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Pipeline Failure Analysis: Bayesian Network Approach from Fault Tree Analysis

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Abstract

Pipeline failures can have catastrophic consequences, posing significant environmental and safety risks. In order to address the pipeline failure issues, a diagnostic Bayesian Network (BN) model was applied for the study of the Root Cause Analysis (RCA). The study aimed to identify the factors responsible for pipeline failures and offer a predictive tool for risk assessment. This study used the Bayesian Network (BN) model using existing Fault Tree Analysis (FTA) data from a past case study on pipeline failures. Translating the potential failure modes and the identified causes using Fault Tree Analysis (FTA) creates the Bayesian Network (BN) model. The results and discussions showed the BN model's accuracy and effectiveness in predicting pipeline failures. Sensitivity analysis highlighted critical factors with substantial influence on system reliability. The model's validation against FTA ensured its reliability in representing dependencies and relationships in the system. The sensitivity analysis revealed that the model categorized the pipe defects into commissioning and material defects, the primary causes of a pipeline to be ruptured. By incorporating a wide range of factors and failure mechanisms, the model offers a comprehensive approach to assessing the risk of pipeline failure incidents. This BN model offers a practical tool for conducting Root Cause Analysis and making informed decisions to improve pipeline system safety.

1. Introduction

A pipeline is an intricate system comprising a communication network that utilises microwave links, cables, and satellites, intake and outlet structures, flowmeters, sensors, and automatic control apparatus, as well as pumps (or compressors), intermediate pumping stations (termed booster stations), and storage facilities.

The positioning of booster stations facilitates pumps or compressors approximately every 100 km, spanning the pipelines [1]. Priyanka et al., [2] stated that pipeline networks primarily convey natural gas, crude oil, and petroleum products. Despite being regarded as the safest method for transporting petroleum products, pipeline failures can still occur, leading to hazardous consequences and significant environmental damage [3]. The occurrence of different pipeline failures varies. Based on the reports of The Pipeline and Hazardous Materials Safety Administration, PHMSA [4], the group of each incident's cause and sub-cause failure data is predicated on the number of incidents over 20 years. The incident is grouped into various categories to represent the reasons or categories of failure of the oil and gas pipelines. These categories include corrosion, material failure of pipes or welds, damage caused by excavation or natural forces, improper operation, and damage from external forces. Table 1 tabulates the causes and sub-causes categorized by PHMSA.

Table 1 *Causes and sub-causes of pipeline failure [5]*

Causes	Sub-causes
	Corrosion
External Corrosion	Galvanic corrosion, Stray corrosion, Microbiological corrosion, Selective seam corrosion
Internal Corrosion	Corrosive commodity, Acid water, Microbiological corrosion, Erosion
	Pipe/Weld Material Failure
Construction, Installation or Fabrication Related	Weld quality, Mechanical damage in the field
Original Manufacturing Related	Weld quality, Manufacturing defect
Environmental Related	Stress corrosion cracking, Deformation related cracking
	Excavation Damage
Operator's Contractor (Second Party)	Excavation practices not sufficient, Locating practices not sufficient, Previous damage
Third Party	One-call notification practices not sufficient, One-call notification center error
Previous damage due to Excavation Activity	One-call notification practices not sufficient, Previous damage
Natural Force Damage	Earth movement, Heavy rains/floods, Lighting, Temperature
Incorrect Operation	Damage by operator or operator's contractor, Pipeline or equipment overpressure, Equipment not installed properly
Other Outside Force Damage	Damage by cars, boats, nearby industry or fire/explosion

According to statistical data from PHMSA covering the period between the years 2010 and 2015, there were 432 oil pipeline failures and 238 gas pipeline failures [6]. In the database, the top three causes of oil pipeline failures were corrosion, pipe/weld material failure, and equipment failure. These flagged incidents require high monitoring. For gas pipeline failures, the primary reasons were pipe/weld material failure, excavation damage, and corrosion [6]. These primary reasons constitute about 75% of the incidents occurred along the American transmission pipelines spanning 480,000 km [7]. Based on statistical reports, Fig. 1 illustrates the distribution of these failures as a percentage of their frequency from 2010 to 2015.

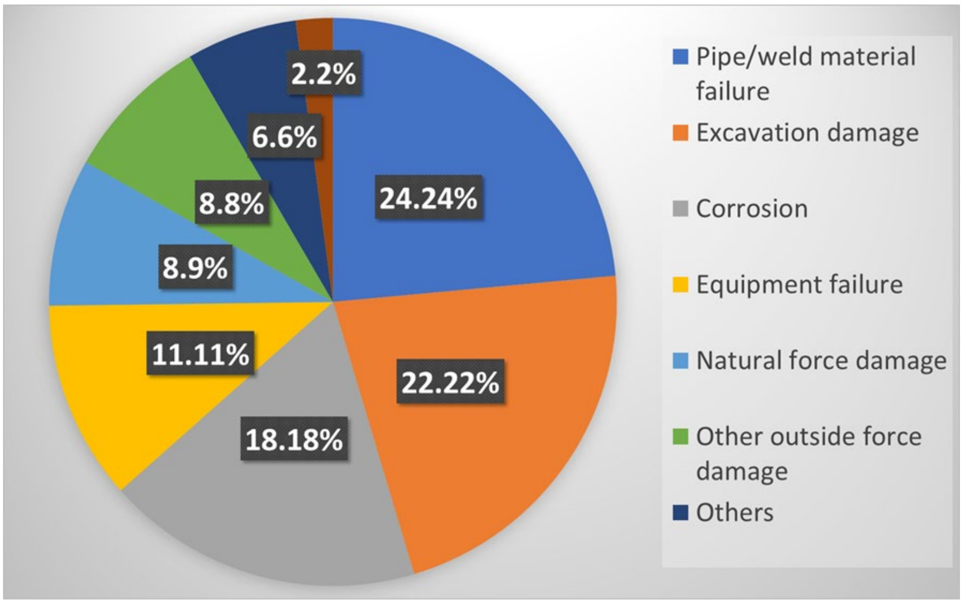

Fig. 1 *Percentage of pipeline failure based on identified factors [6]*

As displayed in Fig. 1, it is vital to maintain the pipeline system's safety and reliability because products such as oil and gas are hazardous and may result in catastrophic disasters. Over the past ten years, numerous models have been created for forecasting pipeline failures and assessing their conditions [3]. Nevertheless, most of these models were restricted to a single type of failure, such as corrosion failure, or depended heavily on analyzing expert opinions. Therefore, it is necessary to analyze data gathered from accessible resources to develop a predictive model for conducting Root Cause Analysis (RCA). Root Cause Analysis (RCA) is a a systematic approach aimed at identifying the underlying reasons behind a failure in a system, such as a pipeline failure [8].

To address these challenges of RCA, a Bayesian Network model was adopted to predict the failure factors of the pipeline. This approach model integrates predictive analytics on pipeline failures using historical data. The utilization of the Bayesian Network is particularly advantageous, as it allows probabilistic inference, which is the ability to predict an event based on prior knowledge and new evidence [9]. There are uncertainties in the data or the relationships between variables in real situations. Bayesian networks can be used for decision-making under these uncertainties using probabilities, allowing for more accurate predictions and decisions [10]. Bayesian networks provide a graphical representation of the relationships between variables, making it easier to understand and communicate complex systems [11].

The purpose of this research is to utilize Root Cause Analysis (RCA) for pipeline failures using the Bayesian Network of GeNIE Modeler. This study also aims to identify the specific factors contributing to pipeline failures. By employing Bayesian Network modeling, the research aims to offer an accurate predictive tool for conducting Root Cause Analysis (RCA). The outcome of this research holds significant potential to advance the understanding of pipeline failure mechanisms and to provide actionable insights for enhancing risk management practices.

2. Methodology

The principal aim of this research is to ascertain the factors responsible for pipeline failures based on the existing case study. A diagnostic model developed using the Bayesian Network of GeNIE Modeler to assess the probability of pipeline conditions, considering various failures and influencing factors, was applied to achieve the purpose of this study. This case study focused on different CO_2-based pipelines, using the reliability data from the fault tree analysis. With embedded reliability data, this fault tree transformed into the Bayesian Network diagnostic model, enabling the incorporation of probabilistic relationships between events and variables [12]. This approach can identify multiple potential failure causes and their interactions and dependencies, resulting in a more thorough comprehension of pipeline failures and more accurate predictions of their occurrence.

Fig. 2 shows the steps to map a fault tree into a Bayesian Network (BN) for pipeline failure causes. In this study, the converted Bayesian Network used the data from fault tree analysis (FTA) of the pipeline system information. This information created the FTA diagram identifying potential failure modes and their causes. For this study analysis, the data was taken from the case study of a CO_2 transporting pipeline conducted by Baig and Ruzli [13]. In the first step, the converted BN from the FTA data comprised each 31 events as risk factors in the FTA represented as a variable in the BN. In the second step, the created BN structure defines the dependencies between variables based on the logical relationships in the FTA. For example, if a valve failure is a cause of a pipeline rupture, the valve failure variable is a parent of the rupture variable in the BN. Based on the data, the BN variables were denoted as assigned probabilities. The estimated probability values were based on the CO_2 transporting pipeline case study, as tabulated in Table 2. Finally, the BN model calculated the probability of different failure modes given specific observations or evidence [14]. Note that, step five of probabilistic inference was not discussed in this paper.

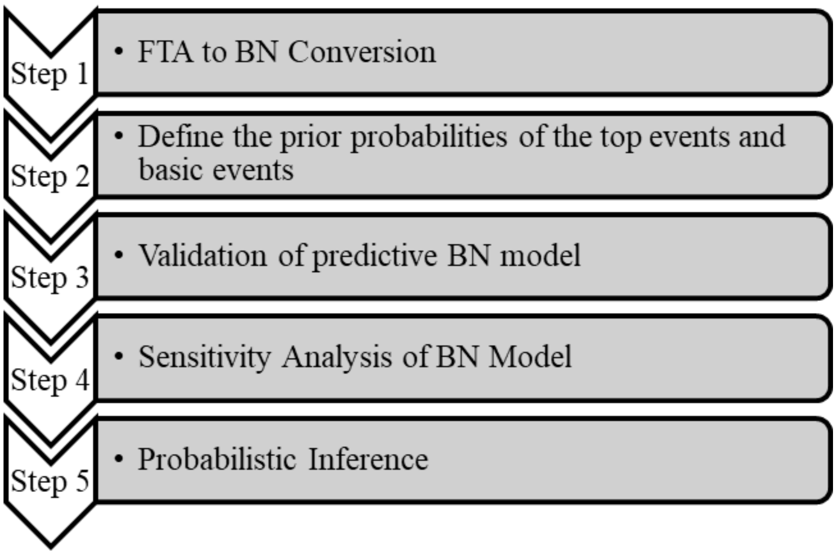

Fig. 2 *The methodological flow of developing the Bayesian Network*

Table 2 *Failure probabilities of basic events [12]*

Basic Events	Description	Probability of Failure
X1	High temp	0.00148
X2	High Pressure	0.003466
X3	Low pH	0.000223
X4	High Velocity	0.000153
X5	Improper Venting	0.002323
X6	Capping and plugs	0.001101
X7	Corrosion monitoring	0.000125
X8	Failure of Coating	0.002739
X9	Deboning and erosion	0.00031
X10	Bad Clear pipe	0.000223
X11	With H_2O	7.9×10^{-5}
X12	O_2	0.00977
X13	H_2S	0.007045
X14	CO_2	0.005
X15	Organic Acid	0.02378
X16	Coarse Grain	0.000418
X17	Bad microstructure	0.000264
X18	Much Inclusion	0.00031
X19	Bad Installation	0.0237
X20	Bad Welding	0.000887
X21	Mechanical Damages	0.000548
X22	Failure Cathodic protection	7.9×10^{-5}
X23	Failure of coating	0.000704
X24	Bad Anti-Corrosion	7.9×10^{-5}
X25	High Temp	0.000125
X26	Low Resistance	3.10×10^{-4}
X27	High water ratio	0.001485

X28	High salt	6.59×10^{-3}
X29	Low pH	0.002323
X30	Bacteria	7.9×10^{-5}
X31	Electrical Interference	0.00048

2.1 Validation of the Bayesian Network (BN) Model

As mentioned in step 3 of Fig. 2, validating a Predictive Bayesian Network (PBN) derived from Fault Tree Analysis (FTA) involves ensuring that the constructed network represents the relationships and dependencies among the variables in the system. The case study illustrates estimating the failure probabilities of a CO_2 transporting pipeline. As shown in Fig. 3, Fault Tree Analysis (FTA) examined the causes of failure. The study analyzed puncture formations in pipelines caused by corrosion, ultimately leading to CO_2 leakage. A significant challenge in dealing with new analysis systems arose from the need for more data or clarity in failure data.

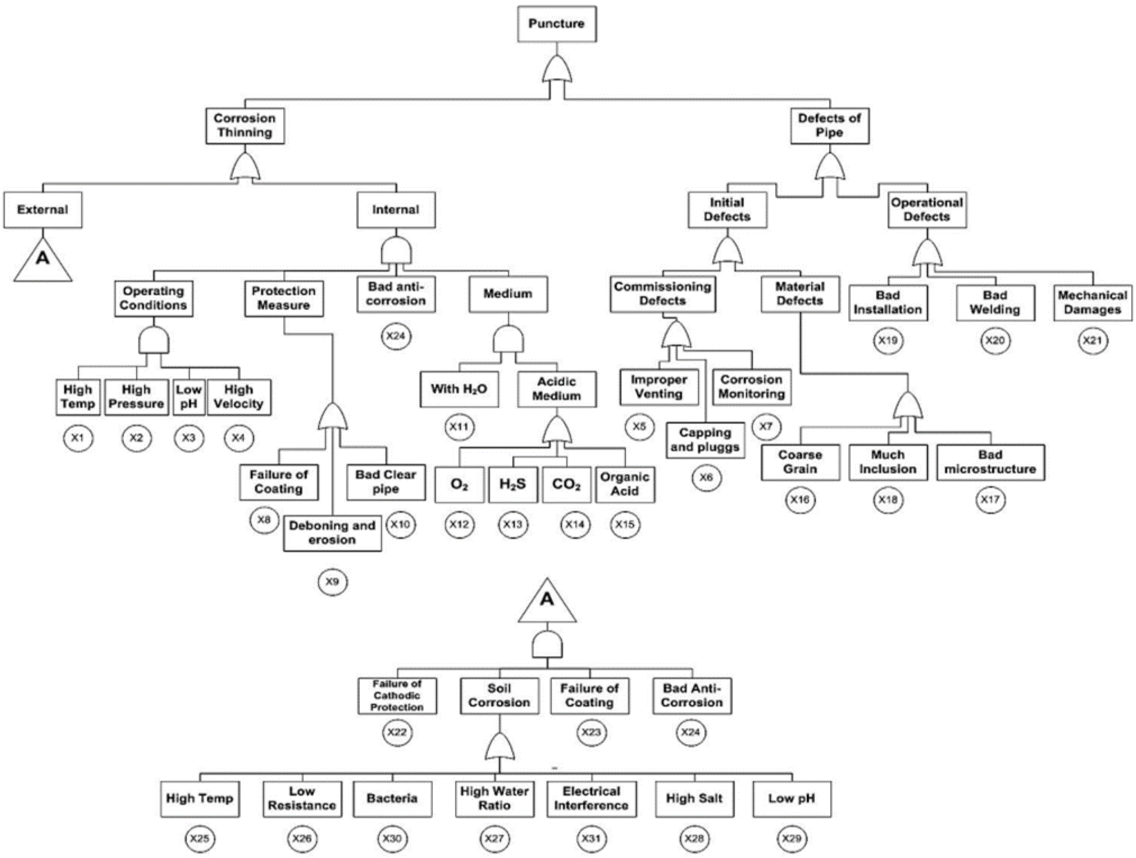

Fig. 3 *Fault Tree Analysis (FTA) of the pipeline [12]*

2.2 Sensitivity Analysis of the BN Model

A sensitivity analysis on the Bayesian Network (BN) model, derived from the conversion of Fault Tree Analysis (FTA), was performed to figure out the factors that had the greatest impact or combinations of variables as a fourth step, as shown in Fig. 2. By perturbing the probabilities of individual nodes, the changes were in the overall system reliability, allowing the identification of critical components and failure modes [15]. In this analysis, the set 'Puncture' node as a target to analyze the factors significantly impacts the system's performance. It highlighted areas where targeted interventions can enhance system reliability. In this analysis, a diverse color scheme played an essential part in enhancing the clarity and distinctiveness of the visual representation.

Nodes colored in red indicate parameters essential for calculating the probability distributions in the target nodes. The intensity of the red color (Fig. 4) represents the magnitude of impact that a specific variable has on the model's outcomes when its probability or state is altered. Variables in a deeper shade of red indicate that even small changes in their probabilities can substantially affect the system's reliability or risk assessment. However, it is essential to note that not all properties simultaneously affected when risk predictions occur.

The color purple represents the principal risk factors that were linked to the potential occurrence of pipeline failures. Subsequently, green was dedicated to signify secondary risk factors, yellow was designated for tertiary risk factors, and light blue was employed to represent quaternary risk factors.

Additionally, neon blue effectively delineated the sub-causal components nested within the quaternary category, further enhancing the comprehension of the intricate relationships within the analysis. This employment of colors enhanced the visual understanding and facilitated the interpretation of the complex interdependencies and risk factors within the CO_2 pipeline integrity assessment context as shown in Table 3.

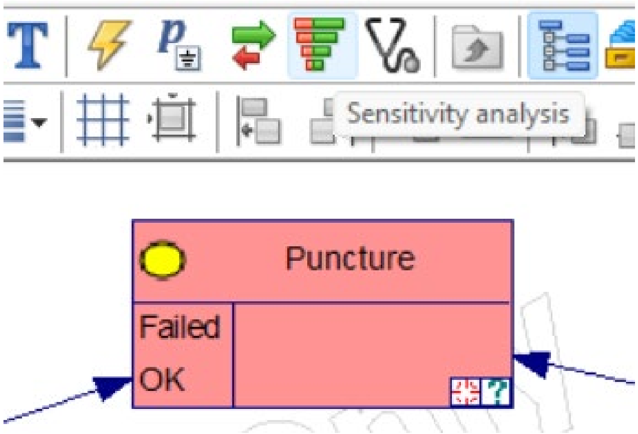

Fig. 4 *Sensitivity analysis of GeNIE Modeler*

Table 3 *Legends of colour node*

Colours	Nodes
	Puncture of CO_2 pipeline
	Main risk factors of pipeline failures
	Secondary risk factors of pipeline failures
	Third risk factors of pipeline failures
	Forth risk factors of pipeline failures
	Sub-causes of forth risk factors

3. Results

This section explains and deliberates upon the outcomes of transforming Fault Tree Analysis (FTA) into a Bayesian Network (BN) paradigm using the GeNIE Modeler. The primary objective of this analysis was to assess the dependability and risk considerations of an involved system, capitalizing on the inherent merits of BN modeling. The constructed model underwent validation procedures. The interrelations among the arcs within the model were established by adhering to the structural framework of a fault tree analysis (FTA). Subsequent sections furnished an exposition of the findings and discourse from the investigation.

3.1 Validation

A Bayesian network framework was developed to quantitatively assess failures within CO_2 pipelines and identify their primary causal factors. The CO_2 transmission pipeline dataset sourced from Baig and Ruzli [13] was employed as the foundational dataset in this investigation. The antecedent probabilities extracted from the fault tree analysis (FTA) database were harnessed to construct a Bayesian Network (BN) model, facilitating the projection of impending CO_2 pipeline failures. Fig. 5 visually shows the fundamental configuration of the network. The formulation of the BN model encompassed the translation of events, gates, and probabilities delineated in the Fault Tree Analysis (FTA) into corresponding nodes and conditional probability tables. This conversion process was methodically executed to portray the interdependencies and associations within the system. Subsequently, the integrity of the Bayesian Network model's structure was subjected to verification against the fault tree analysis (FTA) to ascertain its precision in faithfully encapsulating the details of interdependence and relationality fundamental to the system as shown in Fig. 5 and Fig. 6, indicating Bayesian Network (BN) model for all risk factors.

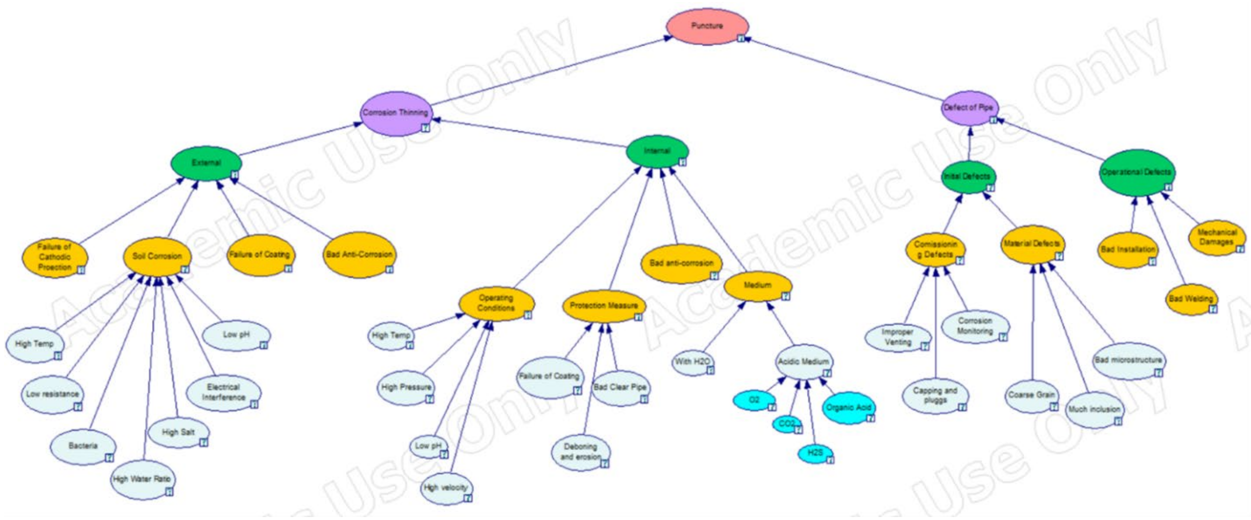

Fig. 5 *Basic Bayesian Network (BN) diagram*

To systematically assess the inherent risks attributed to failures within CO_2 transmission pipelines, an in-depth compilation of indicators was devised to conduct a comprehensive risk assessment. The underlying architectural construct of this analytical framework was partitioned into two predominant causal determinants underpinning potential pipeline breaches, denoted as corrosion thinning and pipe defects, which are visually represented in Fig. 7 and Fig. 8.

A comprehensive analysis was undertaken, encompassing 31 indicators meticulously selected to gauge the various risk factors pertinent to the study. These indicators were organized and systematically structured, ensuring a coherent framework for assessing the complexities inherent in the research subject. Within this overarching structure, each of the core causal factors, namely, corrosion thinning and pipe defects, underwent a process of further subdivision. This segmentation identified distinct sub-causal components that intricately contribute to the overarching causal factors.

Specifically, the aspect of corrosion thinning was subjected to a more granular examination, yielding the identification of four discrete sub-causal elements. These sub-factors included Cathodic Protection Failure, Soil Erosion, Coating Failure, and Inadequate Anti-Corrosion measures. These sub-factors were discerned as the underlying determinants influencing the progression of corrosion thinning within the CO_2 transmission pipelines. Generally, the main factors that affect pipeline deterioration when exposed to CO_2 and H_2S gases include temperature, the quantities of CO_2 and H_2S, water contaminants, speed of the flow, and the chemical composition of the steel [16]. The visual representation of this intricate sub-categorization is depicted in Fig. 7, allowing for a comprehensive visual understanding of the interrelations among these sub-causal elements and their contributions to the overall phenomenon of corrosion thinning within the pipeline system.

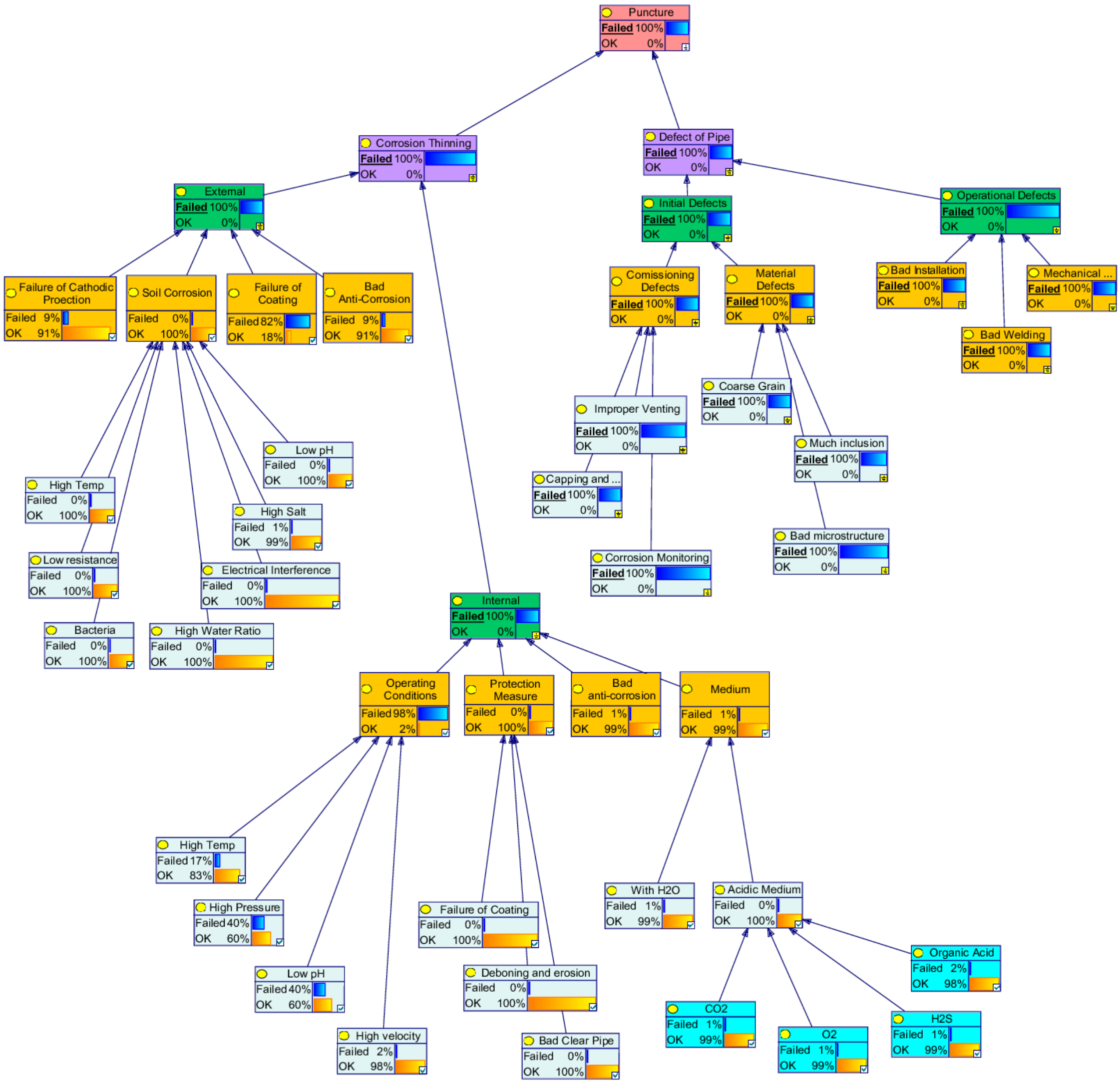

Fig. 6 *Bayesian Network (BN) model for all risk factors*

Conversely, pipe defects were systematically divided into two discrete sub-causal categories: Initial Defects and Operational Defects. This categorization, visually shown in Fig. 8, was orchestrated to disentangle the intricate web of potential factors contributing to pipe defects within the CO_2 transmission pipeline system. Two major factors contribute to the significant pipe defects: cracks and leaks in the pipeline [17]. As shown in Fig. 3, the constructed FTA model is only based on a single case study or situation. However, throughout the BN model, the target event can be focused based on the situation or event, as shown in Fig. 7 and Fig. 8. In addition, the links between each event or factor displayed the impact on focused failure. Although the BN produced a similar outcome to FTA, the disadvantage of the FTA is that the target cannot be adjusted as compared to the BN. The probabilities of addition factors can be adjusted based on the situation and case study. Thus, update the probabilities of the event or factors.

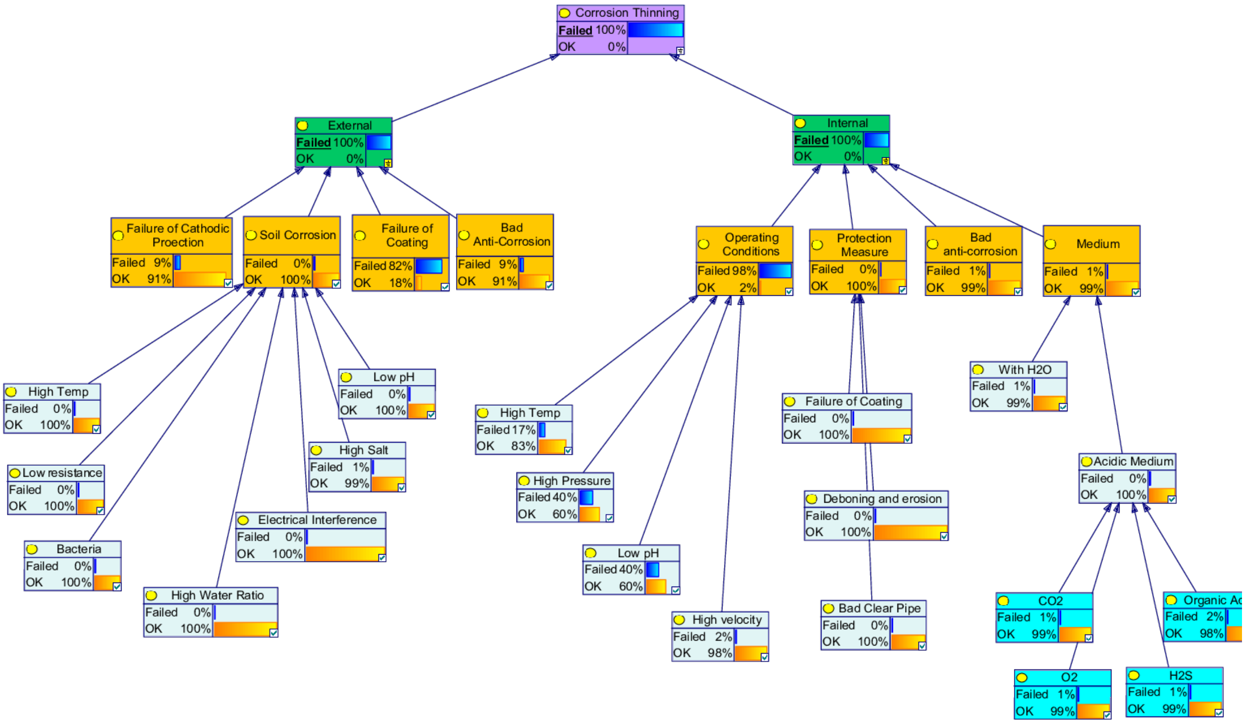

Fig. 7 *Bayesian Network (BN) model for corrosion thinning risk factors*

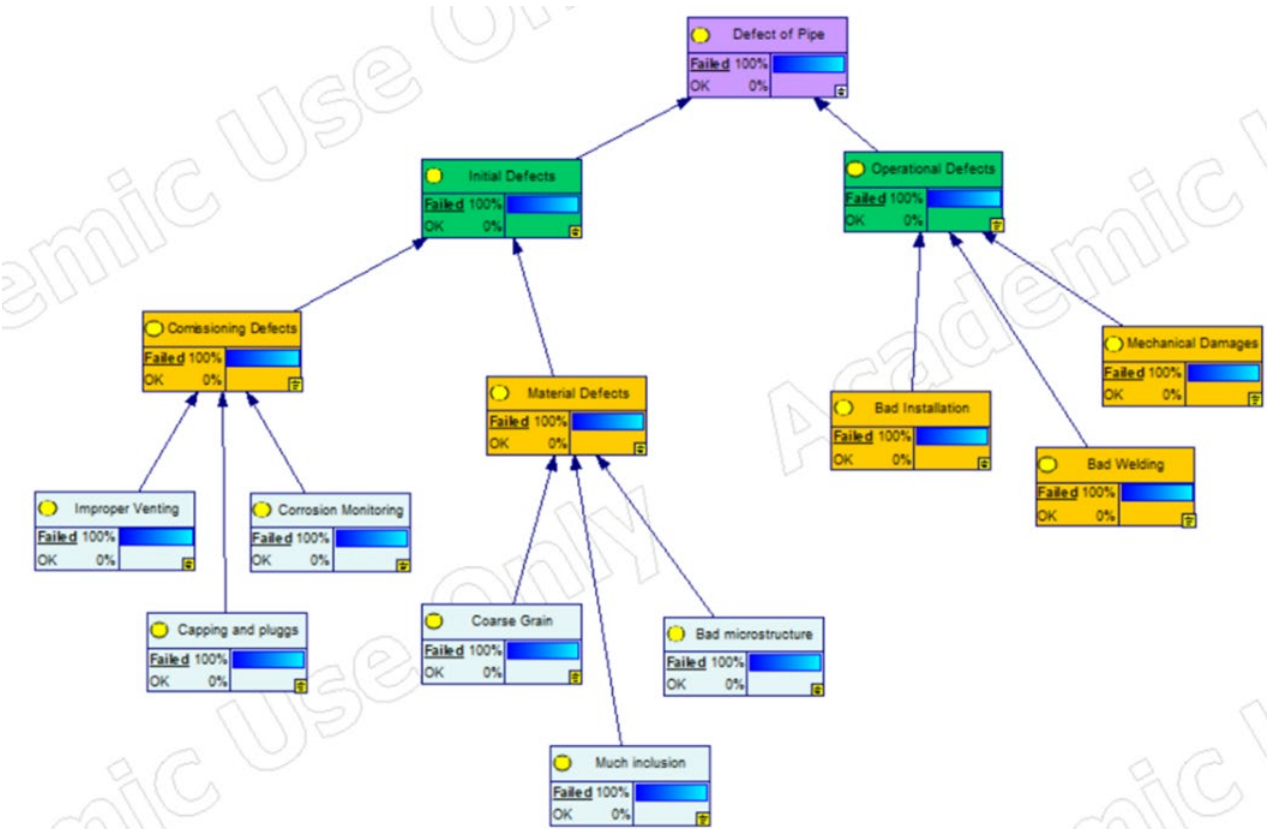

Fig. 8 *Bayesian Network (BN) model for defect of pipe risk factors*

3.2 Sensitivity Analysis and Strength of Influence

The sensitivity analysis revealed a set of crucial variables with significant influence over the reliability and risk of the system under examination. As demonstrated in Figure 9, the designated Puncture node is the focal point, with specific factors highlighted in red to emphasize their notable contributions to respective failure modes. Among these factors, the primary causes of pipeline rupture were attributed to pipe defects. The category for defects that stem from an initial flaw was commissioning and material defects. With commissioning defects, contributing factors included corrosion monitoring, capping and plugs, and improper venting. As for material defects, the factors leading to pipe rupture were identified as microstructure, excessive inclusion, and coarse grain. Commonly, microstructural banding, which is composed of ferrite-pearlite phases, will increase the ability to withstand hydrogen blistering. Despite that, it should be noted that microstructure is just one factor that can contribute to pipeline failure [14].

Another factor contributing to pipe rupture was operational defects, followed by corrosion thinning. Corrosion thinning arises from two significant factors: external and internal sources. The external factors leading to pipe rupture encompass sub-factors, such as cathodic protector failure, soil erosion, coating failure, and inadequate anti-corrosion measures. However, soil erosion was determined to have a less association with pipe rupture than the other factors. Although internal factors are considered contributing factors, their impact remains comparatively minor when contrasted with external ones. This minor impact is due to the pressure exerted by soil overburden on buried pipelines is negligible in comparison to the pressure exerted within. The sole factor considered in this investigation is the internal pressure that is applied to thin-walled conduits that are experiencing corrosion [15]. Compared to the FTA, the most obvious explanation is that BN represents the most likely condition of all variables based on the factors of occurrence. The BN helps to identify weak links and provides a thorough foundation for system risk analysis than the basic cut-sets.

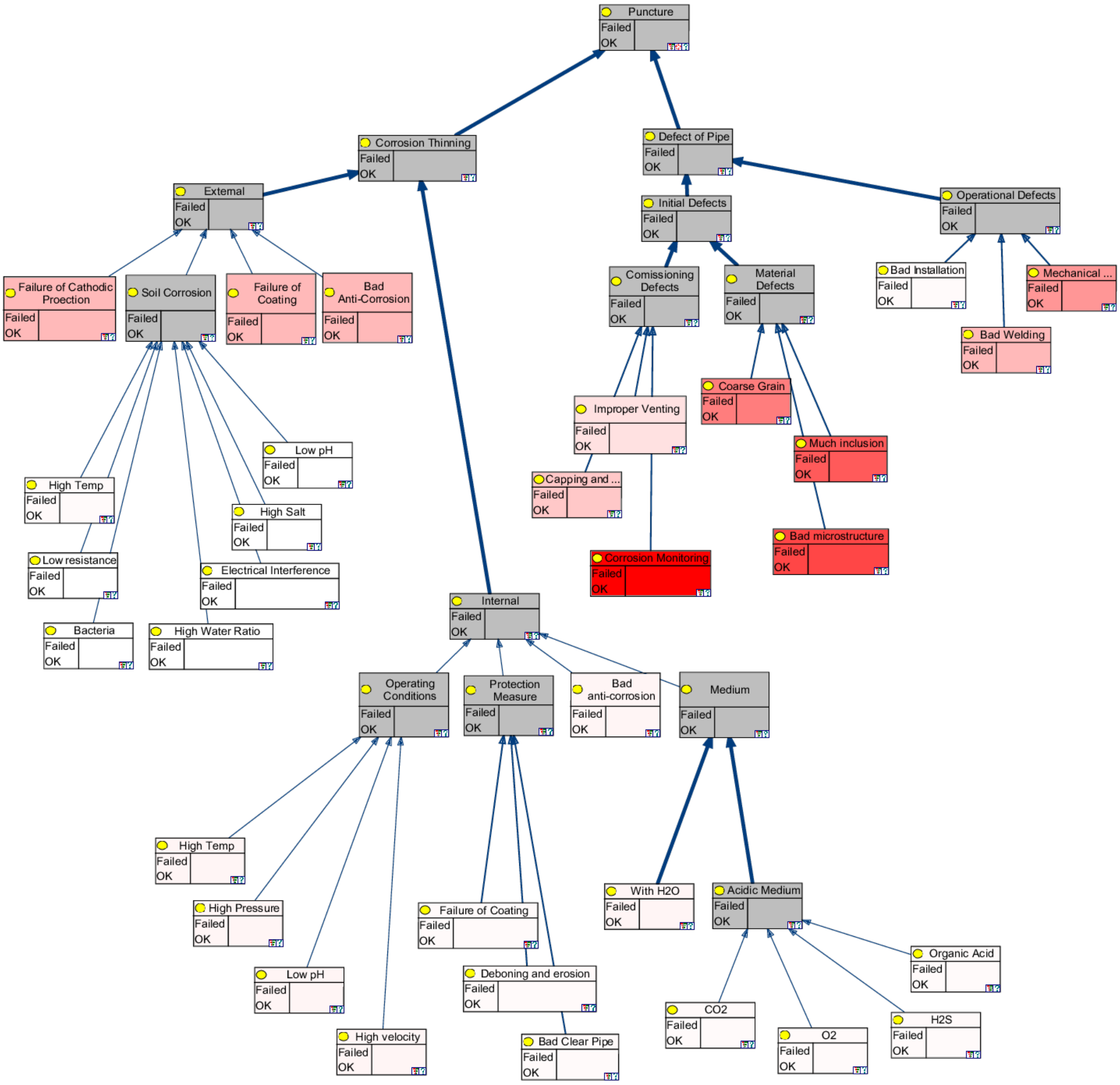

Fig. 9 *Sensitivity analysis of BN model*

4. Conclusions

The results of the Bayesian Network model have demonstrated its capability to effectively predict pipeline failure by leveraging fault tree and failure reliability data. Using existing published pipeline failure data, the model has successfully transformed complex relationships between various input variables into a coherent and informative predictive framework. Although both FTA and BN techniques produced comparable estimates for event occurrence probability, the BN could revise prior views regarding the factors by incorporating new information and updating the probabilities accordingly. By incorporating a wide range of factors and failure mechanisms, the model offers a comprehensive approach to assessing the possibility of pipeline failure incidents. The model results will offer valuable insights and recommendations for mitigating the risk of pipeline failure, adhering to standard guidelines. Pipeline operators and decision-makers can leverage this predictive model to make informed decisions, reducing the likelihood of failure and minimizing its impact.

This research is significant as it improves the understanding of pipeline failure mechanisms and providing a practical tool for risk management and decision-making in the industry. By facilitating proactive measures and preventive actions, the Bayesian Network predictive model aids in safeguarding pipeline infrastructures and ensuring reliable operations. Overall, the Bayesian Network model's performance in predicting pipeline failure represents a significant advancement in pipeline integrity management. It not only adds to the scientific understanding of failure mechanisms but also offers practical applications for ensuring the reliability and safety of pipelines. As a result, this research contributes to improving the efficiency of risk management protocols, ultimately minimizing the environmental, financial, and societal consequences of pipeline failures.

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Conflict of Interest

There is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Omar Mohamed, Muhammad Noor Hisyam, Deprizon Syamsunur;* ***data collection:*** *Omar Mohamed, Muhammad Isha Ismail, Muhammad Azrief;* ***analysis and interpretation of results:*** *Omar Mohamed, Muhammad Noor Hisyam, Noor Safwan Muhamad;* ***draft manuscript preparation:*** *Omar Mohamed, Chow Xi Enna. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Knoope, M. M. J., A. Ramírez & A. P. C. Faaij (2013) Economic optimization of CO_2 pipeline configurations, *Energy procedia,* 37, 3105-3112, https://doi.org/10.1016/j.egypro.2013.06.196

[2] Priyanka, E. B., S. Thangavel & Xiao-Zhi Gao (2021) Review analysis on cloud computing based smart grid technology in the oil pipeline sensor network system, *Petroleum Research,* 6(1), 77-90, https://doi.org/10.1016/j.ptlrs.2020.10.001

[3] Senouci, Ahmed, Mohamed S. El-Abbasy & Tarek Zayed (2014) Fuzzy-based model for predicting failure of oil pipelines, *Journal of Infrastructure Systems*, 20 (4), 04014018 https://doi.org/10.1061/(ASCE)IS.1943-555X.0000181

[4] Vitali, Matteo, Cristina Zuliani, Francesco Corvaro, Barbara Marchetti & Fabrizio Tallone (2022) Statistical analysis of incidents on onshore CO_2 pipelines based on PHMSA database, *Journal of Loss Prevention in the Process Industries*, 77, 104799, https://doi.org/10.1016/j.jlp.2022.104799

[5] Kumari, Pallavi, Qingsheng Wang, Faisal Khan & Joseph Sang-Il Kwon (2022) A unified causation prediction model for aboveground onshore oil and refined product pipeline incidents using artificial neural network, *Chemical Engineering Research and Design*, 187, 529-540, https://doi.org/10.1016/j.cherd.2022.09.022

[6] Dai, Lianshuang, Dongpo Wang, Ting Wang, Qingshan Feng & Xinqi Yang (2017) Analysis and comparison of long-distance pipeline failures, *Journal of Petroleum Engineering* 2017, https://doi.org/10.1155/2017/3174636

[7] Lam, Chio & Wenxing Zhou (2016) Statistical analyses of incidents on onshore gas transmission pipelines based on PHMSA database, *International Journal of Pressure Vessels and Piping*, 145, 29-40, https://doi.org/10.1016/j.ijpvp.2016.06.003

[8] Percarpio, Katherine B., B. Vince Watts & William B. Weeks (2008) The effectiveness of root cause analysis: what does the literature tell us?, *The Joint Commission Journal on Quality and Patient Safety,* 34(7), 391-398, https://doi.org/10.1016/S1553-7250(08)34049-5

[9] Korb, K. B., & Nicholson, A. E. (2010) Bayesian *artificial intelligence*, CRC press, https://doi.org/10.1201/b10391

[10] Morato, Pablo G., Charalampos P. Andriotis, Konstantinos G. Papakonstantinou & Philippe Rigo (2023) Inference and dynamic decision-making for deteriorating systems with probabilistic dependencies through Bayesian networks and deep reinforcement learning, *Reliability Engineering & System Safety*, 235, 109144. https://doi.org/10.1016/j.ress.2023.109144

[11] George, Priscilla Grace & V. R. Renjith (2021) Evolution of safety and security risk assessment methodologies towards the use of bayesian networks in process industries, *Process Safety and Environmental Protection*, 149, 758-775, https://doi.org/10.1016/j.psep.2021.03.031

[12] Przytula, K. W., & Milford, R. (2006) An efficient framework for the conversion of fault trees to diagnostic Bayesian network models, *IEEE Aerospace Conference*, 14, https://doi.org/10.1109/AERO.2006.1656103

[13] Baig, Ahmed Ali & RiszaRuzli (2014) Estimation of failure probability using fault tree analysis and fuzzy logic for CO_2 transmission, *International Journal of Environmental Science and Development,* 5(1), 26.

[14] Xu, Jintao, Rui Ding, Muye Li, Tao Dai, Mengyan Zheng, Tao Yu & Yang Sui (2022) A new Bayesian network model for risk assessment based on cloud model, interval type-2 fuzzy sets and improved DS evidence theory, *Information Sciences,* 618, 336-355, https://doi.org/10.1016/j.ins.2022.11.011

[15] Sulaiman, Nurul S. & Henry Tan (2020) Probability analysis of damages to subsea pipeline, *Process Safety Progress,* 39, 12125, https://doi.org/10.1002/prs.12125

[16] Asadian, M., M. Sabzi & SH Mousavi Anijdan (2019) The effect of temperature, CO_2, H_2S gases and the resultant iron carbonate and iron sulfide compounds on the sour corrosion behaviour of ASTM A-106 steel

for pipeline transportation, *International Journal of Pressure Vessels and Piping,* 171, 184-193, https://doi.org/10.1016/j.ijpvp.2019.02.019
[17] Baroudi, Uthman, Anas A. Al-Roubaiey & Abdullah Devendiran (2019) Pipeline leak detection systems and data fusion: A survey, *IEEE Access*, 7, 97426-97439, https://doi.org/10.1109/ACCESS.2019.2928487
[18] Ohaeri, Enyinnaya, UbongEduok & Jerzy Szpunar (2018) Hydrogen related degradation in pipeline steel: A review, *International Journal of Hydrogen Energy*, 43, 31, 14584-14617, https://doi.org/10.1016/j.ijhydene.2018.06.064
[19] Wasim, Muhammad & Milos B. Djukic (2022) External corrosion of oil and gas pipelines: A review of failure mechanisms and predictive preventions, *Journal of Natural Gas Science and Engineering*, 100, 104467, https://doi.org/10.1016/j.jngse.2022.104467
[20] Zhu, Xian-Kui (2021) A comparative study of burst failure models for assessing remaining strength of corroded pipelines, *Journal of Pipeline Science and Engineering*, 1(1), 36-50, https://doi.org/10.1016/j.jpse.2021.01.008