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Prediction of Corroded Pipeline Performance Based on Dynamic Reliability Models

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Abstract

This paper focusses on developing an initial model for dynamic reliability analysis to predict the aging pipeline performance due to corrosion. The corrosion failure mechanism and the associated data requirements are identified by combining outputs from the literature and project experiences. Bayesian networks (BN) are developed to manage and overcome data uncertainties and the dynamic consideration is utilized to introduce time function into the model to accommodate the time-dependent variables. Several parameters are considered in the model development, such as pipeline content, size and material grade, environmental conditions, operational conditions, internal and external corrosion rates mitigation methods and in-line inspection data on corrosion rates. The application of the proposed model to an industrial case study is presented in this paper, along with the basic event prioritization analysis using the sensitivity approach. The proposed dynamic Bayesian model provides an efficient option for reliability assessment, to predict the future condition of the corroded pipeline based on the current and historical data, leading to rational risk assessment.

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Keywords: Reliability analysis, Subsea pipeline, Bayesian network, Life extension

1. Introduction

The concept of pipeline life extension is currently increasingly important as an alternative to the conventional pipeline end-of-life replacement, in order to improve economic sustainability and to increase profitability. This concept is that with certain processes and criteria, pipeline service life can be extended beyond a specified period without a reduction in margins below safe operating limits. Any failure threats shall all be addressed, and the application should state the basis and assumptions upon which the plans for life extension are based, and if these are sufficiently different from the current basis, a new consent to operate is required before the activities are continued.

Both onshore and offshore pipelines have a similar set of failure threats, such as internal and external corrosions, third party action and natural causes. However, it normally takes longer to mitigate and repair the failures on offshore pipeline due to their complications. Therefore, they will face more serious problem in terms of potential economic consequences. In the PARLOC report [1], which includes a total number of 542 reported pipeline/riser incidents in the North Sea, it is concluded that the incident frequencies are highest towards the end of the pipelines' life. It is more related to changes in infrastructure from the as built, e.g. increased fishing activity or heavier trawler gear and corrosion of the system over time.

Pipeline corrosion is the biggest subsea pipeline threat both in the North Sea and in the Gulf of Mexico area [2]. This threat is a time-dependent random process as any measurement of the corrosion rate will contain a degree of uncertainty. Several studies have focused on assessing the safety and reliability of corroded pipelines with a view to extend their service life. A

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majority of these studies rely on static models to analyze the failure prediction based on corrosion rates, historical data and/or expert judgements. However, the authors' are unaware of any studies considering dynamic modelling for predicting pipeline performance. The main objective of this paper is to propose a preliminary dynamic reliability model for aging pipeline performance prediction, by analyzing the pipeline residual life based on internal and external corrosion rates, and several other variables which influence the performance of the system.

There are several quantitative and qualitative methods that can be utilized to probabilistically model the corroded pipeline residual life [3]. Qualitative methods are frequently based on an index system, whereas quantitative methods are usually based on probabilistic simulations [4]. Correa et al. [5] indicates that machine learning methods such as Bayesian networks (BN) and artificial neural networks (ANN) are the most common techniques to build the probabilistic prediction model.

Various researchers demonstrate the superiority of Bayesian networks compared to artificial neural networks for the predictive analysis when data sources are very limited [5, 6, 7, 8]. Artificial neural networks can be used to develop predictive tools when the pipeline historical data is available. However, when the data is ambiguous or biased, a soft computing technique like Bayesian network is much more effective in quantifying causal relationships and the associated uncertainties. As an initial model, this paper will utilize some qualitative inputs such as experts' judgement and assumptions in the model to fill the data gap, therefore, BN is a better technique to manage and overcome the uncertainties. High ability to express causality is also one of the reasons in utilizing BN, because the network diagram to be developed in this study is based on the causality of each variable, from causes of the corrosion to the effect of the failures. Considering the corrosion failure as a time-dependent process as the analysis needs to capture inspection history data from several years [9], Bayesian networks are preferable as they offer superior ability to handle dynamic data for analyzing corrosion prediction. Therefore, it can be summarized that Bayesian networks are the most suitable technique to build dynamic probabilistic models for corroded pipeline performance prediction.

2. Bayesian Networks

Bayesian network is a probabilistic-based data modelling method that represents the relationships between causes and consequences, and its conditional interdependencies through a directed acyclic graph. The model is very effective for modelling situations where some information is uncertain or partially unavailable and incoming data is already known. Figure 1 shows a simple Bayesian network consisting of two nodes, i.e. H which represents H_2S concentration as the parent node and C which represents internal corrosion rate as the child node. Each node represents a probability distribution, which may in principle be continuous or discrete, and the probability distribution conditional on its direct predecessors (parents), also known as conditional probability table (CPT). The CPT is defined as a set of discrete (not independent) random variables to demonstrate marginal probabilities of each variable with respect to the others. The conditional probabilities can be quantified by using information obtained from the field data, expert opinion, analytical model or a combination of all [10]. However, in a complex process with ambiguous underlying mechanisms, the application of expert knowledge would also be preferable.

One of the main advantages of the Bayesian network is that they allow inference based on observed evidence. Once new information is observed, the prior probabilities are updated in accordance with observations using the Bayes' rule, and thereafter called posterior probabilities. For example, this rule can be a repeating process about an event H given information about event C, every time new or additional evidence/information becomes available. This rule can be shown as:

$$P(H|C) = \frac{P(C|H)P(H)}{P(C)} \tag{1}$$

$P(H|C)$ is the posterior probability of H_2S concentration given internal corrosion rate, $P(C|H)$ is the conditional probability of internal corrosion rate given H_2S concentration in the product, $P(H)$ is the prior measurement of H_2S concentration, and $P(C)$ is the prior or total probability of internal corrosion rate.

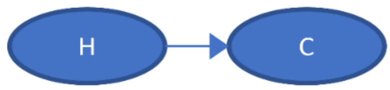

Fig. 1. A simple Bayesian network.

3. Dynamic Models

Dynamic Bayesian network (DBN) are a temporal extension of static Bayesian networks for modelling dynamic systems [11]. While the static Bayesian network shows the cumulative probability distribution over a set of random variables independent of time, the dynamic Bayesian network is a multi–dimensional representation of a random process. Considering the architecture in Figure 1, dynamic model extends the BN to model probability distributions over semi-infinite collections of variables H_2S $\{H_1, H_2, \ldots\}$, where H_t is variable H_2S at time t. A DBN is defined to be a pair $(B_1, B_{\rightarrow})$, where B_1 is a BN which defines the prior $P(H_1)$, and $B_{\rightarrow}$ is a two-slice temporal Bayesian net (2TBN) which defines $P(H_t|H_{t-1})$, where $P(H_{t-1})$ are the parents of $P(H_t)$ from the previous time slice, as shown in Figure 2. The nodes in the first slice of a 2TBN do not have any parameters associated with them, but each node in the second slice of the 2TBN has an associated conditional probability distribution (CPD) for continuous variables or conditional probability table (CPT) for discrete variables.

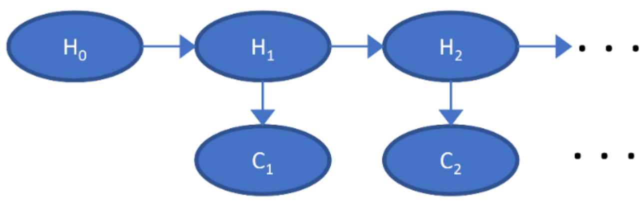

Fig. 2. Dynamic Bayesian network.

The DBN allows the interpretation of the present, the reconstruction of the past and the forecasting of the future, mostly due to the computational complexity of the inference algorithms (time is treated as a discrete variable) [12]. Figure 3 shows the difference between static and dynamic models. Shaded variables represent both parent nodes from the previous time slices. In the actual condition, these variables are taken from any historical data, such as operational data, inspection history data, or data from a previous project with similar pipeline design and condition.

Table 1 presents an example of the 25-year old pipeline failure probability result using static and dynamic Bayesian network model. It can be seen that the static model only provides one probability of failure result which is based on the current condition of the pipeline, whilst the dynamic model provides five results for current and forecasted condition. Dynamic Bayesian network is the best fit for determining the probability distribution of the pipeline performance. In the present work, prior probability will be taken from literatures and some realistic assumptions, while actual projects will be observed to obtain new information. Thus, the model will be updated to determine the posterior probability. Time series will be introduced to the analysis to accommodate the failures on pipelines which are likely to change from time to time. Therefore, future condition of the pipelines which are threatened by corrosion can be forecasted, and the probability distributions can be specified.

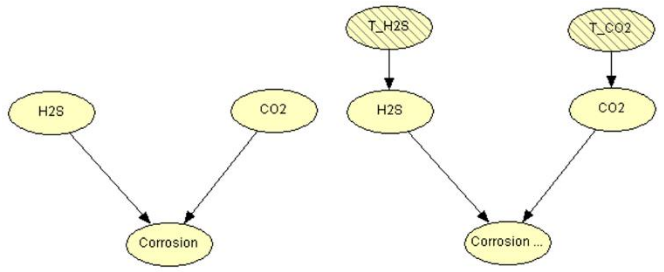

Fig. 3. Static (left) and dynamic (right) Bayesian network model.

Table 1. An example of Bayesian network probability of failure results.

Pipeline service year	Probability of failure result (%)	
	Static BN model	Dynamic BN model
Year-25	5.89	7.20
Year-28	N/A	8.35
Year-31	N/A	9.32
Year-34	N/A	10.12
Year-37	N/A	10.77

4. DBN Model Development

Dynamic Bayesian networks are implemented in this paper to analyse the corroded pipeline residual life. Several factors affecting the pipeline residual life are incorporated in the probabilistic network, such as pipeline content, size and material grade, environmental conditions, operational conditions, failure prevention method, etc. Figure 4 shows a complete Bayesian network which combines information from existing literatures and previous project experiences. It can be seen that fifteen variables are assigned to temporal clones, shown in shaded boxes. These temporal variables represent the condition of the events from the last inspection and/or operational activities.

Two types of corrosion are considered in this model, i.e. internal corrosion and external corrosion. Multiple internal and external factors and their interactions are required to be considered in the analysis. The presence of carbon dioxide (CO_2), hydrogen-sulphide (H_2S), and free water in the production fluid can cause severe corrosion problems in oil and gas pipelines. Internal corrosion in wells and pipelines is influenced by temperature, CO_2 and H_2S content, water chemistry, flow velocity, oil or water wetting, etc., while the external corrosion is mainly affected by seawater condition, such as temperature, salinity, and O_2 rate [13].

To estimate pipeline residual life, several variables were considered in the model, such as defect data, pipeline data and operational pressure. The utilization of these variables is based on the corroded pipeline assessment analysis specified in DNV-RP-F101 [14]. In this paper, dynamic model conditional probability table (CPT) was developed by using information obtained from literatures and some realistic assumptions. The CPT and states will be updated when new data becomes available, such as from analytical model, field data or expert opinion, in further study.

5. Case Study: 14-inch Gas Pipeline

This section presents the application of the proposed dynamic Bayesian model to an actual pipeline. Tables 2 and 3 show the inspection and operational data of a 14-inch subsea pipeline located in the Natuna Sea which is taken from the Operator's pipeline report. The current age of the pipeline is 10 years, while the design life is 20 years. In-line inspection schedule for this pipeline system is conducted biennially. With this information, the probability of pipeline residual life was computed using the proposed dynamic Bayesian network model.

The analysis result shows that the highest probability of pipeline residual life with current condition is in the range of 2.5 to 7.5 years. This result is very close to residual life estimated by the pipeline's Operator, which is in the range of 2 to 10 years, as can be seen in Figure 5. The Operator used their own methodology to analyse the pipeline residual life, which combines calculation set from API RP 581 [15], previous project experiences and experts' opinion. The failure probability of the top event (when the pipeline residual life is zero) is 0.01%. However, the dynamic model predicts that the probability will increase steadily during its service life. Figure 5 also presents the pipeline residual life results with different operational pressure inputs, which summarise that the service life of the pipeline can be extended by reducing its operational pressure.

Table 2. Inspection data of the 14-inch gas pipeline.

Inspected item	Inspection result
Measured internal corrosion rate (mm/year)	0.08
Measured external corrosion rate (mm/year)	0.1
Bacterial corrosion	No

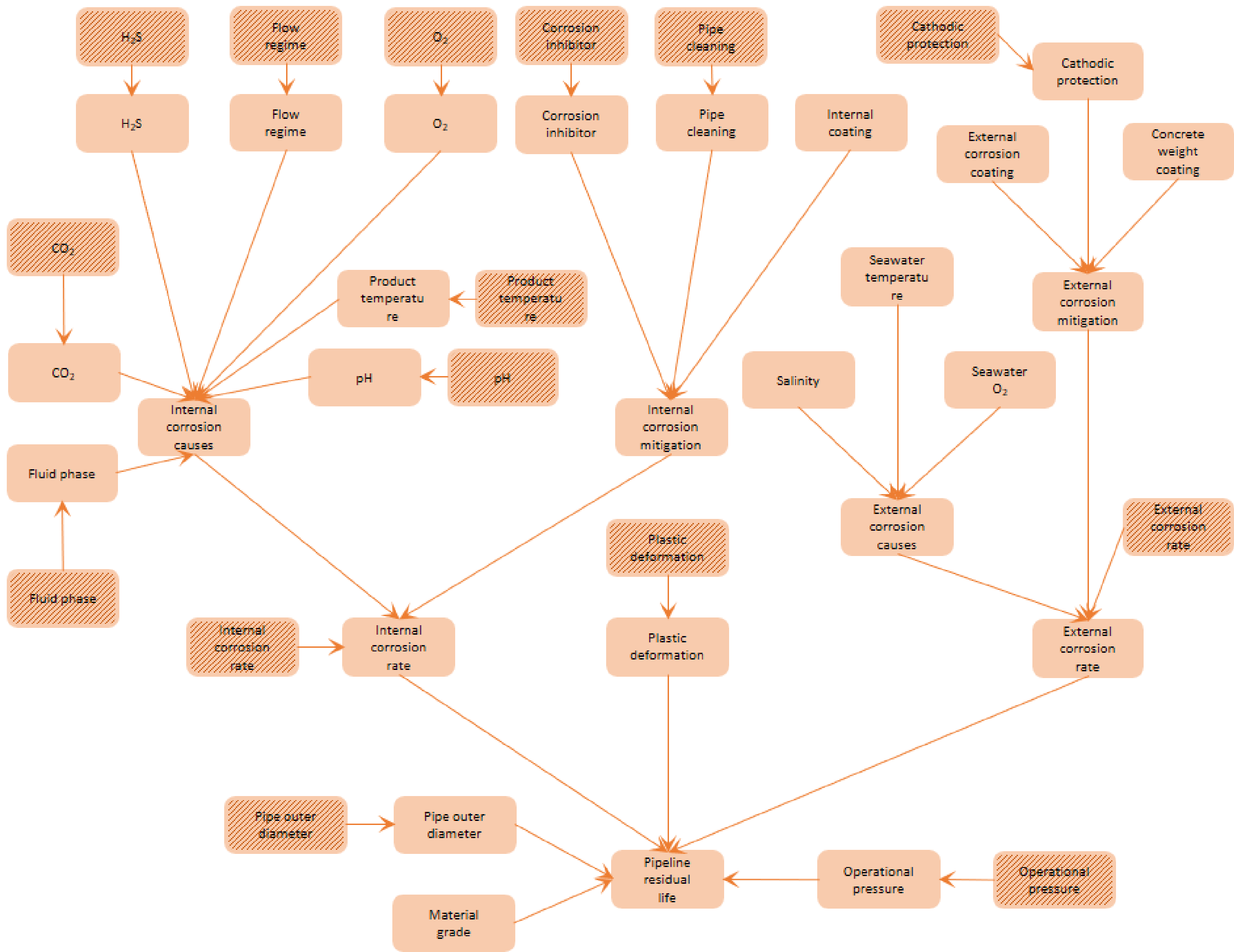

Fig. 4. Dynamic Bayesian network for pipeline failure probability due to corrosion.

6. Sensitivity Analysis

The sensitivity analysis helps to understand how the variations in project's objectives correlate with variations in different uncertainties, and also to prioritise the basic events based on the impact to the top event probability. For this study, the value of a basic event probability was set to one (perfect probability), afterwards, a new calculation for the top event probability was analysed while the probability of the other basic events remained unchanged. Table 4 shows the comparison of the original and new top event probability of failure result for each of the perfect basic events.

Based on the results, operational pressure was observed to have the highest impact on the top event failure. From the network model perspective, it can be seen that between operational pressure as the basic event, and the pipeline residual life as the top event, there are no intermediate events. Therefore, this basic event can be categorised as the immediate cause to the top event probability of failure. It means that if there is a condition when the operational pressure failure probability become one, it will immediately affect the top event, thus the pipe failure probability will increase rapidly.

Table 3. Operational data of the 14-inch gas pipeline.

Type of data (unit)	Value
Nominal diameter (mm)	355.6
Wall thickness (mm)	12.7
Material grade	API 5L X52
Maximum allowable operational pressure (MAOP) (MPa)	13.8
Pipeline design life (years)	20
Corrosion allowance (mm)	3
Cathodic protection system	Sacrificial anodes
External coating type	Fusion Bonded Epoxy
External coating thickness (mm)	0.75
Fluid content	Produced gas
Corrosion inhibition	Yes
CO_2 partial pressure (MPa)	0.03
H_2S partial pressure (MPa)	0
O_2 concentration (ppb)	0
Operating pressure (MPa)	10.1
Operating temperature (^{0}C)	23.33

From the industrial perspective, operational pressure is widely known as the significant cause to the corroded pipeline failure, therefore DNV-RP-F101 [14] placed it as a basis for the corrosion defect assessment. This assessment methodology is subjected to two cases, i.e. internal pressure loading only, and internal pressure loading combined with longitudinal compressive stresses. It also described two alternative approaches to the assessment of corrosion, the first approach includes calibrated safety factors considering the natural spread in material properties, wall thickness and internal pressure variations. Uncertainties associated with the sizing of the defect and the specification of the material properties are specifically considered in determination of the allowable operating pressure. The second approach is based on the Allowable Stress Design (ASD) format. The failure pressure capacity of the corrosion defect is calculated, and this failure pressure is multiplied by a single usage factor based on the original design factor.

Preventive and corrective actions shall be taken to minimise the risk of the operational pressure failure probability. The most common way is to assess the new maximum allowable operational pressure (MAOP) of the product based on the latest pipeline condition. Thereafter, the pipeline product operational pressure shall be maintained under the new MAOP, and this assessment shall be conducted frequently in line with the inspection schedule.

Table 4. Basic event sensitivity analysis of the 14-inch gas pipeline.

Basic events	Prior basic events' probability (%)	Prior top event failure probability (%)	New top event failure probability (%)	Deviation between prior and new top event failure probability
Very high operational pressure	0.05	0.01	21.59	21.58
Deformed wall	0.20	0.01	5.78	5.77
Low pipe grade	0.15	0.01	3.28	3.27
Small pipe outer diameter	0.50	0.01	3.22	3.21
Very high internal corrosion rate from ILI	0.30	0.01	1.18	1.17
Very high external corrosion rate from ILI	0.10	0.01	1.17	1.16
No cathodic protection	0.05	0.01	0.04	0.03
No external corrosion coating	0.05	0.01	0.03	0.02
No corrosion inhibitor	0.35	0.01	0.03	0.02
No concrete weight coating	0.10	0.01	0.02	0.01
No internal coating	0.10	0.01	0.02	0.01
Very high O_2 in seawater	0.30	0.01	0.02	0.01
Very high seawater salinity	0.80	0.01	0.02	0.01
No pipe cleaning	0.10	0.01	0.02	0.01
Very high CO_2 partial pressure	0.80	0.01	0.02	0.01
Very high H_2S concentration	0.60	0.01	0.02	0.01
Very high seawater temperature	0.20	0.01	0.01	Very small
Turbulent flow	0.30	0.01	0.01	Very small
Liquid product	0.20	0.01	0.01	Very small
Very high O_2 concentration	0.40	0.01	0.01	Very small
Very high product temperature	0.30	0.01	0.01	Very small
Very high pH	0.40	0.01	0.01	Very small

7. Conclusion

The present study has illustrated the superior suitability of Bayesian networks compared to other modelling techniques for analyzing the corroded pipeline performance. An application of the proposed dynamic model for comprehensive analysis of corroded pipeline performance is presented, by considering an industrial case study. It was observed that the proposed model produced a realistic result of the pipeline residual life, closely comparable to the residual life specified by the Operator. This paper considered both internal and external corrosion mechanisms. Twenty-two basic events were defined in the model, with fifteen of them being time-dependent hence considered as dynamic variables. These variables are presented as child nodes which are supported by temporal clones (shaded boxes) as their parent nodes. The temporal nodes represent each variable from previous time slices.

Basic events prioritization was analyzed using sensitivity analysis approach. Among the potential basic events, operational pressure has been identified as the most significant variable in the model based on the impact to the top event probability. Therefore, preventive and corrective actions shall be taken to mitigate the failure risk. The development and application of the proposed approach lead to an efficient estimate of the future condition of the pipeline based on the current and historical data.

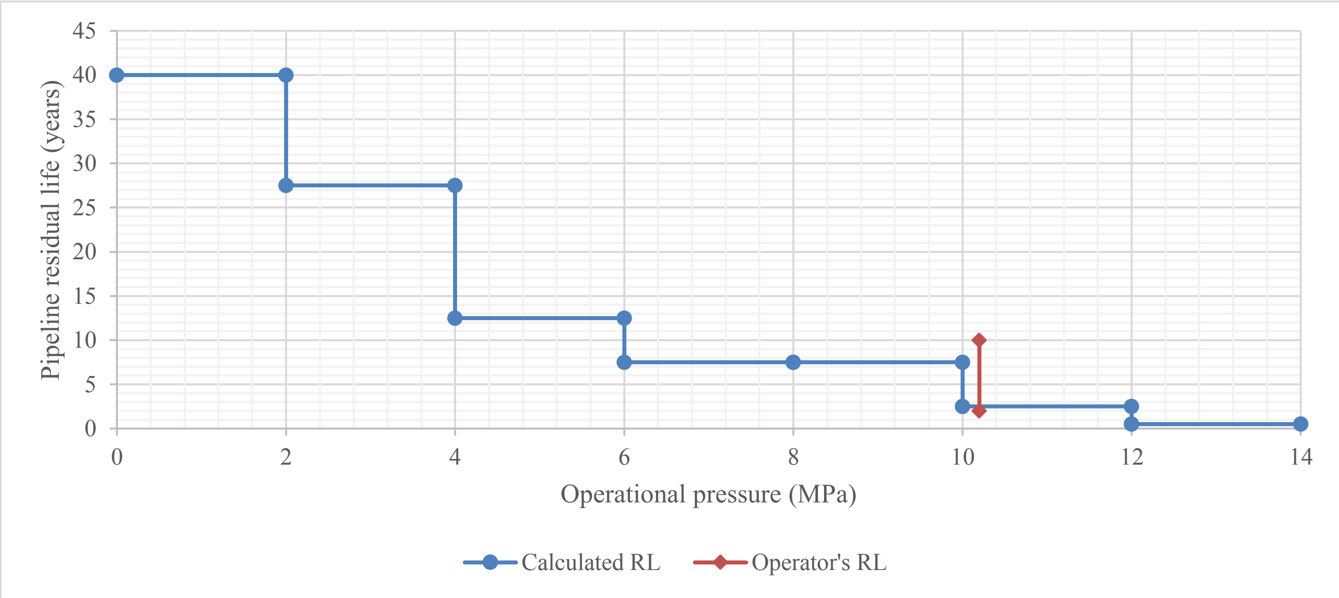

Fig. 5. Probability of failure of the considered pipeline.

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