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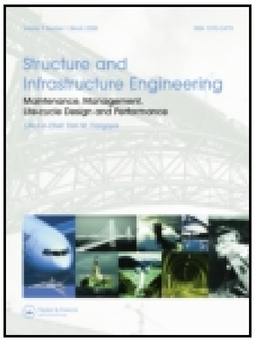

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A model for predicting failure of oil pipelines

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Oil and gas pipelines transport millions of dollars of goods everyday worldwide. Even though they are the safest way to transport petroleum products, pipelines do still fail generating hazardous consequences and irreparable environmental damages. Many models have been developed in the last decade to predict pipeline failures and conditions. However, most of these models were limited to one failure type, such as corrosion failure, or relied mainly on expert opinion analysis. The objective of this paper is to develop a model that predicts the failure cause of oil pipelines based on factors other than corrosion. Two models are developed to help decision makers predict failure occurrence. Regression analysis and artificial neural networks (ANNs) models were developed based on historical data of pipeline accidents. The two models were able to satisfactory predict pipeline failures due to mechanical, operational, corrosion, third party and natural hazards with an average validity of 90% for the regression model and 92% for the ANN model. The developed models assist decision makers and pipeline operators to predict the expected failure cause(s) and to take the necessary actions to avoid them.

Keywords: oil pipelines; failure type prediction; regression; artificial neural networks

Introduction

Pipelines, which are the backbone of the oil industry, transport millions of dollars of various types of products in different environments (i.e. offshore or onshore). The first oil pipeline, which was built in 1879 in Pennsylvania, was 109 mile long and 6 inches in diameter (Kennedy, 1993). Nowadays, more than 60 countries have pipeline networks exceeding 2000 km in length. The USA has the longest pipeline network followed by Russia (Goodland, 2005).

Pipelines represent the safest way to transport petroleum products because they have lower rate of accidents than railways and highways. However, pipeline accidents could cause catastrophic environmental damage due to oil spillage as well as economic losses due to production interruption (Dey, 2001). According to the CONservation of Clean Air and Water in Europe (CONCAWE) report by Oil Companies' European Association for Environment, Health and Safety in Refining and Distribution, oil pipeline failures occur due to the following causes: mechanical, operational, corrosion, natural hazards and third party activity. The CONCAWE is an organisation established in 1963 by a group of leading oil companies to carry out research on environmental issues related to the oil industry.

In order to maintain pipeline in safe condition, frequent inspections are mandatory. Several inspection techniques have been developed in the last decade, such as magnetic flux leakage and ultrasound. These techniques provide the pipeline industry with accurate and effective tools to detect pipelines anomalies that could lead to failure. Although pipeline inspection techniques, especially in-line inspection, clearly detect and/or predict oil pipeline anomalies, they are extremely costly and time consuming. The majority of the developed condition assessment or failure prediction models are either subjective (i.e. depending on expert opinion) or not comprehensive (i.e. dealing with only one failure cause). Therefore, there is a need for the development of a more objective failure prediction model for oil and gas pipelines that is based on historical failure accidents. The model will help pipeline operators take the necessary actions in order to prevent catastrophic failure.

The main objectives of this study are: (1) to identify and study the critical failure causes of oil pipelines and (2) to design a failure prediction model for such pipelines.

Background

Significant efforts have been carried out in the last decade to assess oil and gas pipeline conditions. Noor, Ozman, and Yahaya (2011) and Noor, Yahaya, Ozman, and Othman (2010) used a semi-probabilistic and deterministic

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methodology to predict the remaining strength of submarine pipelines subjected to internal corrosion. Bersani, Citro, Gagliardi, Sacile, and Tomasoni (2010) developed a risk assessment model using historical data from the United States Department of Transportation (DOT) in order to predict the failure caused by the third party activity. Historical failure data were also used to develop a tool to predict the class of each spillage in oil pipes using statistical analysis classification and regression tree (Bertolini & Bevilacqua, 2006). Li, Yu, Zeng, Li, and Liang (2009) presented a methodology to predict corrosion and remaining life of underground pipelines with a mechanically based probabilistic model considering the effect of randomness in pipeline corrosion. Monte Carlo simulation technique was employed to calculate the remaining life and its cumulative distribution function.

Peng, Zhang, and Chen (2009) developed a fuzzy neural network model, which is based on failure tree and fuzzy computing, to predict the rate of failure for long-distance oil and gas pipelines. Dawotola, VanGelder, and Vrijling (2009) proposed a combined analytic hierarchy process and fault tree analysis to support the design, the construction and the inspection and maintenance of oil and gas pipelines by proposing an optimal selection strategy based on the probability and consequences of failure. Furthermore, the analytical hierarchy process was used by Dey (2001) to develop a model to help decision makers select a suitable type of inspection or monitoring technique for pipelines. Hallen, Caleyo, and Gonzalez (2003) presented a probabilistic analysis framework to evaluate the condition of a corroding pipeline and the evolution of its probability of failure with time.

Sinha and Pandey (2002) developed a simulation-based probabilistic fuzzy neural network model to estimate the probability of failure of ageing oil and gas pipelines vulnerable to corrosion. Ahammed (1998) presented a methodology to assess the remaining service life of a pressurised pipeline containing active corrosion defects. A probabilistic approach was adapted in this methodology, where the associated variables were represented by normal or non-normal probabilistic distributions. A failure pressure model, based on fracture mechanics, was adopted for assessing pipeline failure pressure and linear idealisation of the long-term corrosion growth rate.

The above-mentioned models were either subjective or did not cover all the failure causes of oil and gas pipelines. In other words, they lack the objectivity in predicting the different failure types of pipelines.

Oil and gas pipelines failure types/causes

The CONCAWE reports have classified the causes or types of failures that could occur to oil and gas pipelines into the following five categories:

(1) *Mechanical*: a failure resulting from either a design or material fault (e.g. metallurgical defect and inappropriate material specification) or a construction fault (e.g. defective weld and inadequate support). This also includes failure of sealing devices (gasket, pump seal, etc.).
(2) *Operational*: a failure resulting from operational upsets, malfunction or inadequacy of safeguarding systems (e.g. instrumentation and mechanical pressure relief system) or from operator errors.
(3) *Corrosion*: a failure resulting from the internal or external corrosion of a pipeline or a fitting. A separate category is foreseen for stress corrosion cracking.
    (a) *External*: It is an atmospheric corrosion for the above-ground pipeline components exposed to the atmosphere. It is a rare failure mechanism due to the slow rate of the atmospheric corrosion mechanism. External corrosion could also occur as subsurface corrosion in buried pipelines. Subsurface corrosion is more dangerous than atmospheric corrosion due to its complicated mechanism. It could be minimised by using cathodic protection and pipeline coating (Muhlbauer, 2004).
    (b) *Internal*: It attacks the inner surface of the pipeline and is less severe than subsurface corrosion but more dangerous than the atmospheric corrosion. It depends typically on the product being transported by the pipeline.
    (c) *Stress cracking*: It is induced by the combined influence of the tensile stress and the corrosive environment.
(4) *Natural hazard*: a failure resulting from a natural occurrence such as land movement, flooding and lightning strike.
(5) Third party: a failure resulting from an action by a third party either accidental or intentional. It also includes 'incidental' third party damage, which was undetected when it originally occurred, but resulted in a failure some time later.

These major five types of failure vary in their occurrence. Figure 1 shows the distribution of these failures as a percentage of their occurrence over a period of 25 years (from 1971 to 1996) based on two statistical reports from CONCAWE and the U.S. DOT (Bersani et al., 2010). It can be noticed in both reports that the 'Third Party' and 'Corrosion' failure causes represented over 60% of relevancy.

Regression analysis

Regression analysis is a statistical methodology that utilises the relationship between two or more quantitative

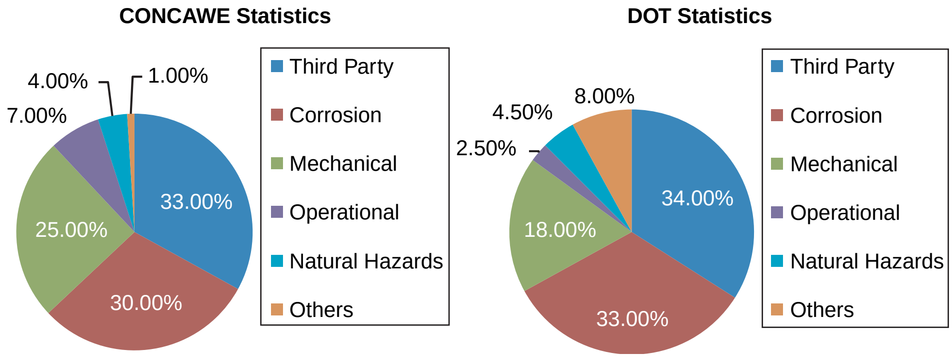

Figure 1. Percentage of failure occurrences (adopted from Bersani et al., 2010).

or qualitative variables to predict dependent variables from the independent variables. In its simplest form, the model can be developed using the following equation (Neter, Kutner, Nachtsheim, & Wasserman, 1996):

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i, \qquad (1)$$

where Y_i is the value of the response variable in the ith trial, β_0 and β_1 are the regression parameters, X_i is the value of the predictor variable in the ith trial and ε_i is the random error. In multiple regression models, more than one variable is used to predict the behaviour of the response variable. Therefore, Equation (1) can be transformed into the following equation:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_{p-1} X_{ip-1} + \varepsilon_i. \qquad (2)$$

The equation is expected to give a best fit curve and to have variation errors given the following assumptions: (1) the errors around a regression line are independent for each value of the predictor variable; (2) the errors around a regression line are assumed constant for all variable values and (3) the errors around a regression line are assumed to be normally distributed at each value of X (Levine, Stephanm, Krehbiel, Berenson, & Bliss, 2002).

Artificial neural networks

In real world situations, the collected data are usually either noisy or incomplete. Therefore, the main challenge for decision makers is how to use the available data to make reasonable predictions and decisions. In these situations, the artificial neural network (ANN) technique provides good predictions based on available historical data. The ANN mimics the ability of the human brain in predicting patterns based on learning and recalling processes. It is an effective predictive tool because of its ability to learn from historical data. Sadiq, Kleiner, and Rajani (2004) stated that ANN is a modelling technique that is useful for applications where causal relationships among variables are unknown. Sawhney and Mund (2002) added that ANN is useful to represent problems where solutions are not clearly articulated or where the relationships among inputs and outputs are not adequately identified. The ANN consists of a large number of artificial neurons that are randomly arranged and connected in different layers (input, hidden and output). The hidden layers are connected to input and output layers as shown in Figure 2 (Zayed & Halpin, 2005).

Data collection

In order to build the intended models, data were mainly collected from a report prepared by CONCAWE in 2010 (Davis, Dubois, Gambardella, & Uhlig, 2010). The report covers 38 years of spillage data on European cross-country oil pipelines with particular focus on spillage volume, clean-up and recovery, environmental consequences and

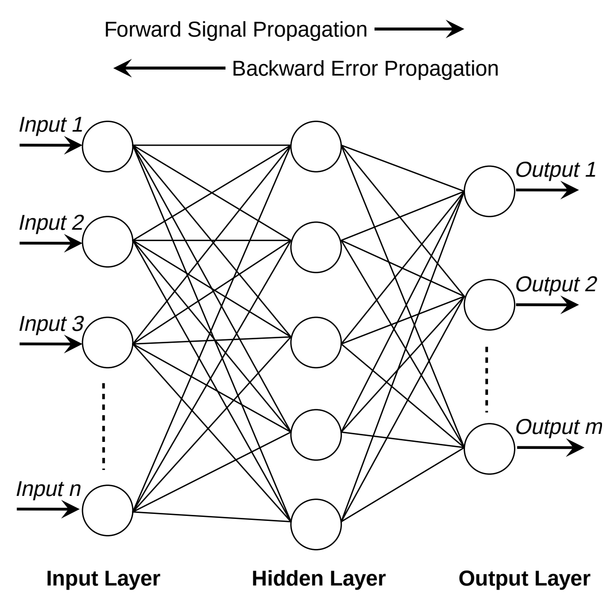

Figure 2. Schematic architecture of ANN with one hidden layer (adopted from Al-Barqawi and Zayed, 2008).

causes of the incidents. It covers the performance of the pipelines in 2008 and a full historical data since 1971. The performance over the period of 38 years is analysed in various ways including gross and net spillage volumes and spillage causes, which were grouped into five main categories, namely mechanical failure, operational, corrosion, natural hazard and third party. Over 70 companies and agencies operating oil pipelines in Europe have provided data for the CONCAWE annual survey. The data were received from 70 operators representing over 160 pipeline systems for a combined length of 35,486 km. The reported volume transported in 2008 was around 780 Mm^3 of crude oil and refined products. The total traffic volume in 2008 was estimated at $130 \times 109\,m^3$ per km.

Twelve spillage incidents were reported in 2008, corresponding to 0.34 spillages per 1000 km of line, somewhat above the 5-year average but well below the long-term running average of 0.54, which has been steadily decreasing over the years from a value of 1.2 in the middle of the 1970s. There were no reported fires, fatalities or injuries related to these spills. The gross spillage volume was 968 m^3, 27 m^3 per 1000 km of pipeline compared to the long-term average of 89 m^3 per 1000 km of pipeline. In fact, 83% of the spilled volume was recovered or safely disposed of.

Most pipeline spillages were small and 20% of the spillages were responsible for about 80% of the gross spilled volume, a figure that has remained fairly stable over the years. Pipelines carrying hot oils, such as fuel oil, have suffered from external corrosion due to design and construction problems. Most of these pipelines have been shut down or switched to cold service so that the large majority of pipelines now carry unheated petroleum products and crude oil. Only 159 km of hot oil pipelines are still in service today. The last reported spill from a hot oil pipeline was in 2002.

Of the 12 reported incidents in 2008, 7 were due to mechanical failures, 1 due to external corrosion and 4 were due to accidental (i.e. non-intentional) third party activities. Over the long term, third party activities remain the main cause of spillage incidents, although the number of events has progressively decreased over the years. Mechanical failure is the second largest cause of spillage. In 2008, a total of 70 sections covering a length of 8446 km were inspected by at least one type of intelligence pig. Most inspection programmes involved the running of more than one type of pig in the same section so that the total actual length inspected was less than 5018 km (14% of the inventory). Most pipeline systems were built in 1960s and 1970s. In 1971, 70% of the inventory was 10 years old or less, by 2008 only 5% was 10 years old or less and 47% was over 40 years old. However, this situation has not led to an increase in the number of spillage.

The 469-recorded-incident database compiled from the CONCAWE report was used for the development of the model. Each spillage incident represents a different case, and is identified by 10 different variables in addition to the main cause of failure, i.e. failure type. A sample of this database is shown in Table 1. The 10 variables listed in the database are pipe diameter, service, fatalities, injuries, spillage volume, method of leak detection, facility part, age and land use. The variables of fatalities, injuries, spillage volume, method of leak detection and facility part are excluded from the model. This is due to the fact that these variables cannot be known before the failure occurrence, while the developed model is supposed to predict the failure type before its occurrence. In addition, some of the 469 incidents' records contained missing data for certain variables. As a result, these incidents were excluded from the model resulting in a total of 351 incidents with complete data.

Failure model development for oil pipeline

The methodology used to build the intended models is described in the following sections (Figure 3). The data obtained from the CONCAWE report were used to represent the factors that have an impact on the condition of oil pipelines. These factors were identified as (1) type of product carried by the pipe, (2) pipe location, (3) pipe age, (4) land use and (5) pipe diameter. Two models were developed to predict the failure type of oil pipelines using regression analysis and ANN techniques, respectively. The factors listed in the CONCAWE report are the main predictors of the developed models while the main output is the failure type as shown in Figure 4. It was essential to convert the three qualitative factors (type of product, land use and pipe location) into quantitative values in order to facilitate their input in the model. Moreover, the other two quantitative factors (age and diameter) have different units. As a result, there is a need to normalise the values of the input and output factors as shown in Table 2. It is important to mention that the scale values assigned in Table 2 are considered as just indices with no physical meaning since they represent different input categories. As a result, the models are intended to predict the failure type based on different combinations of input categories.

Regression model development

As shown in Figure 3, the selection of the proper variables of model development depends on the available data for explanatory and response variables. The model building and validation data-sets are prepared from the collected data to build and validate the developed models. In other words, the validation data-set is not introduced when developing the models. A variety of diagnostics are used to test the developed functions of a regression model as well as the interaction between the model variables. The

Table 1. Sample of CONCAWE database.

Spillage ID	Diameter (inches)	Service	Fatalities	Injuries	Spillage volume (m^3) Gross	Spillage volume (m^3) Net loss	Method of leak detection	Facility	Facility part	Age (years)	Land use	Failure type
1	20	Crude oil	0	0	200	60	R/W surveillance	Underground	Pipe run	8	Industrial/commercial	Third party
2	8	White product	0	0	400	350	R/W surveillance	Underground	Pipe run	2	Residential low density	Third party
3	20	White product	0	0	25	3	Outside party	Pump station	Joint	1	Industrial/commercial	Mechanical
4	12	Fuel oil	0	0	2	NA	Outside party	Underground	Pipe run	14	Residential low density	Corrosion
5	26	White product	0	0	125	45	Outside party	Underground	Joint	18	Residential low density	Natural hazards
6	6	White product	0	0	5	5	Outside party	Underground	Pipe run	47	Residential high density	Third party
7	16	Crude product	0	0	442	111	Pressure testing	Underground	Pipe run	18	Residential low density	Operational
8	10	White product	0	0	252	221	Outside party	Pump station	Pig trap	33	Residential low density	Operational
9	13	White product	0	0	8	1	R/W surveillance	Pump station	Joint	12	Industrial/commercial	Mechanical
10	11	Fuel oil	0	0	325	11	R/W surveillance	Underground	Pipe run	22	Industrial/commercial	Corrosion

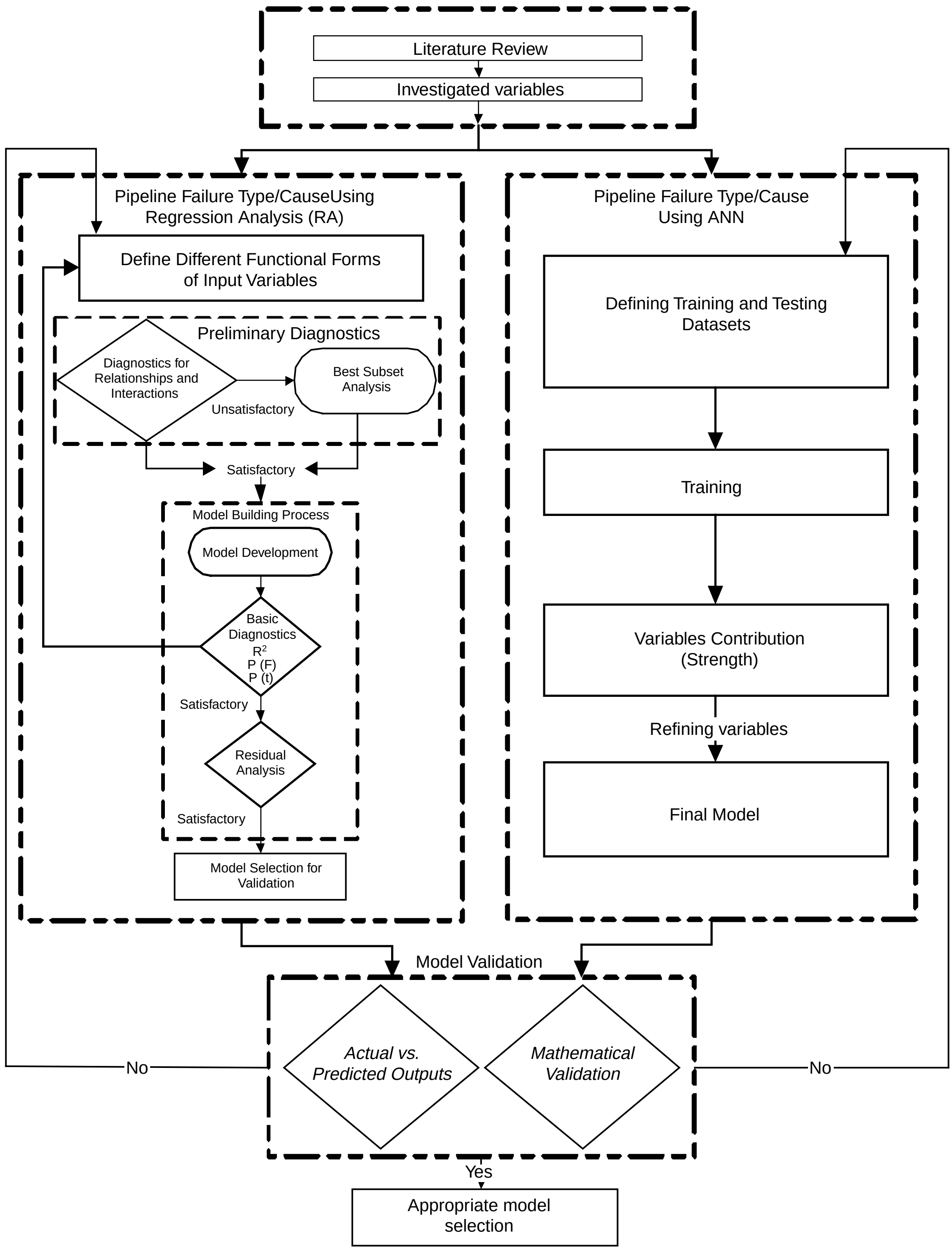

Figure 3. Overview of model building methodology.

validation data-set is used to test the ability of the developed model to predict the outputs. After normalising the input/output values of factors, a regression model is developed using the following steps:

(1) The input/output factors of the intended problem are determined. The input variables include pipeline age, location, diameter, land use and type of product. However, the output variables include failure causes

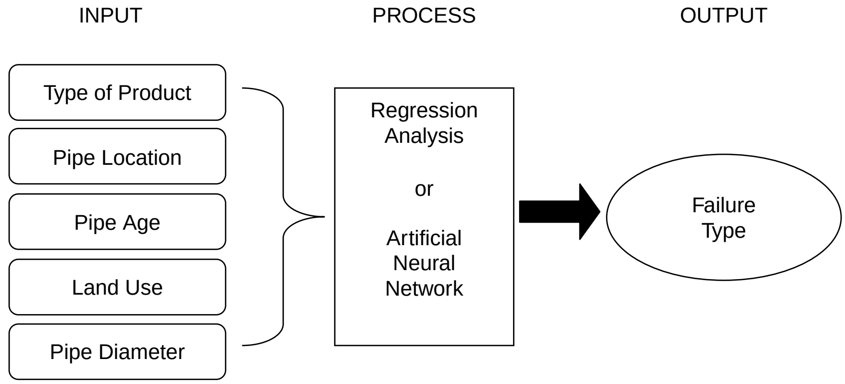

Figure 4. Model overview.

due to corrosion, natural hazard, mechanical, operational and third party.

(2) A statistical stepwise selection procedure is used to select the best number of independent variables that best fit the failure cause against different factors. The MINITAB statistical package is used to perform this selection process. Four selection criteria are used to distinguish between the different proposed models. These criteria are R^2, adjusted R^2, mean square error (S or MSE) and Mallow's C_p. The best model that can represent the collected data-set is selected according to the largest R^2 and adjusted R^2, the minimum MSE and the closest C_p to the number of independent variables. Hence, if the selected model has only five independent variables, the best model is the model with C_p close to five. All these criteria have been considered when selecting the best model to achieve the above requirements. The best model is selected to determine the failure cause.

(3) The best fit model is checked whether it is statistically sound using different statistical tests.

Table 2. Model variables' scale values.

Variable	Sub-variable	Scale value
Type of product (service)	Crude oil	1
	White product	2
	Fuel oil	3
	Crude product	4
	Lubes	5
Pipeline location (facility)	Underground	1
	Above ground	2
	Pump station	3
Land use	Residential high density	1
	Residential low density	2
	Agricultural	3
	Industrial or commercial	4
	Forrest hills	5
	Barren	6
Pipeline age (Years)	0–10	1
	11–20	2
	21–30	3
	31–40	4
	41–50	5
	51–60	6
	61–70	7
Pipeline diameter (inches)	0–10	1
	11–20	2
	21–30	3
	31–40	4
Failure type	Mechanical	1
	Operational	2
	Corrosion	3
	Natural hazards	4
	Third party	5

The above steps are implemented to develop the failure model for oil pipelines. The best subsets analysis determines the best possible combination of variables with respect to the lowest variation and the highest R^2 (adjusted) value. Therefore, the best subset analysis identifies the best regression model that can be constructed with a specific number of variables. As shown in Table 3, each row of the output represents a different model. The first column represents the number of variables or predictors in the model. The second and third columns show R^2 and R^2 (adjusted) percentages. It is clear that the highlighted model with the highest R^2 adjusted, lower C_p and lowest S value is the most appropriate model. The highlighted model is also selected because the number of independent variables (i.e. 5) is closest to the Mallow's C_p value (i.e. 6.0). Therefore, all listed variables should be included in the model. The developed model in Equation (3) is the best fit model. However, it will not be considered as final until the best subset, normality and linearity tests are conducted. The model show that $S = 0.46$, $R^2 = 83.8\%$ and R^2 (adjusted) $= 83.4\%$.

$$\text{Failure type} = 8.01 - 1.03\,S - 1.50\,F + 0.104\,A - 0.059\,L - 0.129\,D, \quad (3)$$

Table 3. Best subset analysis.

Number of variables	R^2	R^2 (adj.)	S	C_p	Type of product	Location	Age	Land use	Diameter
1	48.0	48.5	0.82	398.8		*			
1	19.0	18.6	1.03	738.3	*				
2	81.7	81.5	0.49	24.3	*	*			
2	53.1	52.6	0.79	351.4		*	*		
3	83.0	82.7	0.48	11.4	*	*	*		
3	82.4	82.1	0.48	17.8	*	*			*
4	83.6	83.2	0.47	6.7	*	*	*		*
4	83.4	83.1	0.47	8.4	*	*	*	*	
5	83.8	83.4	0.46	6.0	*	*	*	*	*

where S is the service, the type of product; F is the facility, location of the pipe; A is the age of the pipe; L is the land use and D is the diameter of the pipe. It should be noted that the value given by Equation (3) can be non-integer. However, the failure type value must be an integer to represent one of the five failure types. As a result, the values obtained using Equation (3) are rounded either up or down. For example, a computed value of 2.20 indicates a higher probability of the 'operational failure' type (i.e. 2.0) rather than the 'corrosion failure' type (i.e. 3.0).

Model adequacy statistical tests

Statistical tests for regression analysis include the coefficient of multiple determinations, the F-test for regression relation and the t-test for each regression parameter 'β_k' as shown in Table 4. R^2 and R^2-adjusted values are 83.8% and 83.4%, respectively. The F-test determines $P(F)$ for the entire model. A hypothesis test is carried out in which the null hypothesis (H_0) assumes that all regression coefficients, β_0, $\beta_1 \ldots \beta_{p-1}$, are zero, i.e. $\beta_0 = \beta_1 = \beta_{p-1} = 0$. The alternate hypothesis (H_a) assumes that some of the coefficients are equal to zero. The p-value (statistical significance) in the analysis of variance (ANOVA) table is 0.000. This means that the null hypothesis is rejected, which shows that the estimated model is significant at a significance level of 0.05. Therefore, at least one coefficient in the estimated regression equation is not equal to zero. The next step is to check the significant effect of predictors related to the response variable. To determine the validity of the regression coefficient individually, 't-tests' are carried out separately for β_0, $\beta_1 \ldots \beta_{p-1}$. In case of β_0, the null hypothesis (H_0) of t-test assumes that $\beta_0 = 0$, while alternative hypothesis (H_a) assumes that $\beta_0 \neq 0$. Similarly, the other null hypothesis assumes that $\beta_1 = 0$ and vice versa. The results of these tests are shown in Table 4. It is quite clear that all the coefficients are accepted at a maximum significance level of 4%, which shows that the developed model is statistically sound.

Table 4. ANOVA results for model coefficients.

Predictor	Coef.	SE coef.	T	P	P-value
Constant	8.0095	0.2104	39.01	0.000	0.000
Service	−1.0275	0.05670	−18.12	0.000	
Facility	−1.50438	0.06301	−23.88	0.000	
Age	0.10402	0.02724	3.82	0.000	
Land use	−0.05897	0.03596	−1.64	0.103	
Diameter	−0.12914	0.06164	−2.09	0.038	

Table 5 summarises the results of the F-test for regression relationship of the developed model. The p-value of the entire model is 0.000, which is an indication of robust results. This means that the null hypothesis is rejected for the developed model where not all regression coefficients are zero. Table 5 also presents the results of the 't-tests' carried out separately for each β_k of every selected model. In this case, the p-values are close to 0.000 which reflects satisfactory results.

Residual analysis

This step analyses the residuals of the model and their patterns. These diagnostic checks, which are used to verify the linear regression assumptions, include the normality error, the homoscedasticity and the independence of error. The normal probability and frequency plots of residuals for the developed model are checked visually. The normal probability plot shows that the error terms are nearly normal with small departure from normality, which does not create any serious problem. Therefore, the results are considered satisfactory. The departure points might be outliers. In order to check the possibility of outliers and errors in normal probability plots, unusual observations are removed. The model, which is tested after removing outliers, shows a better correlation. The developed model is constructed considering the outliers because sometimes the outliers represent important patterns in the data.

The assumption that the variation around a regression line be constant for all values of X can be verified by using the plot of the residuals versus the fitted value. In addition, errors around the regression line should be independent for each value of predictors. However, the residuals versus the order of data plot for the model under consideration

Table 5. Summary of statistical results.

			$P(t)$					
R^2 (%)	R^2 (adj.) (%)	$P(F)$	β_0	β_1	β_2	β_3	β_4	β_5
83.8	83.4	0.000	0.000	0.000	0.000	0.000	0.103	0.038

showed positive residuals at inner bands of X values and the outer bands largely consisted of negative residuals. Based on the above statistical discussion, the developed model is considered statistically sound.

ANN model building

The ANN model is developed using Neuroshell 2® package (Ward Systems Group, Inc., 1996). The data for the selected factors are used to train the ANN in order to obtain an ANN-based failure model. The training criteria are the maximum and minimum absolute errors and the number of training cycles without improvements. The data are divided into two randomly selected sets, namely training (80%) and validation (20%), which are used to train and test the network, respectively. The input of validation data-sets is introduced to the trained model in order to generate the predicted output, which is then compared to the actual output. If they are close, the model is valid and vice versa. The selection of input and output variables greatly affects the ANN architecture. The selection of these variables depends upon the nature of the problem. Each variable is represented by one artificial neuron in the network's input layer.

The ANN has only one output neuron that represents the failure type/cause. Hence, the ANN architecture is composed of five neurons in the input layer and one neuron in the output layer. The hidden layer relies on the available model building data-set and the nature of outputs. Several iterations are used to generate the optimal number of neurons in the hidden layer. The ANN achieves the required goal (of an α significance level of 0.05) when the training network has 30 hidden neurons in the hidden layer, a learning rate of 0.05 and 2000 number of epochs. Therefore, the best architecture for ANN includes 5 inputs, 30 hidden and 1 output neurons. After the ANN is trained, it can be recalled to predict the organisation performance for any given input values. The training and testing processes were carried out successfully with reasonable results: the ANN model values of R^2, MSE and mean absolute error (MAE) were found to be equal to 0.91, 0.14 and 0.20, respectively. The results confirm the robustness of the developed model.

The ANN training also provides the per cent of each factor's contribution to the output(s). As shown in Table 6, the highest contributing variables are the 'service' and 'facility' representing about 60% of the factors' contribution, while the remaining 40% contribution is distributed almost equally between the 'age', 'land use' and 'diameter'.

Table 6. Relative contribution (strengths) of factors.

Input factor	Contribution (strength)
Service	0.35153
Facility	0.24604
Age	0.13893
Land use	0.11373
Diameter	0.14976

Validation of the developed models

Mathematical validation

The goal of this step is to test the prediction effectiveness of the developed models using mathematical validation. Equations (4) and (5) show one approach for calculating the average validity/invalidity percentages (i.e. AVP and AIP) in order to predict the error. If the AIP value is closer to 0.0, the model is sound and a value closer to 100 shows that the model is not appropriate (Zayed & Halpin, 2005). Similarly, the root MSE (RMSE) is estimated using Equation (6). If the value of the RMSE is close to 0, the model is sound and vice versa. Also, the MAE is defined in Equation (7). The MAE value varies from 0 to infinity. However, the MAE should be close to zero for sound results (Dikmen, Birgonul, & Kiziltas, 2005)

$$\mathrm{AIP} = \left(\sum_{i=1}^{n} \left| 1 - \left(\frac{E_i}{C_i} \right) \right| \right) \times \frac{100}{n}, \tag{4}$$

$$\mathrm{AVP} = 100 - \mathrm{AIP}, \tag{5}$$

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{n} (C_i - E_i)^2}}{n}, \tag{6}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |C_i - E_i|}{n}, \tag{7}$$

where AIP is the average invalidity per cent; AVP is the average validity per cent; RMSE is the root mean squared error; MAE is the mean absolute error; E_i is the estimated value; n is the number of events and C_i is the actual value.

The results of regression model validation process show that the AVP is 90, the RMSE is 0.09 and the MAE is

Table 7. Comparison of results of regression and ANN model.

Technique	R^2 (%)	AVP (%) First approach	AVP (%) Second approach	AIP (%) First approach	AIP (%) Second approach	MAE	RMSE
Regression	83.40	90.00	71.00	10.00	29.00	0.29	0.09
ANN	90.64	92.00	80.00	8.00	20.00	0.20	0.08

0.29 (Table 7). Therefore, the developed regression model is acceptable and robust. On the other hand, the results of ANN model validation process show that the AVP is 92, the RMSE is 0.08 and the MAE is 0.20, which are considered satisfactory results. The second approach is also used for calculating the value of the AIP. It depends on simply counting the number of incorrect predictions (n_{ip}) and on dividing it by the number of events (n) as follows:

$$\mathrm{AIP} = \frac{n_{\mathrm{ip}}}{n} \tag{8}$$

and the value of the AVP can be calculated using Equation (5) as explained in the first approach.

As shown in Table 7, the use of the second approach for AIP calculation resulted in AVP values of 71% for the regression model and 80% for the ANN model. It can also be noted that the second approach yielded AVP values lower than those obtained using the first approach. This is due to the fact that in the second approach an event is completely wrong if its predicted failure type is different from the actual failure type. In other words, there is no meaning for estimating the deviation of the predicted failure type from the actual failure type like the first approach, since we are dealing with output of categories and not with output of condition assessment for example. In spite of that the second approach shows satisfactory results for both models in terms of AVP.

Visual (graphical) validation

The goal of this step is to compare the actual output value with the predicted values using the developed models for the validation data-set points. Figures 5 and 6 show the ‘actual versus predicted output plot’ results of the regression and ANN models, respectively. Both figures show that the predicted values by the developed models are within the acceptable limits where they are scattered around the actual values of response variable. Therefore, the validation test’s results are satisfactory.

The results shown in Table 7 and in Figures 5 and 6 indicate that the ANN model provides better results than the regression model. The reason behind this observation is that the ANN model considers the nonlinear relation of the dependent and independent variables as well as the correlation between the factors that affect the pipeline failure’s type/cause.

Sensitivity analysis

A sensitivity analysis is carried out for the two developed models in order to examine the effect of changing the values of predictors on the failure type. The sensitivity was made based on four different cases, namely minimum, most likely, average and maximum. In other words, each predictor under study was changed within the range of its scale value (see Table 2) while setting constant the other predictors at their minimum, most likely, average or

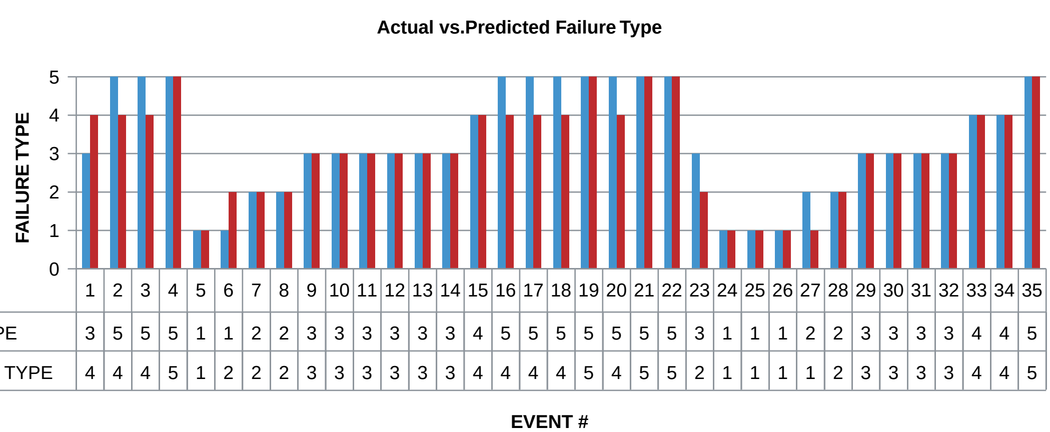

Figure 5. Model validation plot using regression analysis.

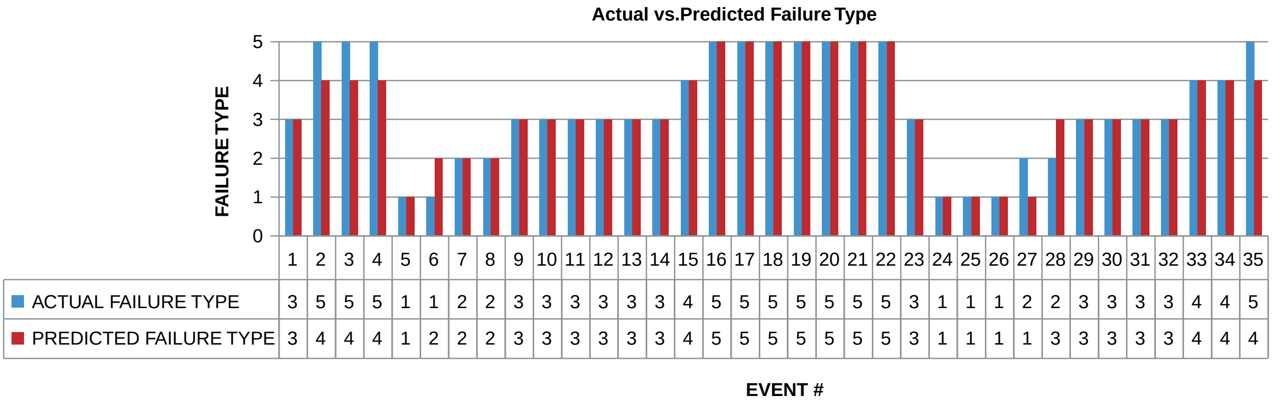

Figure 6. Model validation plot using ANN.

maximum scale value. For example, for the 'facility' predictor, the failure type was calculated three times– since 'facility' is represented by three categories (1, 2 and 3) in four different cases. The first case is when all predictors other than the 'facility' (i.e. service, age, land use and diameter) were set constant at their 'minimum' values, i.e. 1, while the facility value was varied from one to three. The second case is when all predictors other than the 'facility' were set constant at their 'most likely' values while the facility value was changed from one to three.

The 'most likely' value for each predictor is the most repeated value of each predictor among the whole incidents' database. The third case is when all predictors other than the 'facility' were set constant at their 'average' values while the facility value was varied from one to three. The fourth case is when all predictors other than the 'facility' were set constant at their 'maximum' values, i.e. 5, 7, 6 and 4 for 'service', 'age', 'land use' and 'diameter', respectively, while the facility was changed from one to three. Finally, the average of the three failure type values obtained in each of the four cases was calculated and then plotted. This process was repeated with each input or predictor, and then the resultant average failure type values for the regression and ANN models were plotted in Figures 7 and 8, respectively.

The results show that the five predictors of both models are sensitive to the change made to any variable. In both models, all the predictors almost follow the same trend.

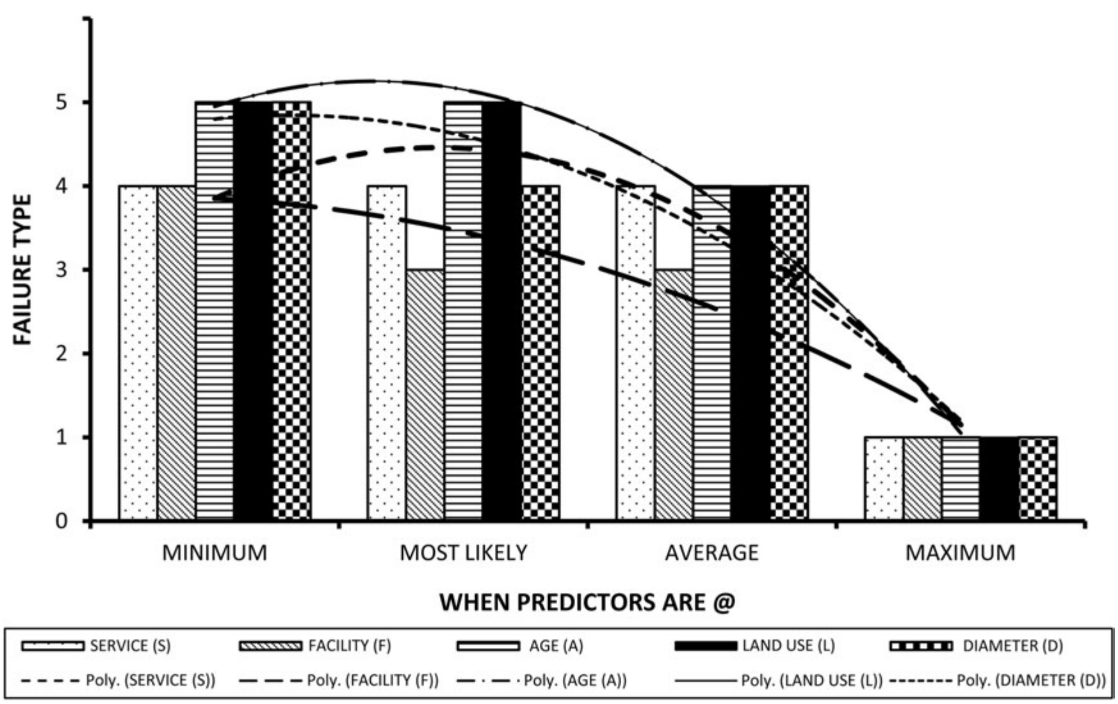

Figure 7. Sensitivity analysis for regression model.

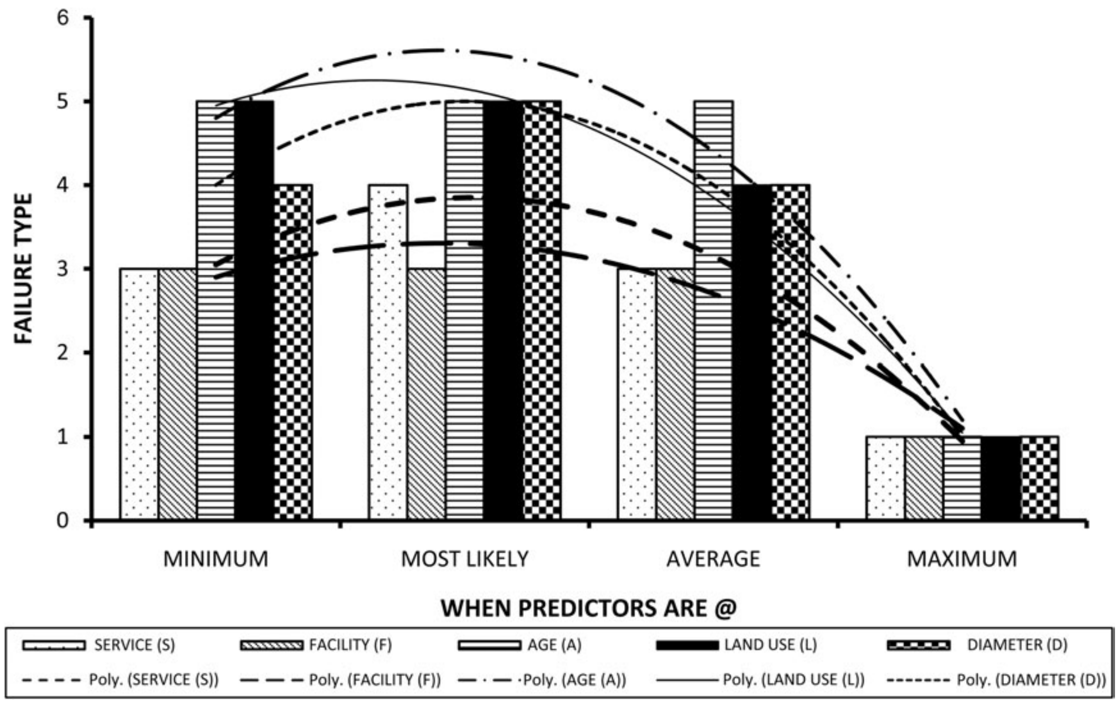

Figure 8. Sensitivity analysis for ANN model.

Also, it can be noted that in both models the curves of the predictors 'age', 'land use' and 'diameter' are very close to each other indicating that they share a similar effect on the output. While on the other hand, the curves of the predictors 'service' and 'facility' have a different effect on the output in each case. This is a re-assurance for the results of the predictors' contribution obtained using the ANN (see Table 6) that showed that both the 'service' and 'facility' represent around 60% of the factors' contribution as mentioned before. The same goes for the regression model that shows that the 'service' and 'facility' predictors have the highest coefficient (see Table 4) among the other predictors.

Conclusions

This study presents the development of two models for predicting the failure type of oil pipelines given a number of predictors, namely service type, facility (location), land use, age and diameter of the pipe. The state-of-the-art in oil pipeline failure was reviewed including the types of failure and the critical factors affecting these failure types. The developed models were validated and verified in which the obtained results were found to be satisfactory. However, the ANN model yielded better results than the regression model with respect to the following parameters: R^2, AVP, MAE and RMSE of 90.64%, 92%, 0.20 and 0.08, respectively. Both the models showed that all factors have a significant effect on the failure occurrence rate. In addition, a sensitivity analysis was carried out to show how the predictors are sensitive to any change in the input variables.

However, as model limitation, it is concluded that both the models are incapable of always accurately predicting the 'natural hazard' failure type when compared with other actual cases. This is due to the fact that the actual cases of 'natural hazard' failure were rare. As a result, both models were not adequately trained to predict such type of failure. In addition, failure of pipelines due to 'natural hazards' is actually mainly associated with the seismicity of the area, yet such comprehensive input was not present in the actual data. Therefore, further studies are needed in order to take such limitation into consideration. Another limitation is the fact that both models do not generate integer values so as to represent the five different failure types. However, this latter limitation was treated by rounding up or down the resultant output. Overall, the developed models benefit both researchers and practitioners as they provide robust models for the failure prediction of oil pipelines due to mechanical, operational, corrosion and third party causes.

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