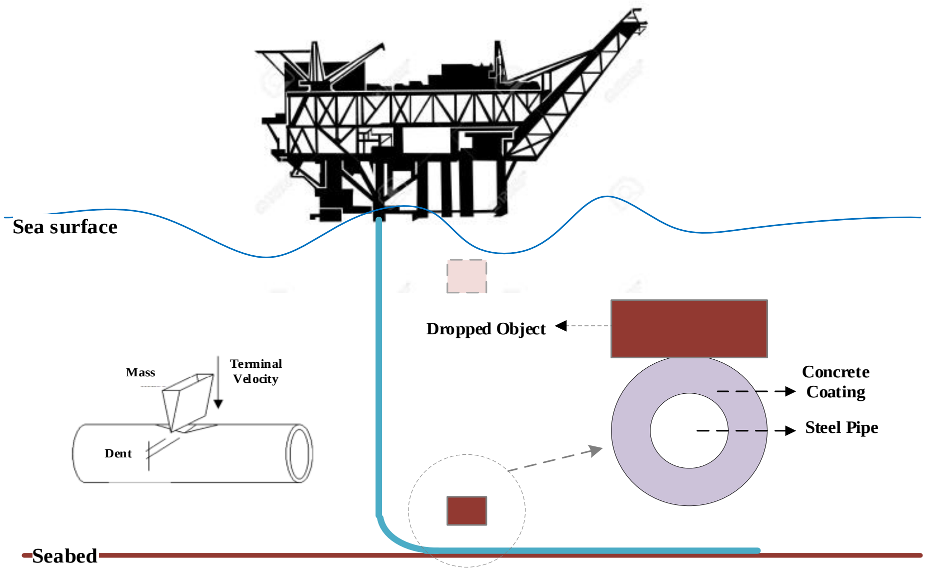

Figure. 3. Dropped object impact on concrete-coated pipeline.

3. Probabilistic modeling and database of submarine pipeline failure due to dropped objects

The effective impact energy formula of the dropped object according to Eq. (3) is as follows:

$$E_E = \frac{(m+\rho_w.C_a.V).(m-V.\rho_w).g}{(\rho_w.C_D.A_P)} \quad (6)$$

Eq. (6) is affected by the mass and geometry of the falling object, which can significantly change during the pipeline's service life due to marine operating conditions. Considering the uncertainty, this study employs a probabilistic model analysis. Random parameters representing these characteristics have been introduced to improve the accuracy of the results. The random parameters belonging to dropped object's mass and geometry include: m = mass categorized in five probable groups as [m_{min}, m_{max}]; m_{min} ={0.9, 2, 4, 6, 12} & m_{max} ={4.6, 8, 10, 12, 30}*tones*, density = m / V normal distribution in [1.1, 1.6] $tons/m^3$, and projected area ratio = A_P / V is between [0.1, 0.5] 1 / m The average energy value, derived from Eqs. (4 and 5), considers the influence of the concrete protective layer, which absorbs a portion of the effective energy. In these equations, the penetration depth (equivalent to coating depth) is treated as an added weight to provide the necessary negative buoyancy force for the on-bottom stability of the pipeline on the seabed. It is calculated using Eq. (7). The minimum allowable coating thickness is 45 mm per DNVGL-RP-F107.

$$x_0 = \frac{1}{2}.[D^2.\rho_c.A_{cs}/(\rho_c-\rho_w)]^{\frac{1}{2}} - D \quad (7)$$

Where ρ_c = density of concrete coating layer (i.e., 3040 kg/m^3) and A_{cs} = Steel pipe cross-section (m^2)

Pitting-type corrosion is the most common corrosion in subsea pipelines. Recent studies have shown that the growth of corrosion pits on the pipeline wall does not follow a linear pattern. The growth of defect depth of the corrosion pit as a function of service life in a year, $d(T)$, can be modeled using the power law [22], as shown in Eq. (8).

$$d(T) = \kappa(T - T_d)^\alpha \quad (8)$$

κ and α are corrosion growth coefficients and assumed to be normally distributed with mean value and coefficient of variation (COV) as taken (0.164/year, 0.2) and (0.780, 0.15), respectively, for unknown soil types [23]. The time required for corrosion initiation was assumed to be T_d = 2.88 years. [24]

Since the ratio of dent-to-diameter of steel pipeline (δ/D) according to Table (1) is used as a criterion for determining the damage level, considering equation (1), the limit state function of the dropped object for probabilistic damage analysis has been derived as Eq. (9).

$$\delta/D = \left[(E_E - E_k)/\left(13.369.M_p.\left(\frac{D}{t_a}\right)^{\frac{1}{2}}.D\right)\right]^{\frac{2}{3}} \quad (9)$$

Where $t_a = t - d(T)$ is the actual wall thickness. By obtaining δ/D from Eq. (9) and referring to Table (1), the damage class and level of the potential threat the dropped object poses for the under-study pipeline can be determined.

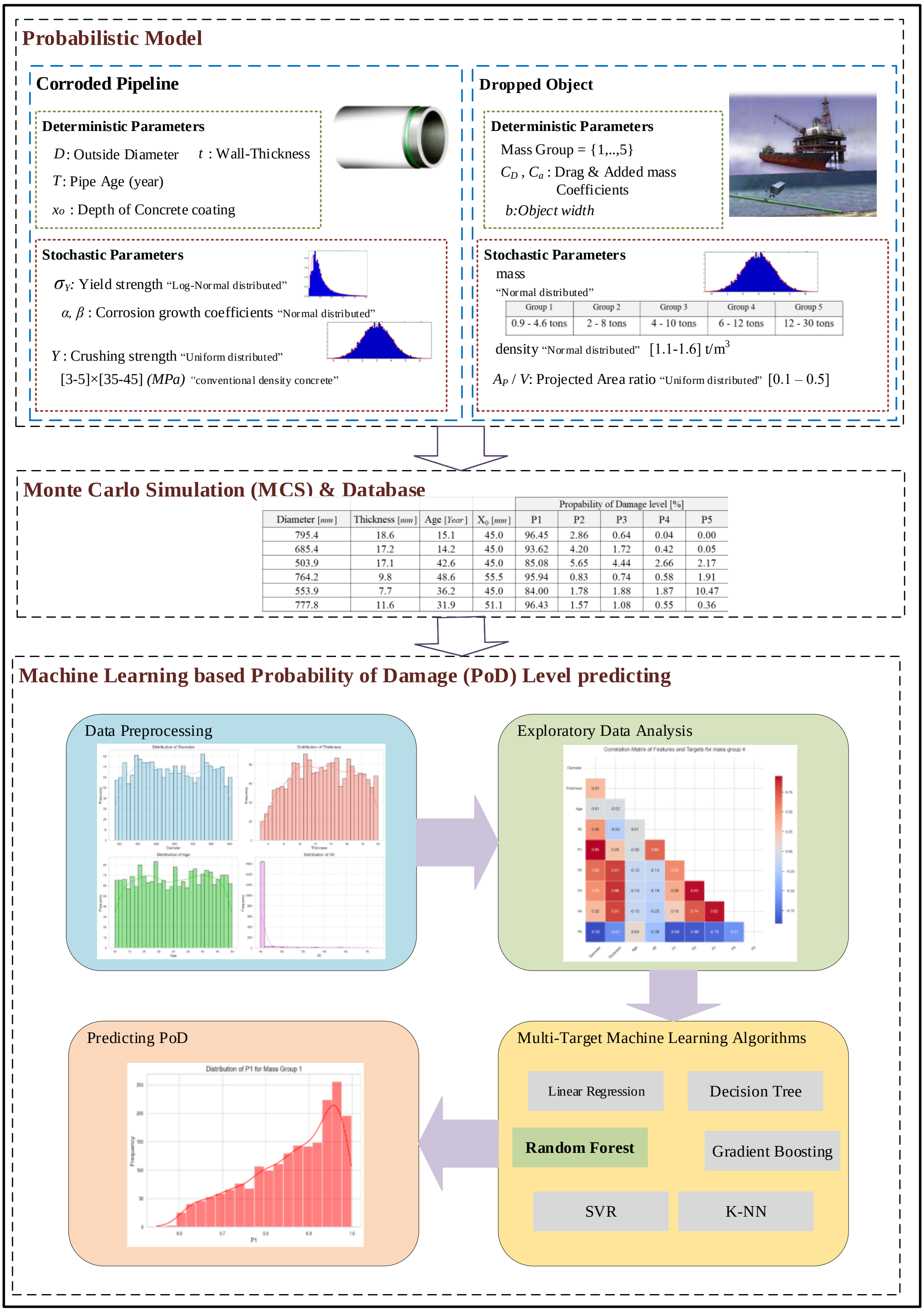

Figure. 4. Methodological Framework for Assessing Probability of Damage level of corroded pipeline under the dropped object threat

In this study, by utilizing the limit state function in Eq. (9) and considering the statistical characteristics of the random parameters as per Table (2), the probability of occurrence of the damage levels specified in Table (1) is calculated through the implementation of the Monte Carlo Simulation (MCS).

Table 2. The statistical distribution of random parameters used in the probabilistic model

Parameters		Mean	COV	Unit	Distribution Type
Pipe diameter, D		-	-	mm	Deterministic
Wall thickness, t		-	-	mm	Deterministic
Defect depth, d		μ_d	0.10	mm	Normal
Yield Strength, σ_Y		μ_{YS}	0.07	MPa	Lognormal
Corrosion growth coefficients	κ	0.164	0.2	mm / yr	Normal
	α	0.780	0.15	---	Normal
Object mass, m		μ_m	σ_m / μ_m	tones	Normal
projected area ratio, A_P / V		0.3	0.04	1 / m	Uniform
Object density, m / V		1.35	0.06	tones / m^3	Normal

Note: COV: Coefficient of Variation.
$\mu_m = (m_{min}+m_{max})/2$, $\sigma_m = (m_{max}- m_{min})/6$

4. Machine Learning-based model of Probability of Damage level predicting

The effectiveness of machine learning (ML) for risk assessment in subsea pipelines under the effect of dropped objects is investigated. Following a multi-stage approach, the study involved data preparation, feature analysis to identify key risk factors, and the development and evaluation of various ML models for risk prediction. The optimal model is selected and integrated into a Python application for practical risk assessment, with different algorithms compared.

Based on the Monte Carlo Simulation (MCS) developed in MATLAB, the probability model is run for five nominated mass groups of dropped objects, generating a separate data set for each mass group, including 2000 samples. Fig. 5 displays the frequency diagram of the data parameters. The data within the specified range have relatively uniform frequencies, thereby enhancing the accuracy of machine-learning algorithms. For x0, as indicated in equation (7), the criterion for the minimum coating thickness to ensure the necessary negative buoyancy for on-bottom stability is that, given the pipeline's weight conditions in the created models, most models have 45 mm as the minimum coating thickness.

The summary statistics table provides a comprehensive overview of the dataset's main characteristics, including measures of central tendency, dispersion, and the range of values for each variable. This Table is a fundamental tool in exploratory data analysis. It presents key statistical measures for each feature and target variable, helping to identify patterns, trends, and potential anomalies in the data. Table (3) presents a sample of summary statistics for mass group 1. P_i represents the probability of damage at the ith level, calculated from the probabilistic model using MCS and treated as the target.

In this Table, Count is the number of non-null data; the average values are indicated with Mean; Std is the Standard Deviation, measuring dispersion or variability around the mean; and the data quartiles for each feature are bounded by Min, 25%, 50%, 75%, and Max.

The correlation matrix plot is a powerful tool in Exploratory Data Analysis (EDA) that reveals relationships among variables in a dataset. By quantifying the degree to which pairs of variables are linearly related (**±1** indicates a perfect positive/negative linear relationship, and **0** means no linear relationship), the correlation matrix helps identify patterns, dependencies, and potential multicollinearity issues. It focuses on the relationships between features and target variables related to pipe risk levels. Fig. 6 shows a sample of the correlation matrix for the relationship between mass group 1's features and target variables.

Multi-target prediction has emerged as a powerful technique in machine learning applications, enabling models to forecast multiple outcomes concurrently. This approach is particularly advantageous when the target variables are interconnected, as it allows the model to leverage these relationships and potentially improve prediction accuracy and efficiency. By training a single model to handle multiple outputs, the inherent dependencies among variables can be effectively captured, leading to more comprehensive and accurate predictions. Since the dataset includes labeled data, supervised machine learning algorithms were used in this study.

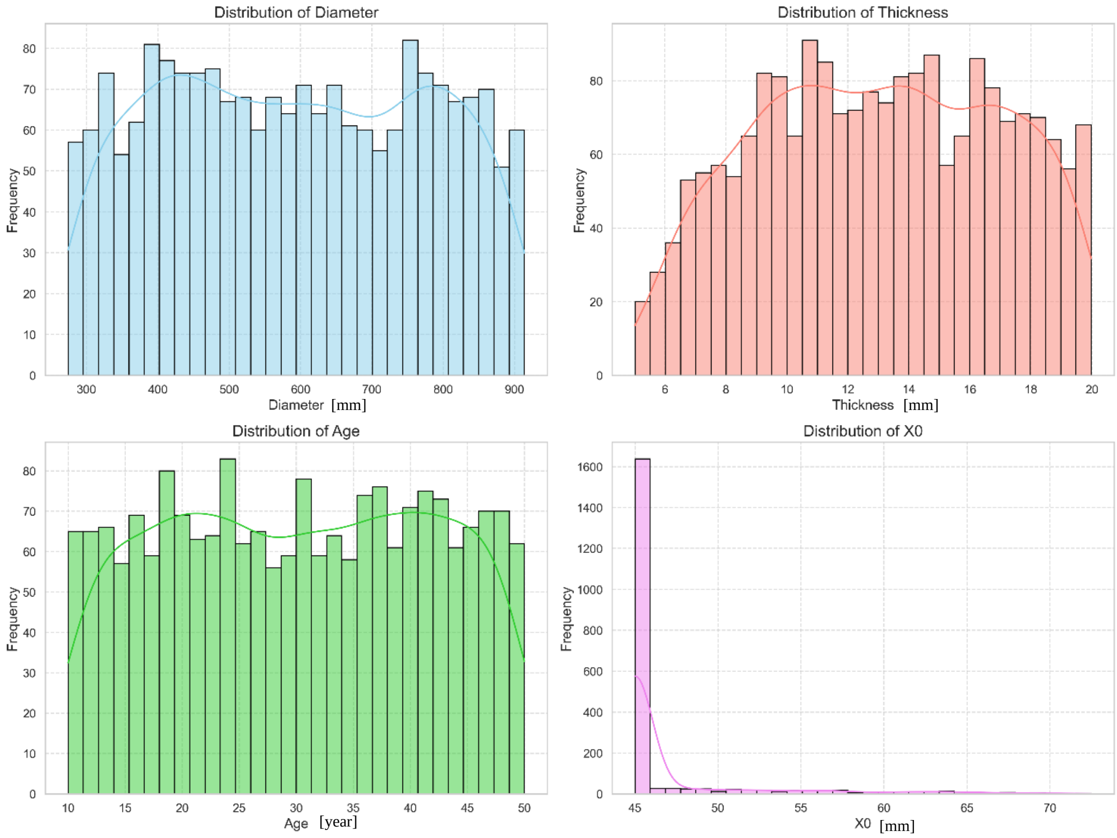

Figure. 5. Summary of Pipelines Data Generated in This Study

Table 3. Summary statistics table for Mass Group 1 (0.9 to 4.6 tones)

		Count	Mean	Std	Min	25%	50%	75%	Max
Features	**Diameter** [mm]	2000	591.96	182.15	274.15	433.29	589.05	756.84	913.68
	Thickness [mm]	2000	13.01	3.92	5.02	9.8173	13.04	16.34	19.97
	Age [Year]	2000	30.12	11.5	10.00	20.15	30.42	40.17	49.98
	x_0 [mm]	2000	46.81	4.78	45	45	45	45	72.48
Target Variables	P_1	2000	0.8582	0.1057	0.5479	0.7853	0.8813	0.9497	0.9984
	P_2	2000	0.0328	0.0177	0.0008	0.0197	0.0312	0.0452	0.0809
	P_3	2000	0.0258	0.0163	0.0005	0.0124	0.0239	0.038	0.0672
	P_4	2000	0.0188	0.0147	0	0.0047	0.0176	0.0297	0.0566
	P_5	2000	0.0644	0.0858	0	0.0019	0.0223	0.1005	0.4165

For model development and evaluation, the dataset for each mass group was randomly partitioned into a training set (70%) and a hold-out test set (30%). Model training and hyperparameter tuning were performed on the training set using K-fold cross-validation (K=5). The final model performance was evaluated solely on the unseen test set to ensure an unbiased assessment of its predictive capability.

The dataset in this study is generated through Monte Carlo Simulation (MCS), providing a synthetic yet controlled representation of risk parameters. This method enables systematic coverage of a wide parameter range and specific accident scenarios—such as dropped objects—where obtaining real-world failure data is often impractical. However, it should be noted that the model is validated in this simulated environment. Consequently, model performance in practical, real-world pipeline applications could be affected by factors not fully represented in the simulation.

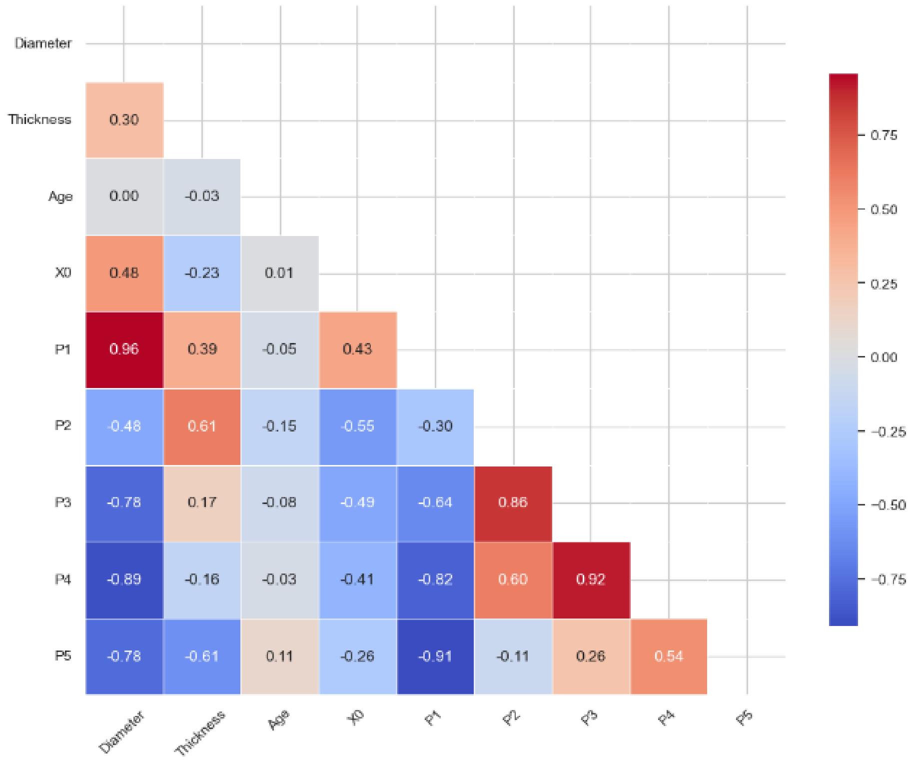

Figure. 6. Correlation Matrix of features and targets for mass group 1

Several algorithms can be adapted for multi-target learning tasks when using labeled data, including Linear Regression**,** Decision Trees, Random Forests, k-Nearest Neighbors (k-NN), Support Vector Machines (SVMs), and Gradient Boosting.

Various error assessment models have been used in this study to evaluate the accuracy and precision of different algorithms on a dataset derived from a probabilistic model that analyzes the probability of damage at various levels. These models include Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 Score (Coefficient of Determination), and Median Absolute Error (MedAE). Each metric provides unique insights into model performance and may be chosen based on the dataset's specific characteristics and the analysis's particular goals.

MSE is often used when more significant errors are particularly undesirable and need to be penalized more, as it squares the error terms; **MAE** is intuitive and straightforward to understand, making it suitable for situations where the average magnitude of errors is of primary concern; **R^2 Score** provides a relative measure of how well the model explains the variability in the response variable and helps compare different models; **MedAE** is useful when dealing with datasets that contain outliers or non-normal error distributions, as it is less sensitive to extreme values.

5. Result and Discussion

This section assesses the efficiency and effectiveness of the machine learning method for estimating the probability of damage at different levels of the submarine pipeline resulting from dropped objects.

For this purpose, a range of data, including features and target variables, has been used to examine the extraction of the relationship for calculating the probability of damage occurrence using standard machine learning algorithms. The effect intensity of pipeline features on the probability of damage at different levels has been investigated using a correlation matrix. The comparison of results obtained from applying various machine learning algorithms in calculating the probability of damage has been examined.

Finally, the feature importance heatmap is analyzed to determine each feature's contribution to the probability of damage at different levels, and the mass groups of the dropped object are categorized in the pipeline. This examination is important from an industrial application perspective, as it can focus on the effective factors and allocate costs for their improvement during the design stages of underwater pipelines, according to the pipeline route and the likelihood of objects falling on the pipeline in specified mass groups, with a priority on the extracted impact levels in this stage.

5.1 Data Description and Features Analysis

As previously mentioned, evaluating the data used for implementing machine learning algorithms is the first step in this process. In this study, to consider all potential scenarios of the dropped object's mass, a dataset has been generated, divided into five mass groups mentioned in section (4) of this paper, using a normal probability distribution according to Table (2) via the MCS method.

The summary statistics table for mass groups 1 to 5 is presented in Tables (3) to (7), respectively. As indicated in these tables, each dataset contains 2000 samples with identical statistical characteristics in the features section, which emphasizes the stability of the probabilistic model under Monte Carlo simulation conditions. In addition, the number of iterations required to calculate Pi in MCS is 105.

Table 4. Summary statistics table for Mass Group 2 (2 to 8 *tons*)

		Count	Mean	Std	Min	25%	50%	75%	Max
Features	**Diameter** [mm]	2000	591.97	182.15	274.16	433.30	589.06	756.84	913.69
	Thickness [mm]	2000	13.02	3.92	5.02	9.82	13.05	16.34	19.98
	Age [Year]	2000	30.13	11.52	10.00	20.15	30.42	40.18	49.99
	x_0 [mm]	2000	46.82	4.78	45.00	45.00	45.00	45.00	72.48
Target Variables	P_1	2000	0.5879	0.1935	0.1879	0.4335	0.6014	0.7522	0.952
	P_2	2000	0.0705	0.0346	0.0079	0.0396	0.0727	0.0993	0.1513
	P_3	2000	0.0642	0.0271	0.0098	0.0439	0.065	0.0835	0.1313
	P_4	2000	0.0523	0.0227	0.0091	0.0333	0.0516	0.0693	0.1051
	P_5	2000	0.2251	0.2002	0.0009	0.0527	0.166	0.3626	0.7825

Table 5. Summary statistics table for Mass Group 3 (4 to 10 *tons*)

		Count	Mean	Std	Min	25%	50%	75%	Max
Features	**Diameter** [mm]	2000	591.43	182.03	274.16	433.09	588.56	756.12	913.69
	Thickness [mm]	2000	13.03	3.92	5.02	9.83	13.06	16.35	19.98
	Age [Year]	2000	30.10	11.53	10.00	20.12	30.39	40.17	49.99
	x_0 [mm]	2000	46.81	4.78	45.00	45.00	45.00	45.00	72.48
Target Variables	P_1	2000	0.3814	0.2106	0.0502	0.1951	0.3637	0.5571	0.8668
	P_2	2000	0.0844	0.05	0.0033	0.0379	0.0814	0.1309	0.189
	P_3	2000	0.0831	0.0399	0.0042	0.0469	0.0891	0.1148	0.1688
	P_4	2000	0.0728	0.03	0.0051	0.0507	0.0745	0.0952	0.1413
	P_5	2000	0.3783	0.2617	0.0128	0.1461	0.3251	0.595	0.9371

Table 6. Summary statistics table for Mass Group 4 (6 to 12 *tons*)

		Count	Mean	Std	Min	25%	50%	75%	Max
Features	**Diameter** [mm]	2000	589.36	182.14	274.16	429.36	585.63	754.27	913.69
	Thickness [mm]	2000	12.98	3.94	5.02	9.79	12.98	16.33	19.98
	Age [Year]	2000	30.05	11.52	10.00	20.08	30.26	40.11	49.99
	x_0 [mm]	2000	46.79	4.75	45.00	45.00	45.00	45.00	72.48
Target Variables	P_1	2000	0.2346	0.1842	0.0146	0.0738	0.1852	0.3712	0.763
	P_2	2000	0.0813	0.0618	0.001	0.0262	0.0672	0.1339	0.2221
	P_3	2000	0.0872	0.0533	0.0013	0.0382	0.088	0.1367	0.1898
	P_4	2000	0.0812	0.0411	0.0017	0.0469	0.0885	0.1134	0.1627
	P_5	2000	0.5158	0.2815	0.0481	0.2565	0.4919	0.7873	0.9814

Table 7. Summary statistics table for Mass Group 5 (12 to 30 *tons*)

		Count	Mean	Std	Min	25%	50%	75%	Max
Features	**Diameter** [mm]	2000	591.97	182.15	274.16	433.30	589.06	756.84	913.69
	Thickness [mm]	2000	13.02	3.92	5.02	9.82	13.05	16.34	19.98
	Age [Year]	2000	30.13	11.52	10.00	20.15	30.42	40.18	49.99
	x_0 [mm]	2000	46.82	4.78	45.00	45.00	45.00	45.00	72.48
Target Variables	P_1	2000	0.0167	0.0282	0.0005	0.002	0.0056	0.0186	0.2131
	P_2	2000	0.0149	0.0211	0	0.0007	0.0044	0.0212	0.1228
	P_3	2000	0.0313	0.043	0	0.0013	0.0099	0.0478	0.2204
	P_4	2000	0.0479	0.0571	0	0.0024	0.0203	0.0808	0.2035
	P_5	2000	0.8891	0.1356	0.4074	0.8159	0.9588	0.9933	0.9993

The distribution plots are shown in Table (8) to compare P1 through P5 across all mass groups visually. By examining the probability distribution of damage occurrence at different levels, it is observed that as the mass of the dropped object increases, the likelihood of more severe damage also increases.

A crucial factor to consider when analyzing these charts is the influence of the pipe's geometric properties, including diameter, thickness, service life, and structural uncertainties arising from material strength, the extent of thickness reduction due to corrosion, and the strength of the concrete coating on the pipe.

As this study considers a wide range of geometries and service life of commonly used subsea oil and gas pipelines, the obtained results have the potential to establish a relationship between the probability of damage at the five defined levels of severity in Table (1) and the pipeline characteristics, including diameter, thickness, service life, and concrete coating thickness while accounting for potential structural uncertainties.

Generally, regardless of pipeline geometry, the probability of damage at levels 1 and 5 (minor damage and pipeline rupture) when an object from mass groups 1 to 4 falls onto the pipeline shows the widest range of values compared to damage at levels 2 to 4. However, the probability of failure at levels 1 and 5 tends to decrease and increase, respectively, with increasing weight group.

The range of variation in the probability of damage at levels 2, 3, and 4, corresponding to the mass group of the object that falls onto the pipeline, is limited to a maximum value of 0.2, 0.175, and 0.16, respectively.

Mass group 5's probability of failure is generally concentrated at levels 3 to 5, with the highest frequency at level 5. Therefore, if the mass of objects likely to fall onto the pipeline is between 12 and 30 tons, special preventive measures should be considered to protect the pipeline against failure and rupture.

5.2 Correlation Matrix of features and targets

In Figure 7, the correlation plot for five mass groups shows the interrelationships among the parameters. A positive correlation indicates a direct relationship, while a zero correlation denotes no association between the parameters. Conversely, a negative correlation signifies an inverse relationship between the parameters.

The aim of studying this matrix is to examine the relationships between the P_i variables as target variables and the pipeline characteristics, including diameter, thickness, service life, and concrete coating thickness. Although the correlation matrix provides information about the relationships among the characteristics and the target variables, this information has no practical value for the analysis discussed in this paper. Studying this matrix and examining the charts in Table(8) will yield valuable results.

As shown in Fig. 7, for mass group 1, the probability of level 1 damage, which has the highest probability among the levels, is most positively influenced by the pipe diameter. Consequently, the influence of the diameter on the likelihood of other damage levels will decrease and be negative, but it will still have a maximal impact.

The depth of the concrete coating and the pipeline thickness rank second and third, respectively, in their influence on P_1. As shown in Table (1), with an increase in the level of damage, the severity and consequences of failure increase. Therefore, if the correlation of a characteristic significantly affects the increase in the probability of a particular level of damage, it will have a decreasing influence on the likelihood of other higher levels. For example, the correlation between the diameter and the concrete coating depth for P1, P_2, P_3, and P_4 can be referred to. The correlation between the characteristics and P_1 is consistent across all mass groups. In all these cases, the diameter, wall thickness, and concrete coating depth increase, while the service life decreases. Observing the correlation results for P5, the most critical level of damage (rupture), it is noted that diameter, wall thickness, and concrete coating depth have the most significant negative effect. In contrast, the operational life has an increasing impact. For other levels of failure, these effects will vary across the mass groups under study.

Table 8. Distribution of P_i in different Mass Groups

5.3 Comparison of machine learning algorithms

After evaluating and preparing the data, selecting an appropriate algorithm for the machine learning process is a significant and effective step. As stated in the methodology section, various valid models exist for assessing the error related to developing the relationship between target variables and the features of the studied problem.

In this study, the accuracy of six machine learning algorithms introduced in section (4), including linear regression, decision tree, random forest, k-nearest neighbors, support vector machines, and gradient boosting, is examined separately for the five mass groups considered in this article, the results of which are presented in Comparative Table (9).

As demonstrated by the results, the random forest algorithm provides the most suitable response among other algorithms, as measured by error evaluation metrics in the machine learning process.

5.4 Feature importances heatmaps

Investigating the intensity of the influence of pipeline characteristics, including diameter, thickness, depth of concrete coating, and age, on the probability of damage at five defined levels is of great importance for the risk control study of subsea pipelines exposed to dropped-object impact.

Heat maps show the impact intensity in the data evaluation using machine learning. Fig. 8 presents an example of this chart broken down by each pipeline feature. By generally surveying these charts and comparing the range of numbers in the color bar next to each, one can generally consider the impact intensity of the pipeline features on the probability of damage occurrence at various levels in the following order: pipeline diameter, thickness, depth of concrete coating, and finally, pipeline age.

These charts indicate that the pipeline's diameter significantly impacts the likelihood of first-level damage (P_1). This impact is most intense in lower mass groups and decreases as the mass of the dropped object increases.

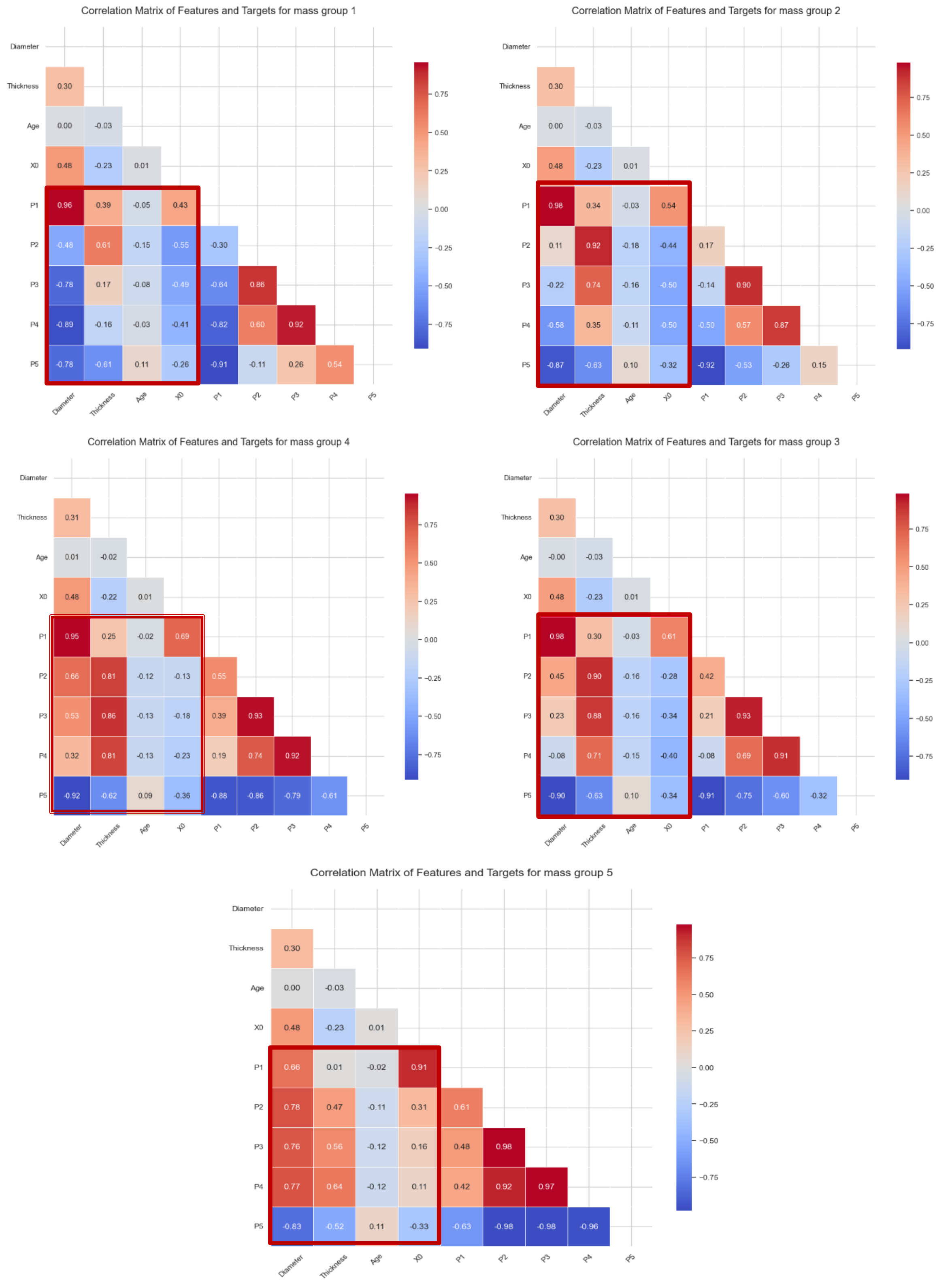

Figure. 7. The Correlation Matrix for all Mass Groups

Table 9. Summary of the Accuracy Results of Machine Learning Algorithms by Mass Groups

		Linear Regression	Decision Trees	Random Forests	k-Nearest Neighbors (k-NN)	Support Vector Machines (SVMs)	Gradient boosting
Mass Group 1	*MSE*	5.69E-04	4.31E-05	1.54E-05	1.42E-05	2.71E-03	3.75E-05
	MAE	1.52E-02	3.11E-03	1.77E-03	2.15E-03	3.90E-02	2.88E-03
	R^2 Score	0.862	0.990	0.996	0.997	0.342	0.991
	MedAE	1.39E-02	1.67E-03	9.97E-04	1.42E-03	4.28E-02	1.55E-03
	Rank (*Ave.*)	4.25	3.75	**2.25**	2.75	4.75	3.25
Mass Group 2	*MSE*	9.54E-04	1.04E-04	3.63E-05	3.93E-05	2.69E-03	9.71E-05
	MAE	2.08E-02	5.90E-03	3.40E-03	3.88E-03	4.24E-02	5.63E-03
	R^2 Score	0.941	0.994	0.998	0.998	0.833	0.994
	MedAE	1.93E-02	4.38E-03	2.40E-03	2.94E-03	4.37E-02	4.13E-03
	Rank (*Ave.*)	4.25	3.75	**2.25**	2.75	4.75	3.25
Mass Group 3	*MSE*	6.63E-04	1.57E-04	4.71E-05	6.46E-05	2.34E-03	1.12E-04
	MAE	1.81E-02	7.55E-03	4.18E-03	5.05E-03	4.11E-02	6.54E-03
	R^2 Score	0.970	0.993	0.998	0.997	0.895	0.995
	MedAE	1.66E-02	5.54E-03	3.04E-03	3.88E-03	4.06E-02	5.20E-03
	Rank (*Ave.*)	4.25	3.75	**2.25**	2.75	4.75	3.25
Mass Group 4	*MSE*	6.49E-04	1.57E-04	5.14E-05	7.37E-05	3.11E-03	1.26E-04
	MAE	2.01E-02	7.78E-03	4.40E-03	5.30E-03	4.88E-02	6.79E-03
	R^2 Score	0.973	0.993	0.998	0.997	0.869	0.995
	MedAE	1.85E-02	5.57E-03	3.23E-03	3.95E-03	5.03E-02	4.89E-03
	Rank (*Ave.*)	4.25	3.75	**2.25**	2.75	4.75	3.25
Mass Group 5	*MSE*	1.14E-03	6.48E-05	1.75E-05	2.30E-05	6.02E-03	8.29E-05
	MAE	2.22E-02	3.78E-03	1.97E-03	2.53E-03	7.27E-02	3.76E-03
	R^2 Score	0.782	0.988	0.997	0.996	-0.151	0.984
	MedAE	2.04E-02	1.30E-03	7.53E-04	1.40E-03	8.33E-02	1.16E-03
	Rank (*Ave.*)	4.25	3.5	**2.25**	3.25	4.75	3

The pipeline thickness feature has the greatest impact on the probability of damage at the second, third, and fourth levels (P_2, P_3 & P_4) due to collisions with objects in mass groups 2, 3, and 4. This feature is nearly insignificant for the probability of first-level damage.

Another important application of this chart in pipeline risk assessment is the hierarchical impact of pipeline features on the probability of a specific damage level due to a dropped object within a specified mass range. For example, the probability of first-level damage (P_1) in the pipeline due to the fall of an object in mass group 1 is primarily influenced by the pipeline's diameter, thickness, depth of concrete coating, and age. In contrast, the probability of third-level damage (P_3) in the pipeline due to the fall and collision of an object in mass group 3 is influenced by the pipeline's thickness, diameter, concrete cover depth, and age.

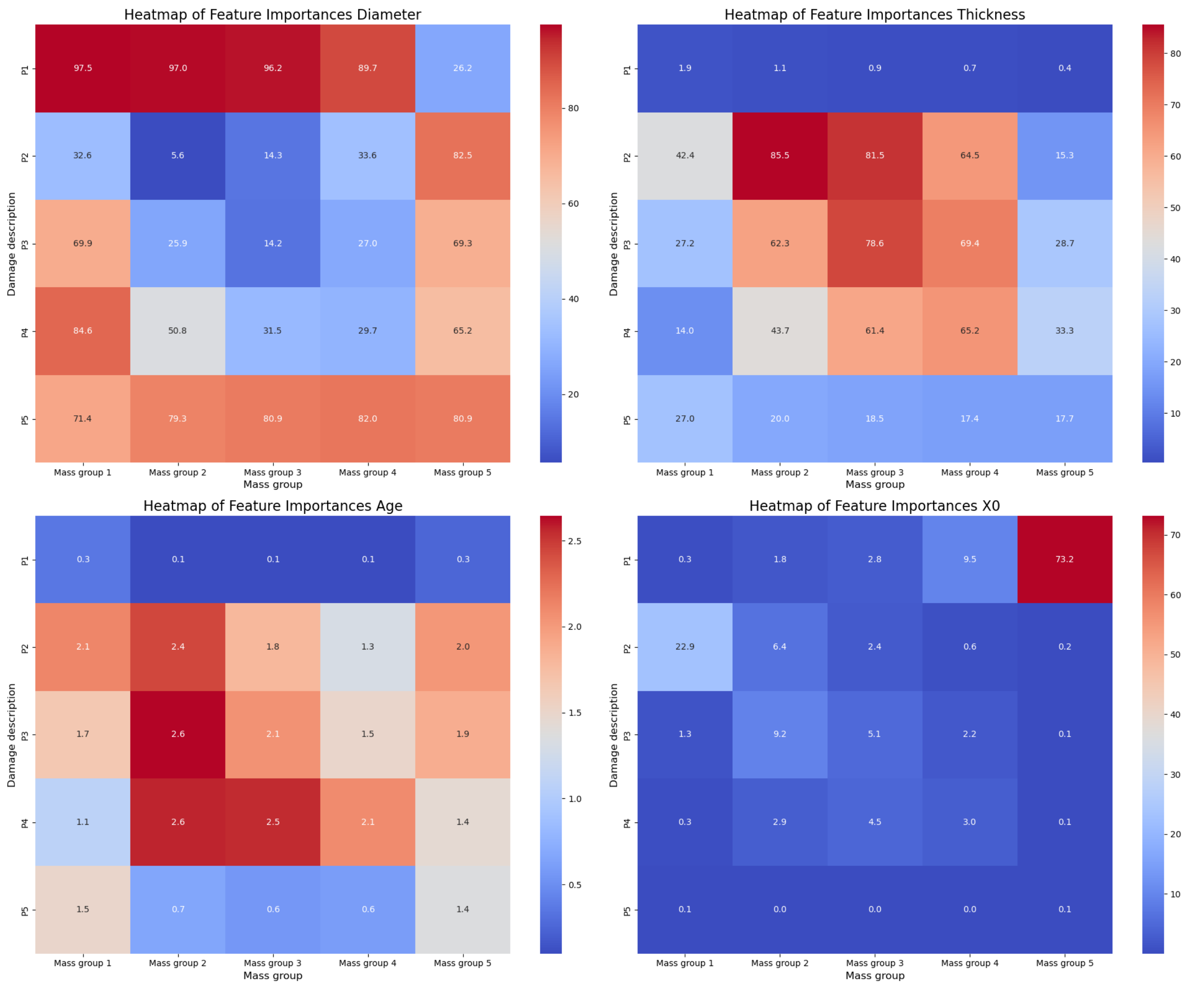

Figure. 8. Mass group importances heatmaps per pipeline features

6. Conclusion

The impact of dropped objects on pipelines has been identified as one of the most common third-party threats. Implementing preventive measures to mitigate damage caused by such impacts on pipelines is significant during the design stage. The probabilistic characteristics of dropped-object events, along with uncertainties in material properties and variations in pipeline thickness due to corrosion, necessitate the development of a probability-based method to derive a relationship between the probability of damage at different levels and the pipeline's nominal characteristics and service life.

This study developed and validated a quantitative, data-driven probabilistic model to assess the risk of subsea pipeline damage from dropped-object impacts. By integrating Monte Carlo simulation with machine learning (ML), the model establishes a predictive relationship between key pipeline parameters (diameter, wall thickness, concrete coating thickness, and age) and the probability of five distinct damage levels (per DNV-RP-F101). The analysis of 10,000 synthetic scenarios across five object mass groups yielded the following conclusions:

- The model quantified the nonlinear influence of pipeline parameters. For example, for Mass Group 3 (4-10 tonnes), increasing the concrete coating thickness from 45mm to 60mm reduces the predicted probability of a Level 5 (rupture) event by approximately 22%. In contrast, for lighter masses (Groups 1-2), pipeline diameter was the dominant protective factor.

- The feature importance analysis revealed a clear hierarchy. Pipeline age was the primary driver of increased rupture risk (P_5), with its effect plateauing at a 10% increase across all mass groups. Conversely, diameter, wall thickness, and coating thickness were consistently protective, reducing rupture probability by up to 35-50% depending on the mass group.

- Among the six evaluated ML algorithms, the Random Forest model demonstrated superior accuracy, achieving an average R^2 of 0.997 across all mass groups and significantly outperforming linear models. This justifies the use of advanced ML to capture the complex parameter interactions in this probabilistic problem.

- The developed model offers a practical, rapid assessment tool for pipeline engineers. Implemented in a user-friendly Python application, it enables proactive optimization of pipeline specifications during the design stage by providing instant, scenario-specific damage probability predictions.

- The model's current limitation is its reliance on synthetic data generated via MCS. Future work will focus on validation against high-fidelity numerical simulations (e.g., finite element analysis) and, where possible, actual inspection data. The framework is also designed to be extended to incorporate additional hazards (e.g., anchor drag) and real-time monitoring data for lifecycle risk management.

The developed method, along with the susceptibility of the damage-level probability to increase or decrease due to pipeline specifications, will serve as a practical tool for implementing preventive measures in the pipeline design phase.

7. List of Symbols

E_s	Dent - absorbed energy for steel pipelines
E_k	Kinetic energy absorbed by concrete coatings
D	Diameter of the pipeline
δ	Pipe deformation, dent depth
t	Wall thickness
σ_y	Yield stress
M_p	Plastic moment capacity of the pipe wall,
m	Mass of the object (kg)
m_a	Added mass
g	Gravitation acceleration (9.81 m/s^2)
V	Volume of the object (the volume of the displaced water) (m^3)
ρ_w	Density of seawater
C_D	Drag-coefficient of the object
C_a	Add mass-coefficient of the object
A_P	Projected area of the object in the flow direction (m^2)
v_T	Terminal velocity through the water (m/s).
Y	Crushing strength
x_0	Penetration depth
b	Object width
D_C	Concrete-coated outside pipeline diameter
ρ_w	Density of sea water (1025 kg/m^3)
ρ_c	Density of concrete coating layer (3040 kg/m^3)
A_{CS}	Steel pipe cross-section (m^2)
$d(T)$	Growth of the corrosion pit defect depth
T	Service life (year)
T_d	The time required for corrosion initiation (2.88 years)
κ & α	Corrosion growth coefficients
t_a	Actual wall thickness (mm)

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