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FINAL PROJECT REPORT

Demonstration of a Multianalytic Risk Management Tool for the California Pipeline Industry

Edmund G. Brown Jr., Governor
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PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division manages the Natural Gas Research and Development Program, which supports energy-related research, development, and demonstration not adequately provided by competitive and regulated markets. These natural gas research investments spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

The Energy Research and Development Division conducts this public interest natural gas-related energy research by partnering with RD&D entities, including individuals, businesses, utilities and public and private research institutions. This program promotes greater natural gas reliability, lower costs and increases safety for Californians and is focused in these areas:

- Buildings End-Use Energy Efficiency.
- Industrial, Agriculture and Water Efficiency
- Renewable Energy and Advanced Generation
- Natural Gas Infrastructure Safety and Integrity.
- Energy-Related Environmental Research
- Natural Gas-Related Transportation.

Demonstration of a Multi-Analytic Risk Management Tool for the California Pipeline Industry is the final report for the Demonstration of a Multi-Analytic Risk Management Tool for the California Pipeline Industry project, grant number PIR-15-016, conducted by DNV GL, a global quality assurance and risk management company, with the assistance of the University of California Los Angeles (UCLA) as a sub-contractor. The information in this report contributes to the demonstration of an advanced risk assessment method as a part of the Energy Commission's Natural Gas Pipeline Safety and Integrity Management Research initiative.

For more information about the Energy Research and Development Division, please visit the CEC's research website (www.energy.ca.gov/research/) or contact the CEC at 916-327-1551.

ABSTRACT

Maintaining natural gas pipeline safety involves making decisions based on multiple sources of information. Integrating information from these diverse sources – real-time data from sensors, older data stored in databases, incident reports, and expert knowledge – into a single framework can be very difficult. To address this challenge, DNV GL created a Multi-Analytic Risk Visualization method to combine information, regardless of its source or degree of uncertainty, to help comprehensively anticipate, prioritize, and manage threats to natural gas pipeline systems in California.

This report provides the activities for modeling two threats chosen by the project's industry partner, Southern California Gas Company. DNV GL, University of California, Los Angeles (UCLA) and Southern California Gas Company selected two pipelines to test the MARV™ method and identified the data needed for the models. DNV GL then developed an external corrosion Bayesian (a type of statistical model) threat model and UCLA developed a Bayesian third-party damage threat model for gas transmission pipelines. The industry partner's confidential data was used for the models to identify the leading indicators: parameters that should be monitored to control the threat.

Keywords: Bayesian Network, cathodic protection, disbondment, external corrosion, forecasting, in-line inspection, Markov process, MARV™, Monte Carlo, natural gas, pipeline, Poisson process, risk assessment, sensitivity analysis, statistical analysis, third party damage

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EXECUTIVE SUMMARY

Introduction

Uninterrupted natural gas supply is vital to California's economy. Nearly one-third of the state's total energy demand is met by natural gas, which is the main source of generating electricity and in 2012 accounted for about 43 percent of all generation. California's intrastate natural gas pipeline system consists of about 10,500 miles of onshore transmission pipeline in addition to gathering and distribution lines. Given California's reliance on natural gas, maintaining and preventing damage and assessing any risks to the pipeline infrastructure is critical. For example, the external corrosion of buried metallic on-shore pipes has been identified as a serious threat to the mechanical integrity of this infrastructure. Congressionally-funded research conducted between 1999 and 2001 determined that the corrosion-related cost associated with the transmission pipeline industry was about $5.4 billion to $8.6 billion a year.

DNV GL, collaborating with the B. John Garrick Institute of Risk Sciences at the University of California Los Angeles and Southern California Gas Company, demonstrated a new risk management method for pipelines. This risk management method, the Multi-Analytic Risk Visualization (MARV™) method allows for more effective, systematic, and verifiable decision-making using all the knowledge and data available to the pipeline company. Many risk assessment approaches are used by pipeline companies. However, as suggested by the 2016 report by the Safety and Enforcement Division of the California Public Utility Commission, these risk models can be improved to reflect the failure probabilities more realistically, be transparent, and have common measures for comparison. An important aspect of improved risk models is a more defensible approach to estimating failure probabilities such as understanding failure mechanisms, integrating diverse knowledge of a pipeline system including internal and external expert knowledge, accounting for uncertainties in the data and automatically learning from sensors, past failures, near misses, and erroneous predictions.

Project Purpose

This project demonstrated the MARV™ method to help anticipate, prioritize, and manage pipeline threats comprehensively to assess the safety and integrity of natural gas pipelines in California. Although risk constitutes probability and consequence, the focus of the proposed project improves the probability aspect of risk. A Bayesian Network (a type of statistical model) approach is used to estimate the probabilities of failure. This project (1) customized the existing Bayesian Network models for corrosion and mechanical threats to the California natural gas pipeline system, (2) demonstrated and validated the advanced risk assessment method by applying it to a natural gas pipeline system of a major Californian pipeline company, and (3) transferred the knowledge gained by openly publishing and presenting the project's results and lessons learned to the industry, government and public sector.

Project Results

DNV GL demonstrated a threat model that has the ability to make threat predictions on a gas pipeline using industry data. The threat model or MARV™ method uses software to show the sections of the pipeline on a map that are most at risk. DNV GL identified indicators that must be monitored to mitigate external corrosion, identified third party-damage probabilities, and created a method that identifies the most useful data using a cost-benefit analysis.

The pipeline industry currently uses many different methods for risk assessment, including qualitative to quantitative methods. Unfortunately, qualitative and semi-quantitative approaches, such as risk indexing, are impossible to validate and are not predictive. The fully quantitative approaches have too much reliance on in-line inspection results. Therefore, these probability threat predictions are inaccurate, especially for pipelines that cannot be inspected and verified. Also, many quantitative risk assessment methods require large amounts of data. The MARV™ method developed in this project overcomes many of these limitations.

The MARV™ method connects causes to their effects through probabilistic models and data. Thus, the MARV™ method is useful if there are many factors leading to a threat, including those that cannot be modeled by a single analytical model. This is the case for external corrosion of pipelines which is the result of a complex set of interactions between soil parameters, water, and pipeline coatings. If a single threat, such as fracture can be completely modeled analytically, then the MARV™ approach is not needed. Even in such a case, the results of the analytical model can be integrated within the MARV™ framework.

Since the Bayesian method used in the MARV™ method can update the probabilities based on new information when available, the MARV™ probability estimation process can be started when only small amounts of data are available. The statistical sensitivity of the probability estimation to causative threat factors can be used to prioritize the collection of additional data. Since the MARV™ method can be updated with new data, it can be integrated with sensors to perform real-time risk assessments. For example, third party damage sensors can be integrated with MARV™ for continuous monitoring and evaluation of threats.

The MARV™ method also predicts and shows the results in a probabilistic distribution format with clear uncertainty (that is, it generates all possible outcomes with corresponding probability). This is different from conventional modeling approaches that use deterministic values to provide narrowly defined results and ignore other possible outcomes.

Southern California Gas indicated that the MARV™-based decision-making approach can help pipeline operators determine what data is most useful and answer questions such as "What data would reduce uncertainty of threats the most?", "What data should we gather first?" and "When do we have enough data?".

Project Benefits

The risk management method improves risk assessment by consolidating and integrating scattered expert knowledge and uncertain data to capture new failure processes. This new method will help pipeline operators better detect potential pipeline failures, and enable more effective decision-making regarding the pipeline failure risks. Although the main benefits of the method are not quantifiable, based on the historical trends of protecting life, property and the environment and if the tool can prevent two incidents per year, it will save gas operators $12 million annually. Southern California Gas has had a number of discussions about obtaining the tool and using the model for other pipelines. While a commercial product is not yet available, one is being developed. At this time, the model is provided as a service and is not being sold as a commercial software tool. However, there is interest by the recipient team in incorporating this in a suite of software tools and eventually selling it commercially.

CHAPTER 1: Project Purpose and Approach

Project Purpose

Natural gas pipelines, which are essential to California's economy, are subject to a complex combination of threats that can affect pipeline safety and security. These threats can cause unanticipated pipeline failures that pose a danger to the public and cause economic hardship. Pipelines are subject to natural forces such as seismicity and soil movement, and are located in different terrains with varying topography, ground cover, and climates. In addition, they are often hidden from sight in crowded areas along with other utility assets that can encroach on them and interfere with their protection systems. While these pipelines transport oil or gas, they also carry impurities and corrosive substances such as hydrogen sulfide and carbon dioxide that can affect pipeline integrity.

A reliable pipeline safety and integrity management system requires a comprehensive risk assessment method to predict these dynamic and interactive threats. The overall goal of this project was to demonstrate an advanced risk assessment method that can comprehensively anticipate, prioritize, and manage pipeline threats to help ensure the safety and integrity of natural gas pipeline systems throughout the state.

DNV GL has developed a risk assessment method called Multi-Analytic Risk Visualization (MARV™) specifically tailored for pipeline threat assessment. The risk assessments approach is probabilistic and calculations are performed using a Bayesian Network, also referred to in this report as Bayesian Belief Network. The Bayesian Network is created by identifying the complex cause-consequence relationships of multiple variables that lead to various pipeline failure modes and threats. Moreover, the method allows linking various types of knowledge, data, and failure modes in a quantitative and transparent way. DNV GL has implemented and demonstrated the feasibility of the Bayesian Network method for a number of oil and gas pipeline companies around the world. To achieve the project goal, the specific project objectives are to:

- Customize the existing corrosion and mechanical threats Bayesian Network models to the California natural gas pipeline system.
- Demonstrate the advanced risk assessment method by applying it to a natural gas pipeline system with a major Californian pipeline company.
- Transfer the knowledge gained by openly publishing and presenting the project's results and lesson learned to the industry, government and public sector.

Bayesian Network Approach

This project focuses on using a Bayesian Network method to model the probability of threats to pipelines. The pipeline risk management approaches can be grouped into four major categories:

- Qualitative or semi-quantitative approaches such as, risk matrices, indexing systems, and bow-tie methods: These approaches are highly subjective, especially for assessing the likelihood of failures and they do not adequately represent the complex interactions among causative factors. Most critically, they cannot anticipate failures which have not occurred.

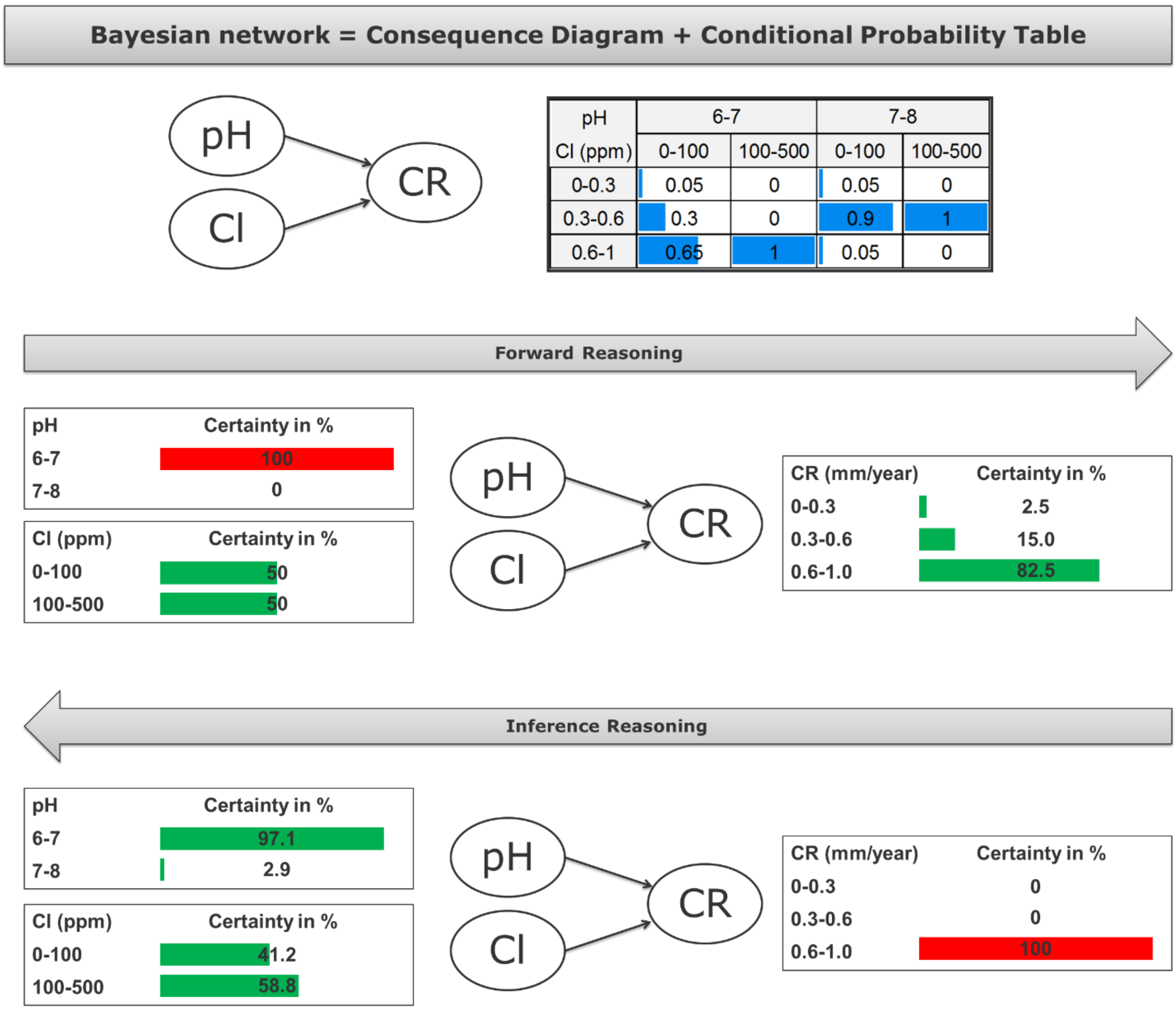
- Statistical data driven approaches such as, the traditional quantitative risk assessment methods: They tend to aggregate failure statistics so that the fundamental causative factors leading to failures are not known. They require a lot of failure data and are inadequate in predicting new failure modes.
- Model-based approaches: These link input data to output performance through mechanistic or empirical models which are then combined with various sampling schemes, such as the Monte-Carlo technique, to derive probability of failures. Although such physics-based approaches are powerful, they require enormous computational power for some complex systems and are generally too slow for real-time risk management.
- Hybrid approaches: These techniques combine elements of statistical, model-based, and expert-driven approaches.

Among the hybrid approaches, the Bayesian Network approach, embedded in MARV™, is able to represent a complex interactive system in a graphical intuitive format. The basis of the Bayesian Network method is the capability of linking multiple causes and consequences through conditional probability relationships as illustrated in Figure 1.

In this overly simplified example, the pH and chloride concentration (for example, in a soil environment) are linked to the corrosion rate of steel through the conditional probability table and graphically represented as nodes in a network. An advantage of Bayesian Network method is that even if pH and chloride concentrations are not known precisely (represented by 50 percent probability for two different ranges of these factors), the probability of corrosion rate can be estimated (upper part of Figure 1). A further advantage of the Bayesian Network is that if the corrosion rate is precisely known (for example, through inspection), the probabilities of pH and chloride concentration can be estimated by reverse inference using Bayes theorem (lower part of Figure 1). The conditional probability table shown in the figure can be derived either from physics-based models or expert elicitation.

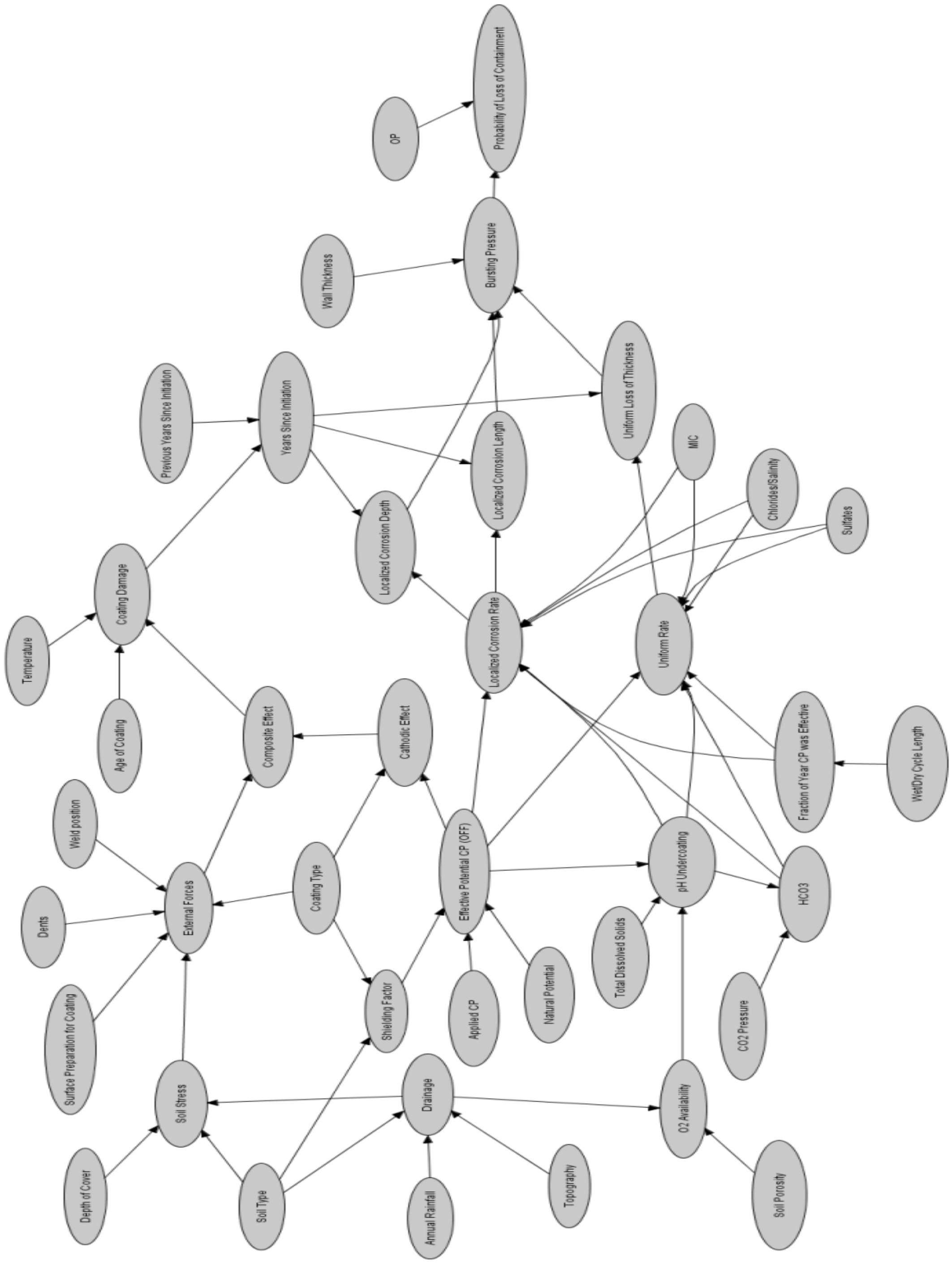
Although Bayesian Networks have been used for quite some time in diverse fields, the application of the Bayesian Network model to pipeline risk management is new and has been pioneered by DNV GL (Ayello, Sridhar, Koch, & Jain, 2014) (Ayello, Guan, & Sridhar, Corrosion Risk Assessment Using Bayesian Networks – Lessons Learned, 2016). The Bayesian Network for a pipeline threat is more complex for an external corrosion threat (Figure 2).

Figure 1: Simplified Example of a Bayesian Network



Source: DNV GL

Figure 2: Bayesian Network of External Corrosion Threat for a Pipeline

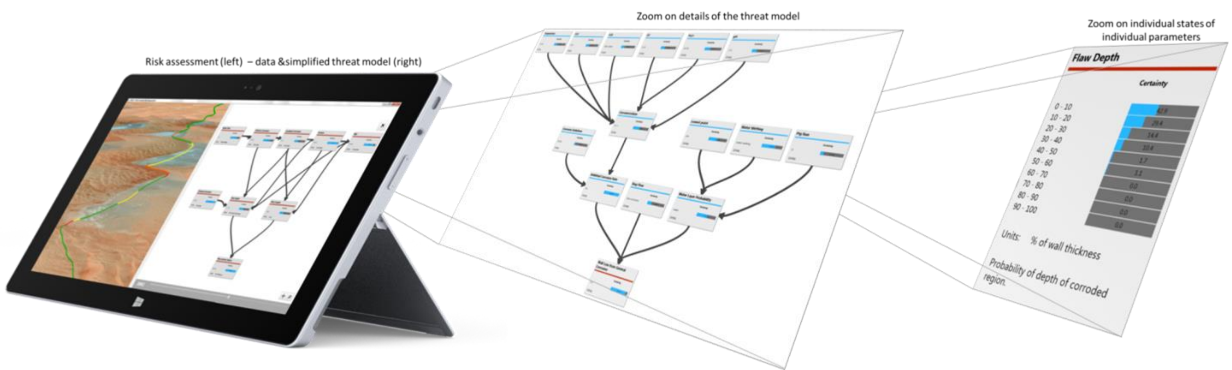


Source: DNV GL

A particular advantage of a Bayesian Network approach is that additional factors can be added, such as direct current stray current effects which were added to this Bayesian Network. The Bayesian Network is intuitive, graphical, and transparent enabling a variety of stakeholders to question and improve it. The probability distribution of any node can be compared to field data to demonstrate assumptions and update the model. A specific challenge in using such a complex Bayesian Network (and for that matter any risk assessment method) for a pipeline requires entering location-specific data along 100's of miles of pipeline.

DNV GL has developed a tool to rapidly input pipeline data along a pipeline and to present the resulting probabilities along the pipeline in a visualizer. Another challenge is in presenting the results of a risk assessment to different stakeholders. High-level decision makers wish to obtain an overview of risk along a pipeline rapidly, for example, through color coded map regions. Technical experts wish to drill down into the model to examine data and model assumptions. Field personnel may wish to see the results of specific actions they take on calculated probabilities. DNV GL has developed MARV™ as a layered tool that presents different levels of details depending on the desired resolution of information. More recently, others have applied the Bayesian Network approach to different pipeline threats (Shabarchin & Tesfamariam, 2016).

Figure 3: Layered Information in MARV™ for Communication to Different Decision Makers



Source: DNV GL

The large number of nodes in pipeline cases often results in large conditional probability tables that require both efficient design of Bayesian Network and computational techniques. B. John Garrick Institute for the Risk Sciences at UCLA, a partner in this proposal, has pioneered the development of efficient computation techniques.

CHAPTER 2:
Pipeline External Corrosion

Pipeline External Corrosion Threats

There are three primary reasons for the focus on the threat from pipeline external corrosion: potential cost and pipeline integrity consequences, regulatory requirements for external corrosion control systems, and challenges associated with quantitatively assessing pipeline external corrosion rates and the probability of failure.

Potential Consequences

The external corrosion of buried metallic on-shore piping has been identified as a serious threat to the mechanical integrity around the world (Sánchez & Kowalski, 2016). In the United States, a congressionally funded research project conducted between 1999 and 2001 determined that the corrosion-related cost associated to the transmission pipeline industry was approximately $5.4 billion to $8.6 billion annually (Thompson & Beavers, 2006) (Corrosion Costs and Preventive Strategies in the United States, 2002).

Difficulty of Control

The requirement for an external corrosion control system is dictated by governmental regulations and is a part of the design specifications and operating parameters. The design of the external corrosion control system depends on pipeline design, operating factors (operating temperature and pressure, designed life), external environment, and geographic location. A proven method of external corrosion control of buried or submerged steel pipelines is the application of coating supplemented by cathodic protection (CP) (Standard Practice Control of External Corrosion on Underground or Submerged Metallic Piping Systems, 2013). When a balance between the coating condition and the level of CP is maintained, adequate external corrosion control can be achieved. External corrosion normally occurs when adequate balance between the coating condition and the cathodic protection level cannot be established, and the rate at which external metal loss occurs is typically controlled by the environment in contact with the steel surface exposed at coating "holidays" (defects or holes) or under an unbonded section of coating. For buried pipelines, this environment is mainly controlled by soil, groundwater movement and composition, products from the electrochemical reactions (reduction and oxidation), and the type of coating. Numerous attempts have been made to establish which soil characteristics have significant impact on the rate at which metal loss occurs and also to develop predictive models for corrosion rates based on soil properties and other parameters.

Between 1911 and 1957, the National Bureau of Standards (later called National Institute of Standards and Technology [NIST] under the United States Department of Commerce[1]) conducted a large corrosion study that included the measurement of the external corrosion damage to metal coupons (strips used to evaluate a material's life expectancy) that were

[1] National Bureau of Standards is referred to in this report as NIST. See www.nist.gov.

exposed to real-world environments. These coupons were neither coated nor catholically protected. In 1910, the United States Congress authorized NIST to study corrosion caused by stray electrolytic currents and possible methods of its mitigation. Stray current corrosion was originally assumed to be responsible for all corrosion of metals buried in soil. Field and laboratory investigations were conducted over a 10-year period. The results indicated that, though serious corrosion resulted from stray currents, significant corrosion also occurred when underground metallic structures were not in the presence of stray current. NIST continued the investigation to determine the cause of this corrosion and the relation between some properties of the soil and the corrosion of buried metals. The depths of the deepest pits on approximately 90 ferrous specimens removed from each test site were used to derive the various relations to be considered later. Some of the conclusions from the NIST field tests having a direct bearing on the conduct and interpretation of burial tests are listed below (Logan, 1945):

- Soils differ greatly in corrosiveness.
- Rates of corrosion change with the period of exposure. This change is not the same for all soils.
- The depth of the deepest pit on a corroded area is a function of the area exposed.

Under apparently uniform soil conditions, the rates of corrosion of two specimens of the same material may differ widely.

Prediction Challenges

The research into mechanistic quantitative assessment of pipeline external corrosion rates and the probability of failure of a buried pipeline has not progressed significantly. The reason is the complex mechanism of external corrosion, numerous factors affecting it, and the uncertainty in the knowledge of the variables.

Due to the large complexity and uncertainty of many variables involved in the process of external corrosion, empirical models with advanced stochastic approaches have been considered to predict external corrosion risk in pipelines (Caleyo, On the Estimation of Failure Rates of Multiple Pipeline Systems, 2008) (Rivas, 2008) (Wang, 2014). For instance, Valor et al. modeled the formation and growth of pits using nonhomogeneous Poisson process and nonhomogeneous Markov process, respectively. Results were compared with laboratory data using various materials. (Valor, 2007) Additionally, Caleyo et al., built mathematical approximations to generate probability distributions using Monte Carlo simulations on corrosion pits depth and growth in buried pipes with collected field data on depth of corrosion pits and soil properties of more than 250 excavation locations. (Caleyo, Probability distribution of pitting corrosion depth and rate in underground pipelines: A Monte Carlo study, 2009) (Velazquez, 2009)

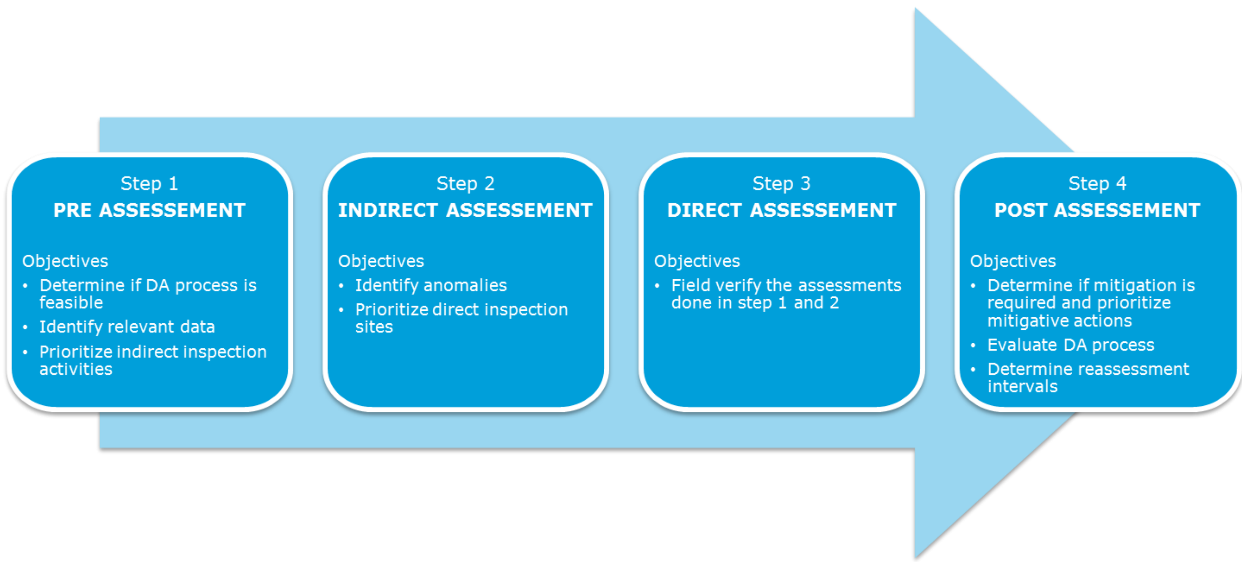
The results of the models described above are less conservative than the mechanistic and deterministic models currently available. Despite the use of some of the chemical and physical aspects of the external pipeline system in the model assumptions, these stochastic models (as acknowledged by those authors) do not account for other corrosion causing mechanisms as microbiologically influenced corrosion and stray current. As mentioned earlier, corrosion in external pipelines is a very complex and uncertain process, and to fully comprehend and predict failures it is imperative for a modeling approach that accounts for the various mechanism and possible interactions between mechanisms. Additionally, available field data to calibrate models is often scarce.

Pipeline External Corrosion Threat Control Methods

External Corrosion Direct Assessment

One of the current widely accepted pipeline external corrosion threat controls is based on a method developed by NACE International[2] (NACE) called External Corrosion Direct Assessment (ECDA). The ECDA process is a valuable tool for pipeline risk management as it shows that pipeline external corrosion preventive measures (for example, coating, cathodic protection) are working properly. The ECDA process is based on four steps (Figure 4). Implementation of the ECDA process required an understanding of external corrosion and the NACE standard practice document NACE SP502 (Pipeline External Corrosion Direct Assessment Methodology, 2002).

Figure 4: The Four Steps of the External Corrosion Direct Assessment Process



Source: DNV GL

Step 1: Pre-Assessment

The pre-assessment step of the direct assessment process helps determine if the direct assessment process is feasible, identify relevant data and prioritize indirect inspection activities. This step requires gathering data and determining which data is most useful for the next step of the ECDA process.

Step 2: Indirect Inspection

The objectives of the indirect inspection step are to identify anomalies such as water accumulation or holidays (defects or holes) and help prioritize dig sites that will be investigated during the direct examination step (step 3). This step must select dig sites that are representative of the entirety of the pipeline to avoid reaching incorrect conclusions.

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[2] See www.nace.org.

Step 3: Direct Examination

The main objective of the direct examination step is to use direct pipeline inspection to verify the assessments performed in step 1 and 2. This is often the most expensive part of the direct assessment process because it requires excavating the pipeline in multiple locations. Once direct inspection results are collected, it is important to check if field results match modeling results.

Step 4: Post Assessment

The main objectives of the post assessment step are to use data provided by steps 1 through 3 to determine if mitigation is required (and prioritize mitigation actions), evaluate the entire ECDA process, and determine the time of the next ECDA.

In-line Inspection

Another widely accepted pipeline external corrosion threat control is called in-line inspection (ILI) and is also referred to as "pigging". This practice use "smart pigs" tools that are sent down a pipeline and are propelled by the pressure of the flow, taking measurements as they travel through the pipeline. ILI provides insight into the state of the pipeline with great spatial resolution. The size of the flaws detected by the "smart pigs" is often used to predict the remaining strength of the pipeline (In-Line Inspection of Pipelines, 2010).

Value of the Multi-Analytic Risk Visualization Method

The main goal of this project was to demonstrate a new risk assessment method called Multi-Analytic Risk Visualization (MARV™), developed by DNV GL Strategic Research and Innovation. The method is novel as it uses Bayesian Networks to evaluate pipeline threats. Also, the MARV™ platform provides a quantifiable and verifiable way to incorporate the effects on risk of mitigation actions and monitoring activities. The method is particularly well suited to help the ECDA and ILI processes because the method allows (1) mechanistic models and expert knowledge to be combined, and (2) these models to use any type of information to update risk results.

How the Multi-Analytic Risk Visualization Method Complements External Corrosion Direct Assessment

Step 1: Pre-Assessment

The ECDA pre-assessment step presents two challenges to pipeline operators:

1. To successfully implement the ECDA process, pipeline operators must identify relevant data. This is difficult when data has been lost or is uncertain (acknowledging that all data has a degree of uncertainty). MARV™ risk models use distributions as inputs, so the method can be run using uncertain and unknown data. When data is uncertain, then results are uncertain. This key point allows allocation of resources to the correct data gathering activity. Through sensitivity analysis, MARV™ determines which data should be gathered to reduce uncertainty the most. Focusing on the correct data gathering activities allows using resources to gather only data that is useful to the ECDA.

2. Prioritizing indirect inspection activities and deciding which inspection technique is the most useful to the ECDA is an important part of this step. MARV™ models are displayed graphically by showing a network of causal relationships leading to pipeline failure due to external corrosion. This shows what could happen to the pipeline through cause-consequences and helps pipeline operators decide which inspection technique is the most appropriate for step 2. It is not possible to make a generic list of the data required for the ECDA because degradation mechanisms evolve over time and even interact; therefore, the data most useful to the ECDA change by location and over time. Consequently, the MARV™ method uses the data is readily available and lets the model indicate what additional data should be gathered to reduce direct assessment uncertainties. This allows resources to be focused on gathering useful data.

Step 2: Indirect Inspection

The indirect inspection step also presents two challenges to pipeline operators:

1. The main challenge in this step is to use all the pipeline data available. This includes general information collected during pre-assessment (step 1) and specific data collected during indirect inspection (step 2). Combining data in different formats and with different degrees of uncertainty is difficult but can be done using Bayesian inference. It requires making Bayesian Network models linking any type of plausibly available data with the physics of the pipeline, all linked though causal relationships. Consequently, MARV™ models do not have the required sets of inputs. MARV™ models use known parameters (with various degrees of certainties) to update unknown parameters through Bayesian inference. This allows pipeline operators to be sure that all data available has been used in the indirect assessment step of the direct assessment process, thus increasing the certainty that chosen dig sites are representative of the pipeline.
2. A second challenge is determining the correct number of pipeline excavations needed to reduce pipeline external corrosion failure below an acceptable level. Bayesian inference can be used to calculate the optimal number of excavations required to reduce threats to the pipeline.

Step 3: Direct Examination

When the predictions resulting from step 2 and the results from step 3 agree, planning mitigation actions or reassessment intervals (step 4) is straight forward. However, models and field results often disagree, and it is important to understand why. There are two causes for a mismatch between models and field results: incorrect data and unreliable models. MARV™ models cam help address these challenges in the following ways:

1. Discovering incorrect data is an important part of any risk assessment program. For example, the direct examination step might provide wall loss thickness data that are inconsistent with predicted values. This is particularly useful because this new evidence (measured external wall loss) can be propagated though MARV™'s Bayesian Network external corrosion threat model, helping to identify the erroneous data.
2. Sometimes a discrepancy between modeled results and field data comes from the threat models themselves. No model is perfect, and even though the MARV™ external corrosion model created during this project is based on the latest understanding of

external corrosion, new knowledge on corrosion is generated by the scientific community every year. Consequently, MARV™ models are able to learn from mistakes. No model should make the same error twice, thus improving models' reliability for the future ECDAs.

Step 4: Post Assessment

The MARV™ method has two features helping the final step of the ECDA process:

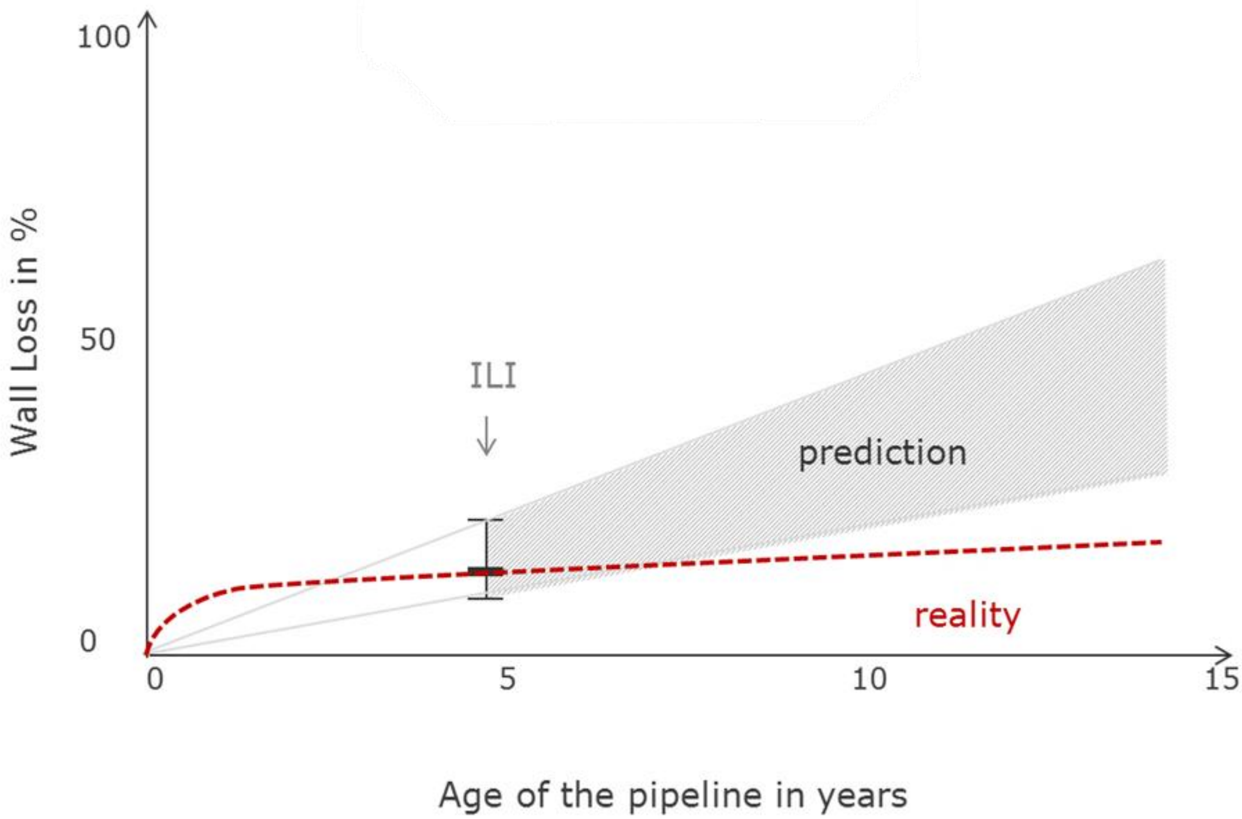
1. The first feature is the MARV™ external corrosion threat model visualization interface. Risk management is being done effectively using subject matter experts, but the impact of such risk management is not effectively communicated to all the stakeholders. Visualization of risk management of complex aging systems has been done, but at best it was simplistic, useful for some idealized systems, not real, complex systems. The MARV™ visualization tool extracts information out of the data generated by the model and makes it easy to find useful information (probability of failure, mode of failure, changes over time) by displaying this information on a touch screen interface. The MARV™ graphical representation is designed to allow hundreds of parameters to connect, making complex problems easy to understand, and can be used to decide what is the best course of action needed to mitigate the risk of failure.
2. Forecasting is an area where MARV™ models can have the most impact. Determining the appropriate date of the next direct assessment is a difficult task: if the next direct assessment is done too late, catastrophic failures might occur; but if the next direct assessment is done too soon, resources that could be spent on risk management will be wasted gathering data.

In-Line Inspection

When using ILI results, it is tempting to make a simple linear projection to forecast the state of the pipeline in time. Such a linear projection is often used to decide when to do the next inspection. A simple linear interpretation of ILI results can lead to two scenarios.

1. If corrosion was high in the early life the pipeline and then slowed down over time (depicted by the red line in Figure 5), then the next ILI will be done too early, since the prediction (depicted by the grey line) shows higher wall loss than the reality. This scenario is safe because the next ILI will be performed before it is needed. However, this scenario can lead to negative consequences:
   - When predictions are repeatedly worse than what really happens, they can lead to a false sense of safety over time.
   - Spending too many resources on pipelines that do not require inspections can drain resources from other pipelines that do.

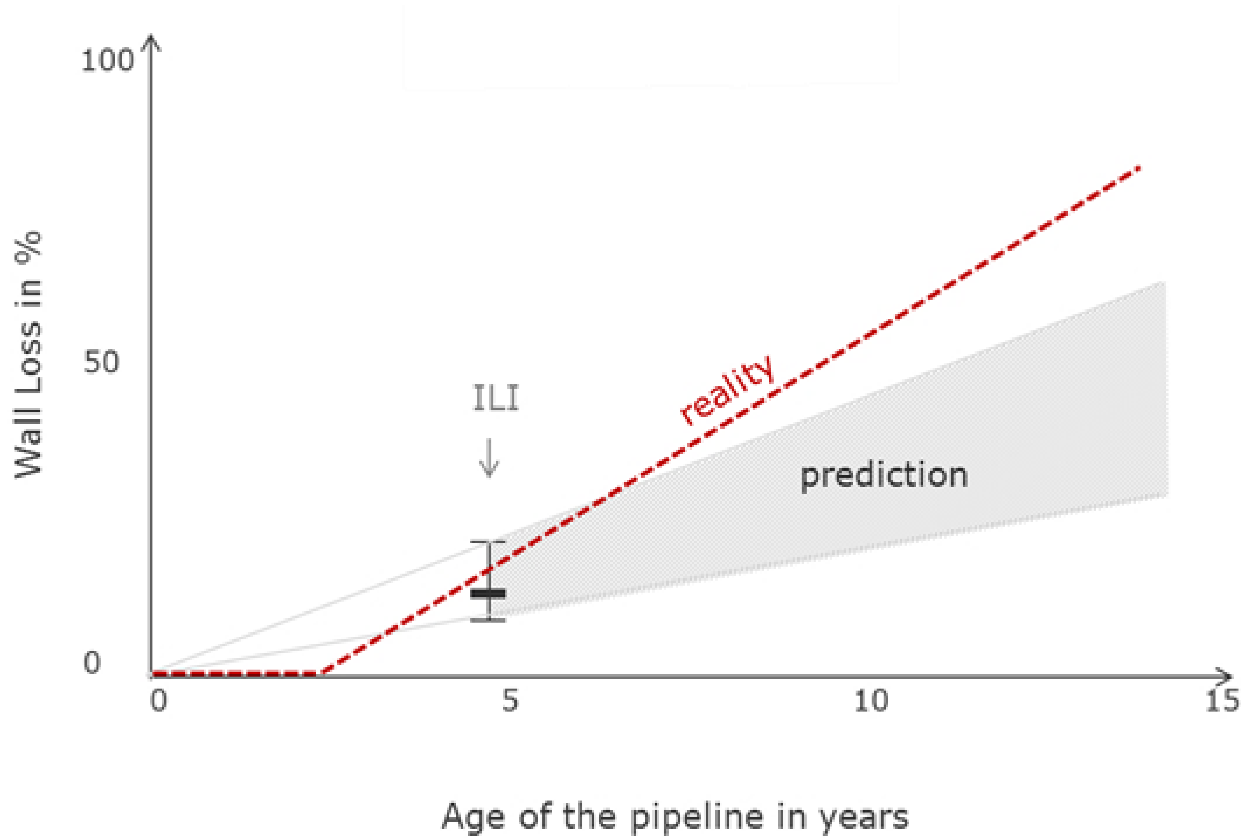
Figure 5: Safe Prediction Can Lead to Unsafe Practices



Source: DNV GL

2. The opposite scenario is also problematic. If corrosion is low in the early life of a pipeline and then increases over time (depicted by the red line in Figure 6), then the next ILI would be done too late since the prediction (depicted by the grey line) shows less wall loss than what actually occurred.

Figure 6: Unsafe Prediction Can Lead to Pipeline Failure



Source: DNV GL

The MARV™ method combines ILI data with environmental data to predict the evolution of the corrosion rate over time, thus using resources on the most useful data while reducing overall threat to the pipeline.

Modeling Pipeline External Corrosion Threat with Bayesian Networks

The Issue

Many engineers are not inclined to trust corrosion models because model results are often inconsistent with field results. There are several reasons for these inconsistencies. First, no single model is accurate in all situations. Simple empirical models work reasonably well in the conditions for which they have been developed, but provide uncertain results outside of these conditions. Also, complex mechanistic models will only work as long as all applicable mechanisms are entirely understood, which is rare for complex aging systems. Therefore, no risk model can be used indiscriminately, and engineers should be aware of each model's limitation.

Second, the input data used to run the models is never exact; often some of the data required to run the models is missing. Engineers should be aware of the uncertainty associated with each parameter that is used by the model. In some cases, the uncertainty will not affect the final results, while in other cases even a small amount of uncertainty is unacceptable.

Third, model developers often lack the operator's knowledge of the system. Practical knowledge of a specific system can be hard to quantify, since it is often in the form of cause-consequence relationships (for example, "if X happens Y is likely"). Quantifying this knowledge is valuable and necessary.

Finally, as systems age, the probability of failures increases. The number of failures, however, does not follow a simple easily predictable linear progression. The number of failures follows the so-called "bath-tub curve" in which the number of failures is relatively low for most systems during their normal life, until one day, the number and severity of failures increase suddenly and unexpectedly.

Bayesian Networks are used to solve these issues. A Bayesian Network is a type of probabilistic graphical model, which can simultaneously represent many relationships between variables in a system. The graph of a Bayesian Network contains nodes (representing variables) and directed arcs that link the nodes. The arcs represent the relationships of the nodes. Unlike traditional statistical models, Bayesian Networks do not have to distinguish between independent and dependent variables. Rather, a Bayesian Network approximates the entire joint probability distribution of the system under study. This allows the researcher to carry out "omnidirectional inference," that is, to reason from cause to effect (simulation), or from effect to cause (diagnosis), all within the same model.

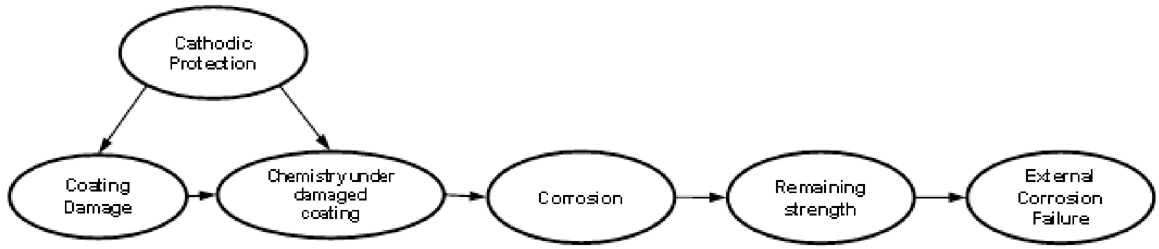
A Bayesian Network is particularly well suited to assess pipeline threats for several reasons:

- The graphical representation of Bayesian Networks shows all cause-consequence relationships leading to pipeline failure, making the best course of action to reduce the probability of failure clear to engineers.
- While a problem in most modeling frameworks, data uncertainty is not a problem for Bayesian Network which have been developed to reason under uncertainty. Consequently, the lack of data is not a problem for the MARV™ method as the models can run with uncertain and missing data.
- The model predicts all possible outcomes rather than one outcome. The variability in the possible outcomes arises from uncertain data. When certain data is added to the model, outcomes have low variability; when uncertain data is added to the model, possible outcomes have a higher variability. Variability of the outcome helps determine the best course of action. In a high risk/high variability situation, gathering more information is the most appropriate course of action (risk might be reduced simply by gathering data). On the other hand, in a high risk/low variability situation, gathering data will not help so risk mitigation in the best course of action. Understanding variability can also help with deciding what data should be gathered and what data is not necessary, thus saving on data gathering cost.

Original Pipeline External Corrosion Model

External corrosion of buried pipelines is the result of a complex set of interactions between the soil, groundwater, coating, cathodic protection, pipeline design and construction, and material related factors, such as mill scale and welds. The eventual failure can occur either through gradual leakage of products or the burst of a pipeline depending on the flaw size, the fracture properties of the material, and internal pressure. The external corrosion Bayesian Network developed by DNV GL assesses the probability of failure of a buried pipeline due to external corrosion. A schematic layout of the model structure is shown in Figure 7: Overview of the Original External Corrosion Model.

Figure 7: Overview of the Original External Corrosion Model



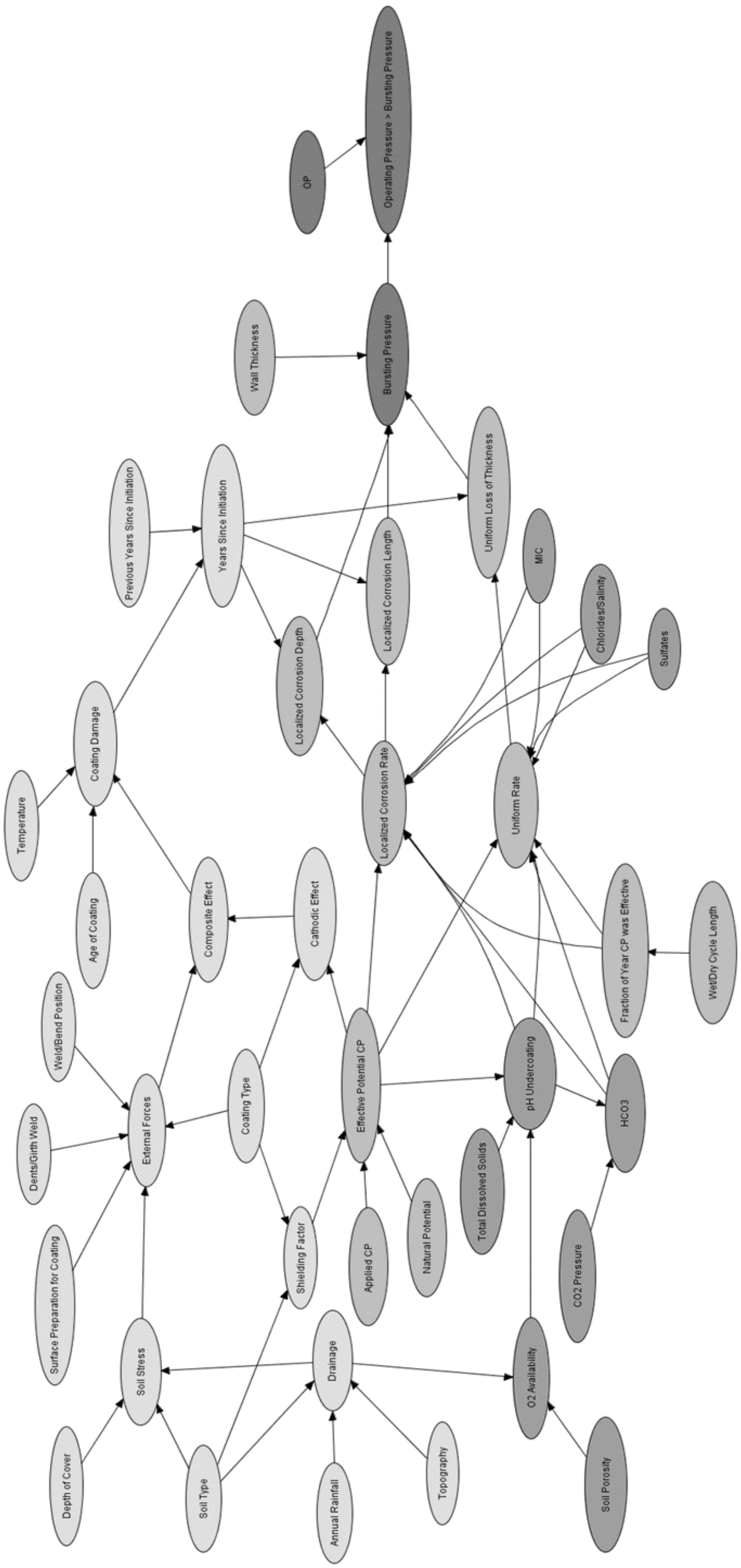
Source: DNV GL

The model is divided into six modules:

1. Cathodic Protection (CP): The CP module corresponds to the probability distribution of the level of CP applied to the pipeline based on the information about CP history, close-interval potential survey data, soil properties, mill scale, coating type (to account for shielding), wet and dry cycles, stray currents, and formation of galvanic cells due to diverse characteristics of the steel surface or the soil. The level of CP influences the external corrosion through coating damage and the chemistry developed under the damaged coating.
2. Coating Damage: The Coating Damage module estimates the probability that the coating has damaged in a given section. Coating damage depends on several factors, such as soil stress, cathodic disbondment (loss of adhesion between coating and the metal substrate), age of coating, manufacturing defects, drainage, topography, soil type, coating type, operating temperature, etc.
3. Chemistry under Damaged Coating: The environment that is generated under the damaged coating is quantified in the Chemistry under the Damaged Coating. That environment depends on the CP potential, coating permeability, the soil properties such as total dissolved solids, oxygen availability, pH, and soil carbon dioxide pressure.
4. Corrosion rates: The Corrosion module assesses the probability distribution of corrosion rates (uniform and localized corrosion). The severity of the corrosion rates will depend on the concentration of aggressive species such as chloride ions, sulfate ions, and bacteria.
5. Remaining Strength: The Remaining Strength module indicates the probability distribution of the estimated bursting pressure at which the pipeline will fail.
6. External corrosion failure: Finally, the External Corrosion Failure module estimates the probability of failure due to external corrosion for a given pipe section at one year intervals. When the operating pressure exceeded the bursting pressure, the pipeline is assumed to fail.

The full Bayesian network resulting from the above modules is more complex and is shown in Figure 8.

Figure 8: Complete Original Bayesian Network Model of External Corrosion Threat



Source: DNV GL

New Bayesian Network Threat Model for Pipeline External Corrosion

Industry Partner Requirements

After discussion with the industry partner and other pipeline operators, three major modifications of the pipeline external corrosion Bayesian network threat model were required:

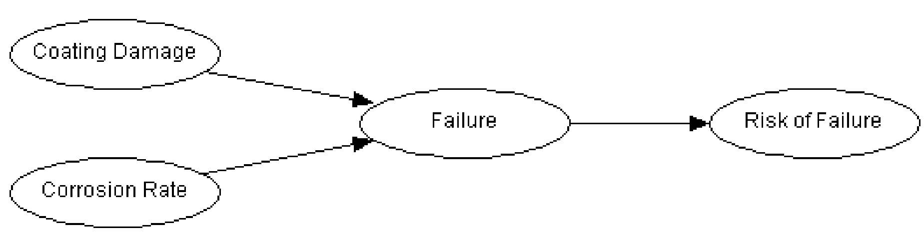
1. Simplification of the model: parts of the original model used information that is not used by United States pipeline operators and therefore should be removed from the model (Swati, Sanchez, Guan, Ayello, & Sridhar, 2015).
2. Ability to use all data available: the model should be able to use all data available to United States pipeline operators that can influence external corrosion.
3. Conversion to British Units: nodes in the model should be modified from the international system unit to more commonly used British Units.

New Model Overview

Although the physics of the pipeline external corrosion threat model are very similar to the original model (that is, cause-consequence relationships), the structure of the model (groups of nodes) has been simplified to fewer groups, as shown in Figure 9:

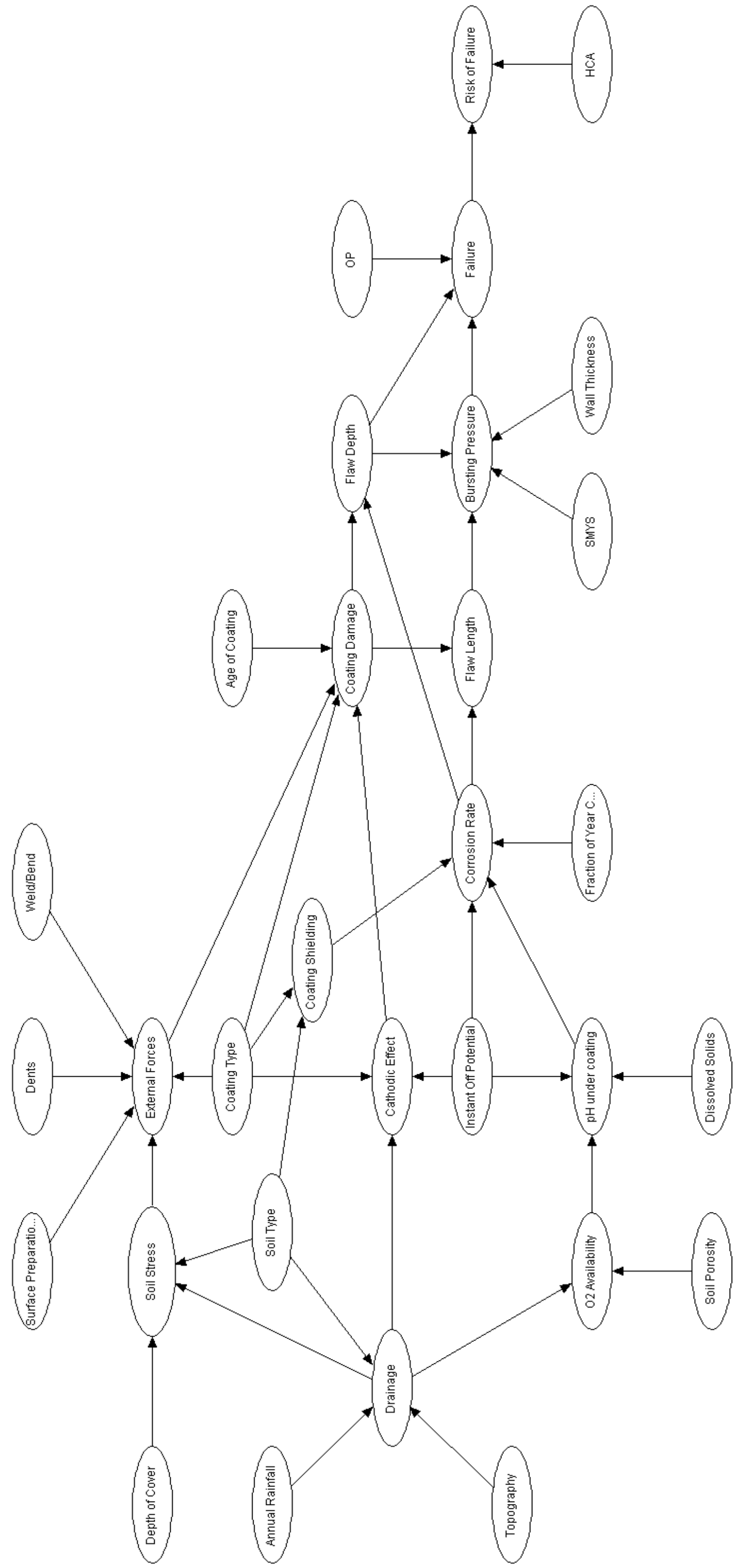
1. Coating damage module
2. Corrosion rate module
3. Failure module
4. Risk of failure module

Figure 9: Overview of the Modified External Corrosion Model



Source: DNV GL

Figure 10: Bayesian Network Model for Gas Pipeline External Corrosion Threat



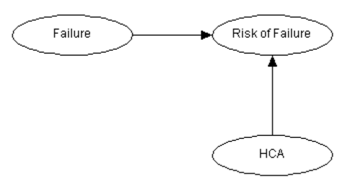
Source: DNV GL

New Model Details

Risk of Failure Module

The risk module was added to the original external corrosion pipeline threat model because the High Consequence Area (HCA) is part of the data provided by industry partner. HCAs are commonly found close to populated areas (for example, a shopping center), but in some instances, rivers, streams, lakes, and tribal land might be considered as an HCA. The risk module adds information to the probability of failure calculated by the previous module and results in a risk score. The model still allows the user to see the calculated probability of external corrosion. The risk of failure depends on the type of failure evaluated in the previous model (pipeline burst has more impact than leaks) and the presence of a HCA (HCA has more effect on the risk of failure than no HCA). Technical Advisory Committee members requested that the risk module be very simple since pipeline operators have their own ways to assess consequence of failures.

Figure 11: Pipeline External Corrosion Threat Model: Risk Module

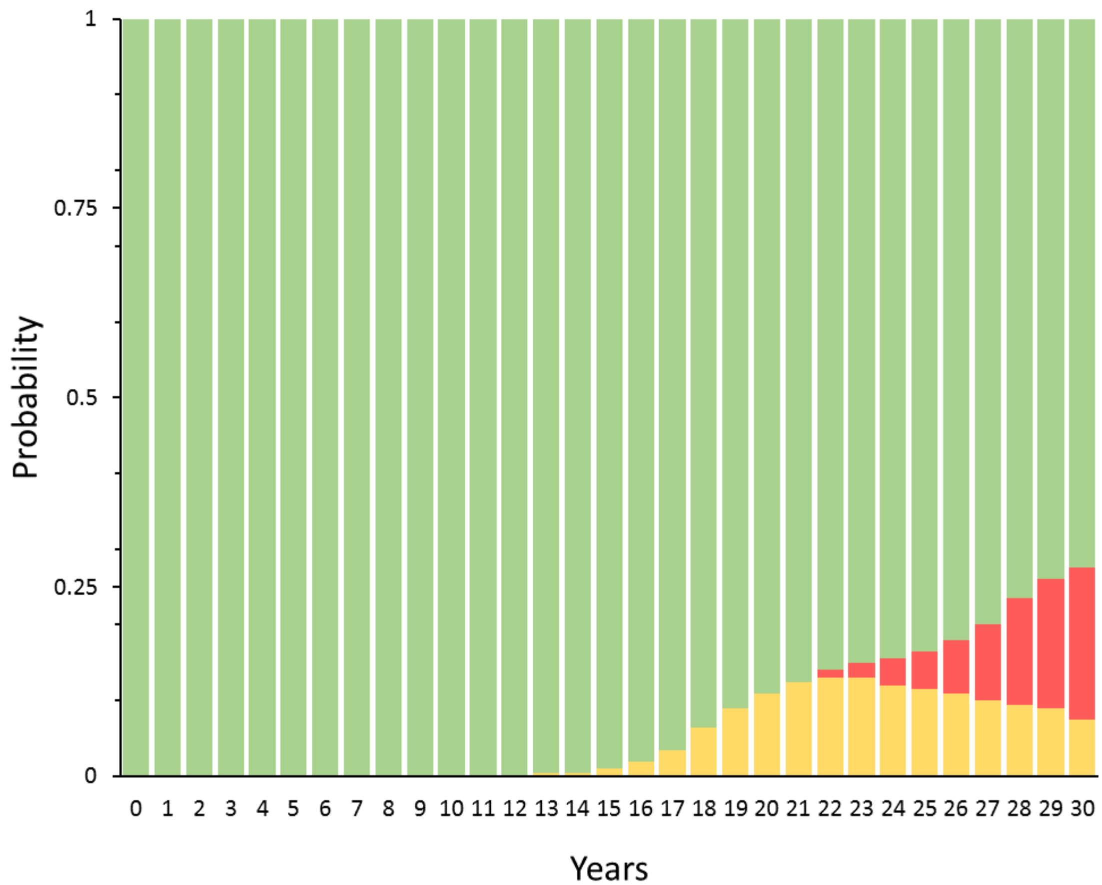


Source: DNV GL

Model inputs are:

- HCA: Probability that a pipe section is in an HCA. The MARV™ method could also be used to calculate the potential impact circle of a pipeline failure, but this is out of the scope of this project.
- Failure: This node calculates the probability of pipeline failure – a leak or a burst pipeline – due to external corrosion. However, even this node can be an input. If it is known that a pipe section failed, it is possible to enter this evidence to infer other inputs. The current limit value of wall loss is 80 of original pipeline wall thickness. Therefore, the model could predict that a pipeline will leak before it suffers a more catastrophic pipeline burst (Figure 12).

Figure 12: Example of Evolution of Leak (Yellow) and Burst (Red) Probabilities as a Function of Time. Green Represents the Probability of No Failure.



Source: DNV GL

Table 1: Description of the Nodes in the Risk Module of the Pipeline External Corrosion Threat Bayesian Network Model

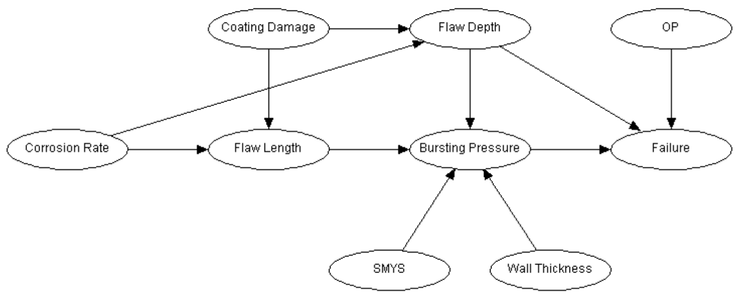
Node	Description	States	Causes	Consequences
Risk of failure	Risk ranking of the pipeline sections	High Medium Low	HCA Failure	-
HCA	Presence of an HCA	Yes No	-	Risk of failure
Failure	Probability of pipeline section leak or burst during the selected year	Leak Burst No Failure	Failure module	Risk of failure module

Source: DNV GL

Probability of Failure Module

The probability of failure module calculates the probability that a pipeline section will fail due to external corrosion (not to be mistaken with frequency of failure). The new model now differentiates between leak and burst, allowing the model to predict the probability that a pipeline section will leak due to external corrosion, burst due to external corrosion, or not fail at all (other threats excluded). The addition of all three probabilities must be equal to one (or 100 percent). The module is shown in Figure 13.

Figure 13: Pipeline External Corrosion Threat Model: Pipe Section Failure Module



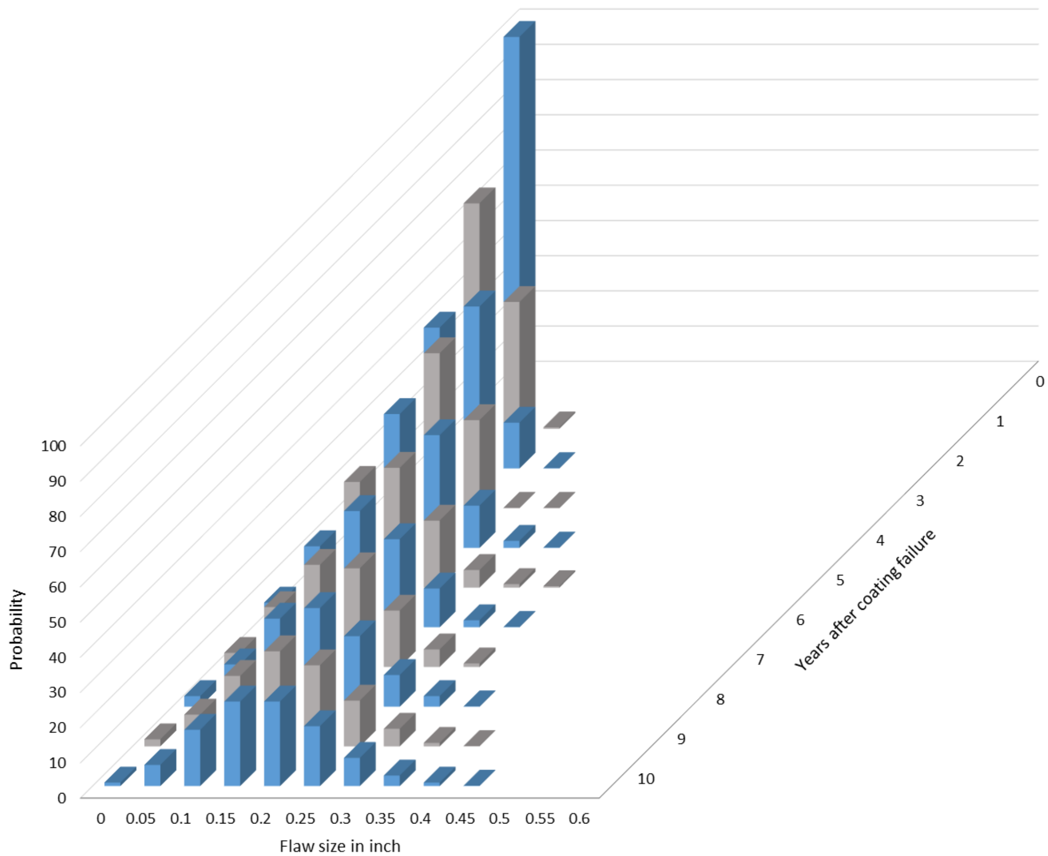
Source: DNV GL

The module first uses the localized corrosion rate and the probability of coating damage to calculate a distribution of external corrosion flaw sizes. Then, the module uses software developed by DNV GL to calculate the bursting pressure (Jaske, Beavers, & Harle, Effect of Stress Corrosion Cracking on Integrity and Remaining Life of Natural Gas Pipelines, 1996). If the bursting pressure is lower than the operating pressure, the pipeline may burst. If wall loss is higher than a value of wall thickness recommended by an industry partner, then the pipeline may leak.

The inputs of the module include:

- Operating Pressure: The pipeline operating pressure is the distribution of pipeline operating pressure over the year studied for a pipe section. The pipeline operating pressure has an impact on estimating pipeline burst due to external corrosion. The operating pressure interval range is 400 psi to 1,000 psi.
- Bursting Pressure: The distribution of the bursting pressure was calculated using a fracture mechanics model called CORLAS (Jaske, Vieth , & Beavers, Assessment of Crack-Like Flaws in Pipelines, 2002), developed by DNV GL. The distribution of the bursting pressure was made using Monte Carlo simulation to derive the conditional probability distribution tables of bursting pressure for a set of diameter, wall thickness, yield strength, and flaw dimensions (external corrosion flaw depth and length).
- Flaw depth: This node corresponds to the depth of the external corrosion flaws. Pipeline flaw due to external corrosion will grow only if the corrosion rate allows it and the pipeline coating has been damaged. Figure 14 shows an example of corrosion flaw size distribution growing for 10 years after the pipeline coating has been damaged. In the first year, there is a high certainty that the wall loss is negligible and on year 10, the flaws have grown both in size and in uncertainty.

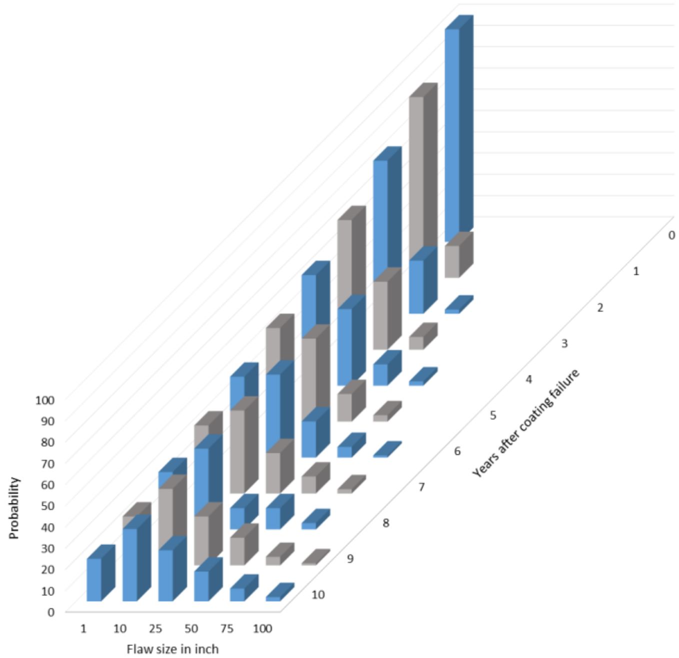
Figure 14: Evolution of Probability of External Corrosion Flaw Size (Depth) as a Function of Time After Coating Has Been Damaged



Source: DNV GL

- Flaw length: This node corresponds to the size (or length) of the external corrosion flaws. Depending on corrosion flaw size and proximity, the corrosion defects will coalesce and grow exponentially. Figure 15 shows an example the growth of pipeline external corrosion flaws over a 10-year period. In the first-year, flaws are small and the certainty is high, while after 10 years, the flaws are larger and the uncertainty in the size of the flaws has increased (distribution closest to the reader in Figure 15).

Figure 15: Evolution of Probability of External Corrosion Flaw Size (Length) as a Function of Time After Coating has been Damaged



Source: DNV GL

- Wall Thickness: The wall thickness node influences the bursting pressure value. The states of this node are based on the pipeline operator's data.
- Specified Minimum Yield Strength (SMYS): The SMYS node is the specified minimum yield strength for steel of the pipe section. The SMYS node influences the bursting pressure value. The range of SMYS is 52,000 to 70,000 psi.

Table 2: Description of the Nodes in the Risk Module of the Pipeline External Corrosion Threat Bayesian Network Model

Node	Description	States	Causes	Consequences
Failure	Probability of pipeline section leak or burst during the selected year	Leak Burst No Failure	Operating Pressure Bursting Pressure Flaw depth	Risk of failure module
Operating Pressure	Probability of operating pressure in pipe section	400-450 psi 450-500 psi 500-550 psi 550-600 psi 600-650 psi 650-700 psi 700-750 psi 750-800 psi 800-850 psi 850-900 psi 900-950 psi 950-1000 psi	-	Failure
Bursting Pressure	Probability of bursting pressure of pipe section	400-450 psi 450-500 psi 500-550 psi 550-600 psi 600-650 psi 650-700 psi 700-750 psi 750-800 psi 800-850 psi 850-900 psi 900-950 psi 950-1000 psi	SMYS Wall Thickness Flaw Length Flaw Depth	Failure

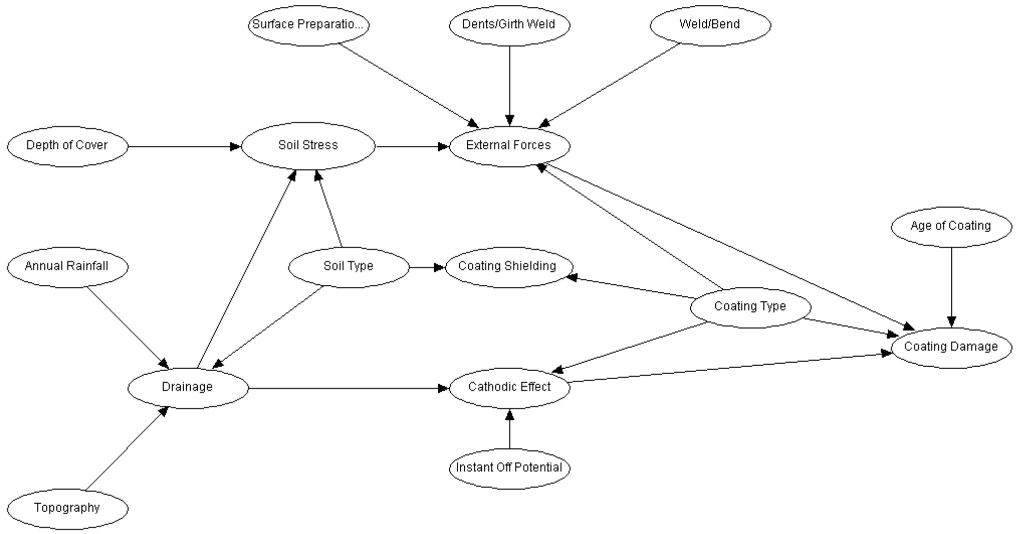
Node	Description	States	Causes	Consequences
Flaw depth	Probability of external corrosion flaw size: depth	0-0.05 inch 0.05-0.1 inch 0.1-0.15 inch 0.15-0.2 inch 0.2-0.25 inch 0.25-0.3 inch 0.3-0.35 inch 0.35-0.4 inch 0.4-0.45 inch 0.45-0.5 inch 0.5-0.55 inch 0.55-0.6 inch	Corrosion Rate Module Coating Damage module	Bursting Pressure
Flaw length	Probability of external corrosion flaw size: length	0-1 inch 1-10 inch 10-25 inch 25-50 inch 50-75 inch 75-100 inch	Corrosion Rate Module Coating Damage module	Bursting Pressure
Wall Thickness	Probability of wall thickness	0.375-0.499 inch 0.499-0.625 inch	-	Bursting Pressure
SMYS	Probability of pipe section SMYS	52000-60000 psi 60000-70000 psi	-	Bursting Pressure

Source: DNV GL

Coating Damage Module

The coating damage module of the pipeline external corrosion rate Bayesian network threat model calculates the probability that the pipeline coating is damaged at a specific location and date. Pipeline coating damage can take different forms (for example holidays, disbondment) and coating damage initiates the corrosion process if sufficient CP does not propagate into the damaged area. The coating damage module balances coating adhesive forces (such as surface preparations) with external forces (for example, soil stress) while considering the type of coating and the age of the coating. Figure 16 shows an overview of the coating damage module.

Figure 16: Pipeline External Corrosion Threat Model: Coating Damage Module



Source: DNV GL

The inputs of the model are:

- Coating Damage: Calculated probability that the pipeline's coating is damaged at specific location and date. If coating damage is observed, it is possible to use this node as an input.
- Age of Coating: The age of the coating is the age of the coating since it was applied on the metal surface. Coating repairs reset the age of the coating of the repaired pipeline section. The age of the coating increase with time. This node has a direct impact on the estimation of the "Coating Damage" node.
- Coating Type: The coating type indicates the type of protective coating that was used along the pipeline. The coating acts as a barrier against corrosion. There are various types of coatings used in the industry. The states of this node are: 3PE, Extruded Polyethylene, Polyethylene Tape, Fusion Bonded Epoxy, Asphalt and Coal Tar. This node has a direct impact on the "Shielding Factor," "External Forces," and "Cathodic Effect" nodes.
- External Forces: The external forces are a combination of the effects of the surface preparation of the coating, the dents/girth weld presence and weld/bend presence. The conditional probability table of this node was prepared with the help of subject matter experts and literature review.
- Soil Stress: The estimation of the soil stresses depends on a combination of the type of soil, drainage and depth of cover. The conditional probability table of this node was prepared with the help of subject matter experts and literature review.
- Dents: The location of the girth welds between pipe joints and the dents (mechanical deformation of pipeline due to external forces) is important to know due to the effect they have on the "External Forces" node. Girth welds require coating to be applied in the field as compared to the rest of the pipe body that may have a factory applied coating. Such field applied coatings tend to be worse in terms of their ability to create coating disbondments and shielding of CP than factory applied coatings. Similarly, the

locations of the pipeline bends are also important. The states of these nodes are: At dent/girth weld and Away from dent/girth weld.

- Surface Preparation for Coating: The purpose of surface preparation is to clean and/or abrade the pipeline metal surface for better adhesion of the coating. There are various types of surface preparation methods described in Industry standards (for example, National Association of Corrosion Engineers or NACE) and these are specified by coating manufacturers. The states of this node are: water blasting, abrasive blasting with walnut shells, abrasive blasting with silica sands, power wire brush and no preparation. This node has a direct impact on the "External Forces" node, as lack of coating adhesion due to poor surface preparation can affect coating damage probability. It should be noted that the presence of mill scale also affects the corrosion potential of the steel surface in cases where CP does not penetrate to the coating defects (for example, during dry periods when continuous water layer is absent). However, for simplicity, this second-order effect is ignored in this model.
- Cathodic Effect: Cumulative effect of potential, drainage and coating type have on coating disbondment. High CP potential is known to increase coating disbondment for certain coatings.
- Depth of Cover: This node refers to the soil cover above the pipeline. High depth of cover protects the pipeline from third party damage and facilitates the flow of current when polarizing the pipeline under a cathodic protection system. The states of this node are with the 0 meter to 5 meter range. This node impacts the "Soil Stress" node.
- Instant Off Potential: The Instant Off-Potential is the polarized pipe-to-soil potential measurement taken immediately after turning off the cathodic protection current. This potential approximates the pipe-to-soil potential without an IR drop when the current was on.[3] This node impacts the "Cathodic effect" node.
- Drainage: Probability of the type of drainage found around the pipe section, from well-drained soil to poorly drained soil. The drainage node has effects on the "Soil Stress" node and the "Cathodic Effect" node.
- Annual Rainfall: The average annual rainfall at the location of the pipe section. Rainfall is important for the understanding of the soil chemistry and its effect on corrosion rates. Wetting and drying cycles can exacerbate corrosion rate through a combination of the reduction in the duration of CP, increased access of dissolved oxygen, concentration of the electrolyte, and the creation of higher valence iron oxides that in turn increase the oxidizing potential of the environment contacting the pipe. This node has a direct impact on the "Drainage" node.
- Topography: The local topography at the pipeline right-of-way provides an indication of the water table, soil water absorption, drainage capacity etc. This node has a direct impact on the "Drainage" node. The states are: undulating, ridges, inclined, depressed, leveled and side slope.

[3] IR drop is the electrical potential difference between the two ends of a conducting phase during a current flow. This voltage drop across any resistance is the product of current (I) passing through resistance and resistance value (R).

- Soil Type: The soil type provides an indication of the soil chemical and physical properties, which would have a direct impact on the soil stress, CP shielding, and drainage. The states of this node are: sand, clay, loam and mixed soils.

Table 3: Description of the Nodes in the Coating Damage Module of the Pipeline External Corrosion Threat Bayesian Network Model

Node	Description	States	Causes	Consequences
Coating Damage	Probability that coating is damage at pipe section	Yes No	Age of Coating External Forces Coating Type Cathodic Effect	Failure module
Age of Coating	Probability of the age of the coating	0 - 5 years 5 - 10 years 10 - 15 years 15 - 20 years 20 - 25 years 25 - 30 years 30 - 35 years 35 - 40 years 40 - 45 years 45 - 50 years	-	Coating Damage
Coating Type	Probability of coating type	3PE Extruded polyethylene Polyethylene tape Fusion Bonded Epoxy Asphalt Coal Tar	-	Coating Damage Cathodic Effect External Forces
External Forces	Probability of external forces applied to the pipe section	High Medium Low	Soil Stress Dents Surface Preparation Welds/Bends	Coating Damage
Cathodic Effect	Cumulative effect of potential, drainage and coating type have on coating disbondment	High Medium Low	Drainage Instant Off Potential Coating Type	Coating Damage

Node	Description	States	Causes	Consequences
Soil Stress	Probability of soil stresses around the pipe section	High Medium Low	Soil Type Depth of cover Drainage	External Forces
Dents	Probability of a dent being present	Yes No	-	External Forces
Surface Preparation for Coating	Probability of the type of surface preparation used before application of coating on pipe section	Water blasting Abrasive blasting with walnut shells Abrasive blasting with Silica sands Power wire brush No preparation	-	External Forces
Welds/Bends	Probability of presence of a weld or bend in pipe section	Yes No	-	External Forces
Depth of Cover	Probability of the pipe section depth of cover	0 m 0-1 m 1-3 m 3-5 m	-	Soil Stress
Instant Off Potential	Probability of effective surface potential in mV (reference: saturated calomel electrode)	-500 to -650 mV -650 to -700 mV -700 to -750 mV -750 to -800 mV -800 to -950 mV -950 to -1100 mV -1100 to -1200 mV -1200 to -1500 mV	-	Cathodic Effect

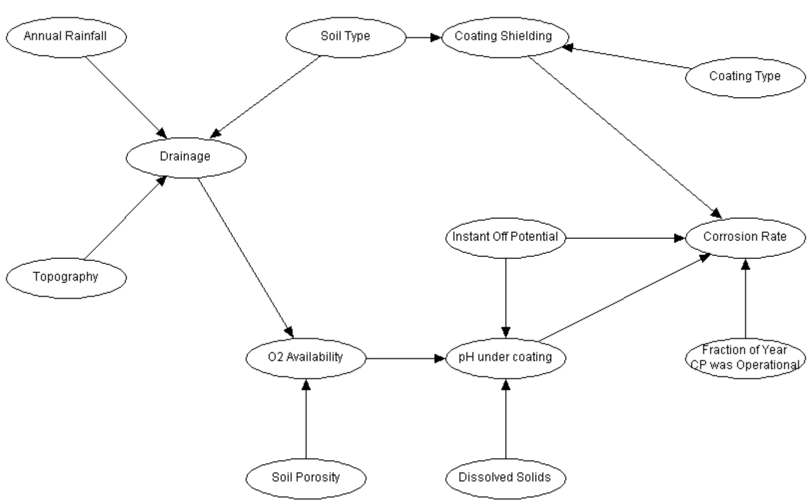
Node	Description	States	Causes	Consequences
Drainage	Probability of the type of drainage found around the pipe section	Well drained Moderately drained Poorly drained	-	Soil Stress Cathodic Effect
Annual Rainfall	Probability of the annual rainfall	1000-100 mm/year 100-10 mm/year 10-0 mm/year	-	Drainage
Topography	Probability of the type of topography above the pipeline	Undulating Ridged Inclined Depressed Level Side slope	-	Drainage
Soil Type	Probability of type of soil	Sand Clay Loam Mixed Soils	-	Drainage Soil Stress

Source: DNV GL

Corrosion Rate Module

The corrosion rate module of the pipeline external corrosion rate Bayesian network threat model calculates a range of possible corrosion for specific pipe sections and dates. Figure 17 shows an overview of the coating damage module.

Figure 17: Pipeline External Corrosion Threat Model: Corrosion Rate Module



Source: DNV GL

The inputs of the model are:

- Corrosion Rate: Field data on corrosion rates for pipeline external corrosion rates were obtained from a National Institute of Standards and Technology (NIST) report[4] (Ricker, 2006). The study assessed corrosion of mild steel coupons buried in various locations of the United States with different soil types and chemical composition (chlorides and sulfates), analyzed at frequent intervals. Results indicated the corrosion rate of the various coupons. A distribution of the values for the localized corrosion rates was used to populate the conditional probability table of the corrosion rate node. Localized corrosion rate data were used because rates are higher than for uniform corrosion. NIST data was modified using a Monte Carlo simulation approach to generate external corrosion rates for all ranges of pH, CP potential and shielding effect according to NACE standards SP0775. (Preparation, Installation, Analysis, and Interpretation of Corrosion Coupons in Oilfield Operations, 2013)
- Fraction of the Year CP was Operational: This node corresponds to the period in a year in which the CP system was operating. The states of this node range from zero (no CP at all) to one (CP system worked perfectly all year). The unit is the fraction of a year CP system was operational. This node affects the corrosion rate.
- pH Undercoating: This node affects the corrosion rate. The pH of the solution under the disbonded coatings will depend on the potential under the coating disbondment and the availability of the cations to compensate for the bicarbonates or carbonates. High pH solution is the result of reduction of oxygen or water due to cathodic protection. Therefore, enough oxygen should be available for the reduction and the CP potential should be high for alkaline conditions to prevail under the disbonded region. On the other hand, if CP does not penetrate into the disbanded region, the hydrolysis of the dissolved ferrous ions from corrosion may decrease the pH. Detailed mathematical models for the pH under disbanded coatings are available (N.Sridhar, D.S.Dunn et al. 2002, King, Jack et al. 2004, Been, King et al. 2005, Song and Sridhar 2006, Song and Sridhar 2008, Song 2010, Song 2010, Song 2012). However, for the purposes of this work, subject matter expert input was used.
- Oxygen (O_2) Availability: The amount of available oxygen in the soil is an estimation based on the type of drainage and the porousness of the soil. The available oxygen affects the pH in disbonded coating regions by its cathodic reduction.
- Dissolved Solids: The total dissolved solids correspond to the total amount of charged ions, including minerals, salts or metals, dissolved in the soil per liter of water (mg/L). This node directly impacts the estimation of the pH under the coating. The states of this node range from 0 to 800 mg/L.
- Instant Off Potential: This node is the same as the "Instant Off Potential" node described in the previous module, and has an additional effect on the corrosion rate.
- Coating Shielding: The coating shielding node accounts for the probability of developing shielding at the coating surface, which depends mainly on the type of coating and soil (essentially the resistivity of the ground water). For example, polyethylene tape shields

[4] National Institute of Standards and Technology, formerly National Bureau of Standards, www.nist.gov.

the CP from entering the disbonded region because it has a poor ionic conductivity. Combined with its shielding tendency, the polyethylene tape also undergoes significant wrinkling under differential soil stresses, creating disbonded regions.

- Soil Porosity: The soil porosity may indicate the retention of moisture in the soil and provides an indication of the oxygen permeability of the soil. Consequently, this node has an impact on the "O_2 availability" node. Generally, porous soils allow greater oxygen access to the water contacting the pipeline. Node states are 0 percent to 60 percent.
- Drainage: This node is the same as the "Drainage" node described in the previous module, but it has additional effect on the corrosion rate by influencing the amount of oxygen available around the pipe.

Table 4: Description of the Nodes in the Corrosion Rate Module of the Pipeline External Corrosion Threat Bayesian Network Model

Node	Description	States	Causes	Consequences
Corrosion Rate	Probability of the external corrosion rate value	0-2 mm/year 2-5 mm/year 5-10 mm/year 10-15 mm/year 15-30 mm/year	Fraction of the Year CP was Operational pH Under Coating Coating Instant Off Potential	Failure module
Fraction of the Year CP was Operational	Probability of the fraction of the year CP system was operational	0-0.25 0.25-0.5 0.5-0.75 0.75-1	-	Corrosion Rate
pH Under Coating	Probability of pH value under coating	6-8 8-9 9-11	Dissolved Solids O2 Availability	Corrosion Rate
O2 Availability	Probability of oxygen availability in the water around the pipe section	High Medium Low	Soil Porosity Drainage	pH Under Coating
Dissolved Solids	Probability of concentration of total dissolved solids in the ground water	0-4 mg/L 4-50 mg/L 40-110 mg/L 110-800 mg/L	-	pH Under Coating

Node	Description	States	Causes	Consequences
Instant Off Potential	Probability of effective surface potential in mV (reference: saturated calomel electrode)	-500 to -650 mV -650 to -700 mV -700 to -750 mV -750 to -800 mV -800 to -950 mV -950 to -1100 mV -1100 to -1200 mV -1200 to -1500 mV	-	pH Under Coating Corrosion Rate
Coating Shielding	Probability that the coating is susceptible to shielding	Yes No	Soil Type	Corrosion Rate
Soil Porosity	Probability of the soil porosity value	0-0.1 0.1-0.2 0.2-0.45 0.45-0.6	-	O2 Availability
Drainage	Probability of the type of drainage found around the pipe section	Well drained Moderately drained Poorly drained	-	O2 Availability
Annual Rainfall	Probability of the annual rainfall	1000-100 mm/year 100-10 mm/year 10-0 mm/year	-	Drainage
Topography	Probability of the type of topography above the pipeline	Undulating Ridged Inclined Depressed Level Side slope	-	Drainage
Soil Type	Probability of type of soil	Sand Clay Loam Mixed Soils	-	Drainage Coating Shielding

Source: DNV GL

- Annual Rainfall: This node is the same as described in the previous module. The "Annual Rainfall" node influences the corrosion rate by influencing the amount of water present around the pipe section. If sufficient water is not present to raise the water level cover the pipeline surfaces, then the CP may not propagate effectively into coating defects.

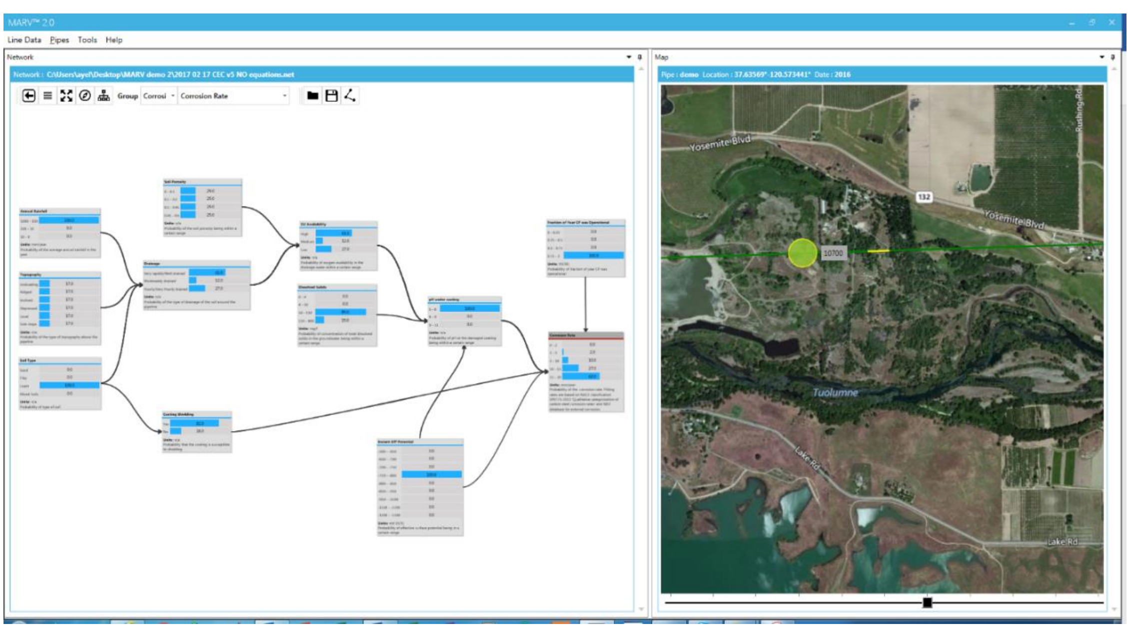
- Topography: This node is the same as described in the previous module. The "Topography" node influence the corrosion rate by influencing the amount of water present around the pipe section.
- Soil Type: This node is the same as described in the previous module. The "Soil Type" node influence the corrosion rate by influencing the amount of water present around the pipe section and the resistivity of the water.

Pipeline External Corrosion Results and Decision Making

Interface Overview

Task 3 results are delivered to the industry partner using DNV GL proprietary software called MARV™. The software has an easy-to-use touch-screen interface combining geographical maps, models, and prognostication (Figure 18: MARV™ Graphical User Interface Pipeline Threat Model and Data (left) and Results on a Map (right)). The MARV™ software allows the user to easily visualize the cause-consequence relationships between various factors that impact a threat's likelihood in a layered manner. The user can access information to the desired level of detail by a drill-down approach. Inputs and outputs of models are clearly shown on a graphical user interface. Therefore, all data are displayed with no assumptions hidden to the user, and failure modes are obvious (using cause consequence analysis). The software displays three major features: (1) the threat module window which shows the Bayesian Network model using a drill-down feature, (2) the map window which shows the location at which the threat is modeled, and (3) the time slider at the bottom right panel which allows the user to prognosticate the threat probability.

Figure 18: MARV™ Graphical User Interface Pipeline Threat Model and Data (left) and Results on a Map (right)



Source: DNV GL

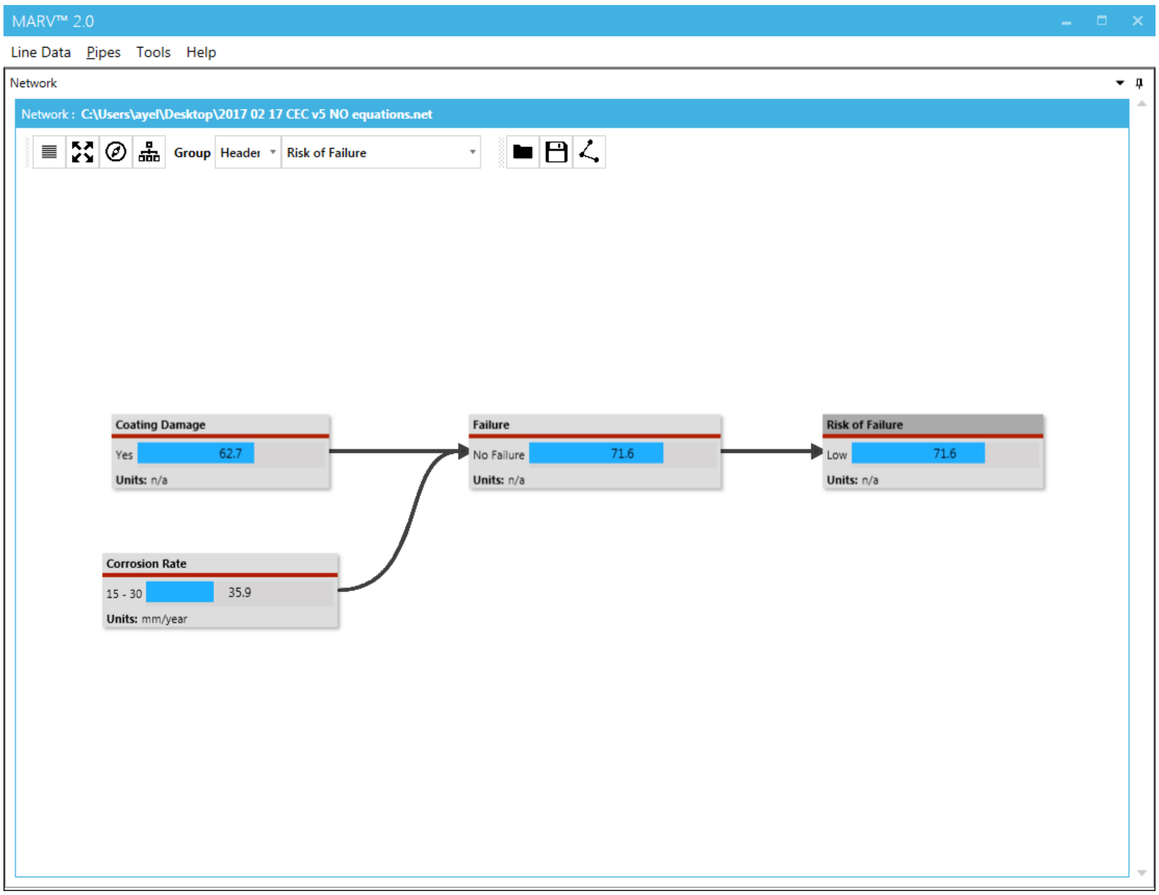
MARV™ Interface Details

Threat Model Window

The threat model window shows an overview of the pipeline threat model as described in section 2.2. The model overview shows the main mechanism of pipeline failure. It is possible to use a drill down approach to look for more information on any specifics of the threat.

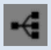
Users can click on the button "Show Group Command" to look for more information about that specific node as shown in Figure 20 to Figure 23. To return to the original viewer, click on the "back" button.

Figure 19: MARV™ Threat Model Window



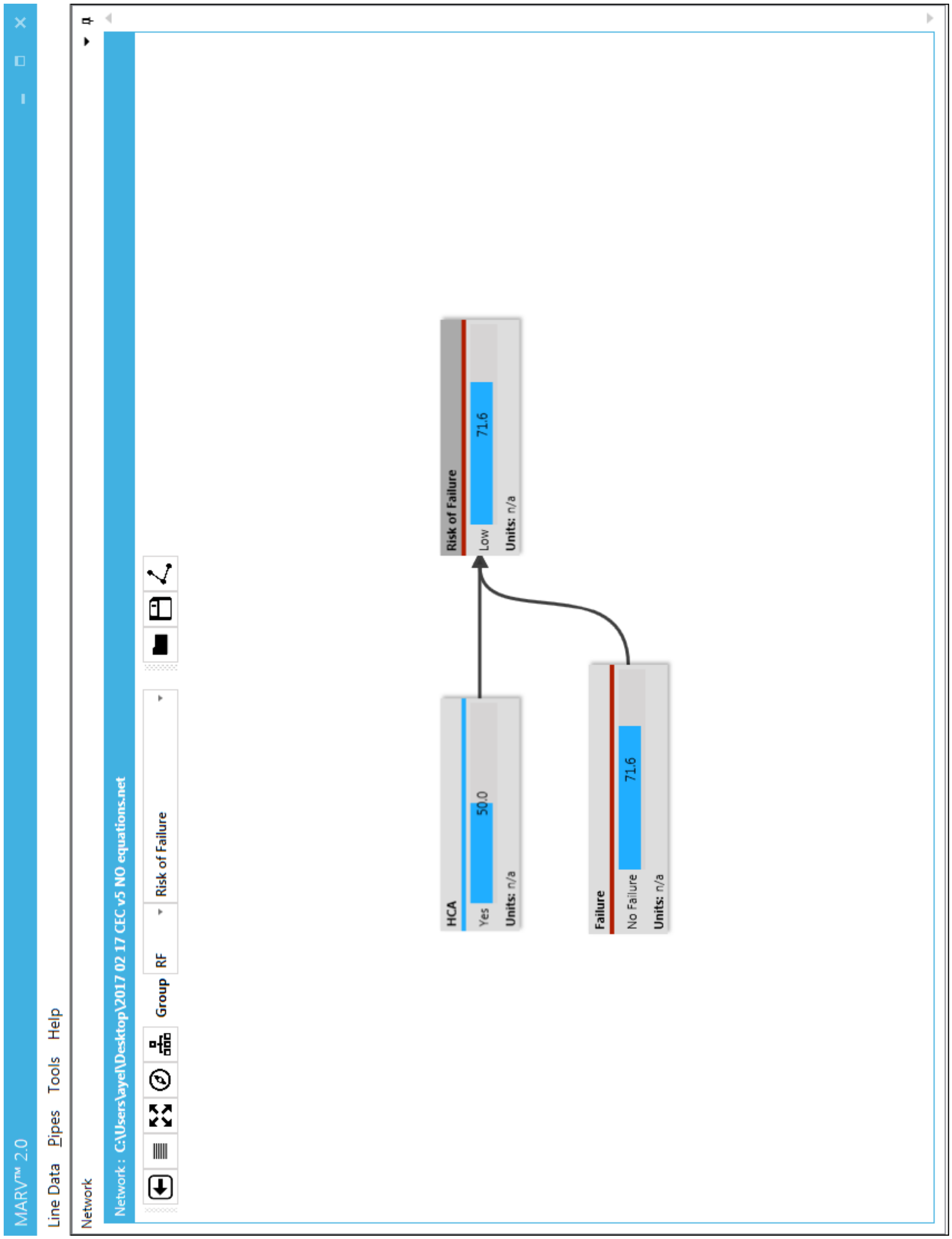
Source: DNV GL

Table 5: List of MARV™ Network Window Commands

Icon	Description
	Show Group Command. This button shows the details for the group that this node represents. When the group details are show, you can click on the back button to get back to the main view.
	Back button
	Fits the network to available space
	Show and Hide navigation pane
	Toggles automatic layout mode. When automatic layout mode is on, the application intelligently handles the position of the nodes and the user cannot move the nodes anymore. If the user wants to position the nodes this mode should be turned off.
	Expand/Collapse Command. Expands the node to a full view or collapses it to a summary view. In full view, the user can see all the possible states for that node and a short description of that node.

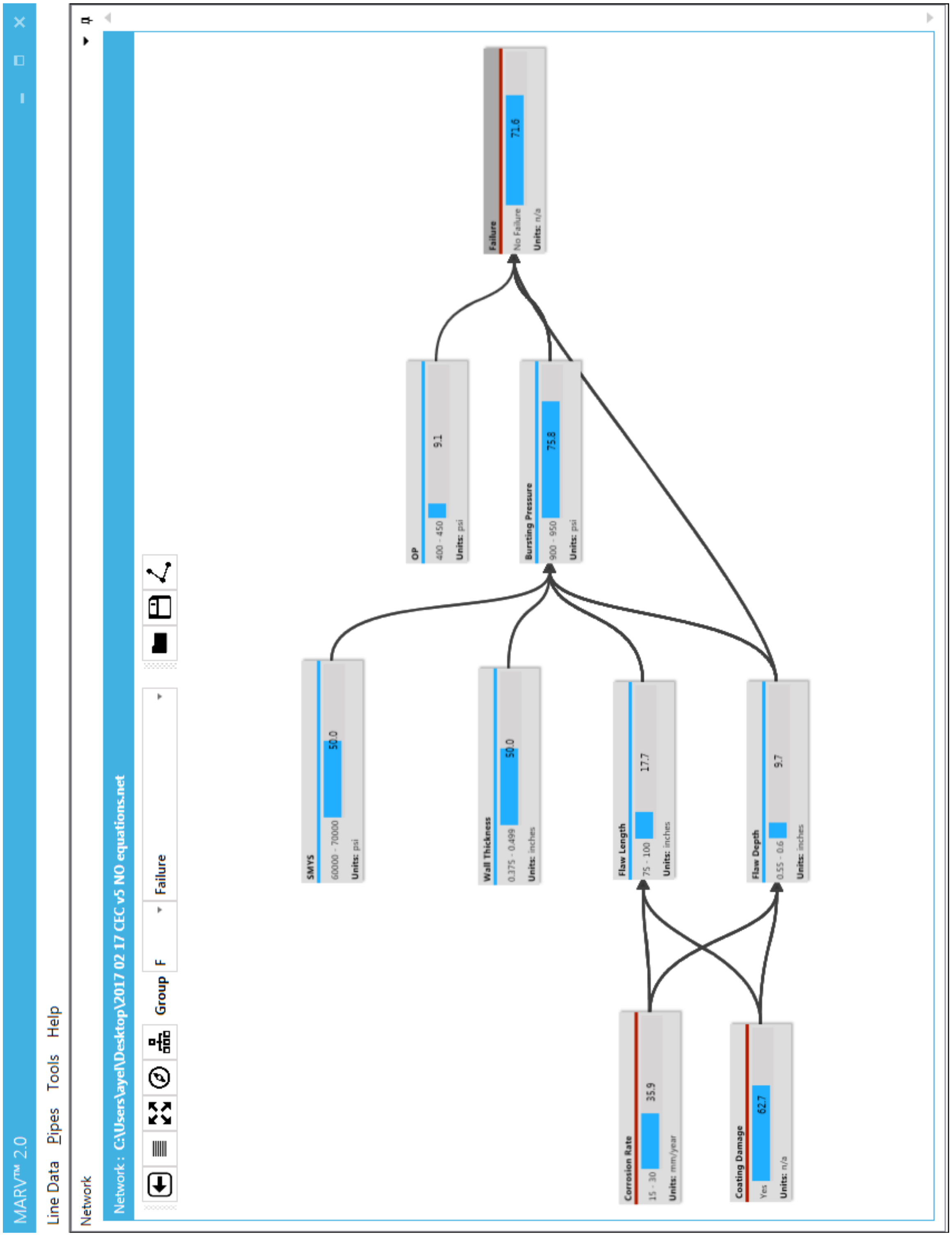
Source: DNV GL

Figure 20: MARV™ Threat Model Window: Risk Module



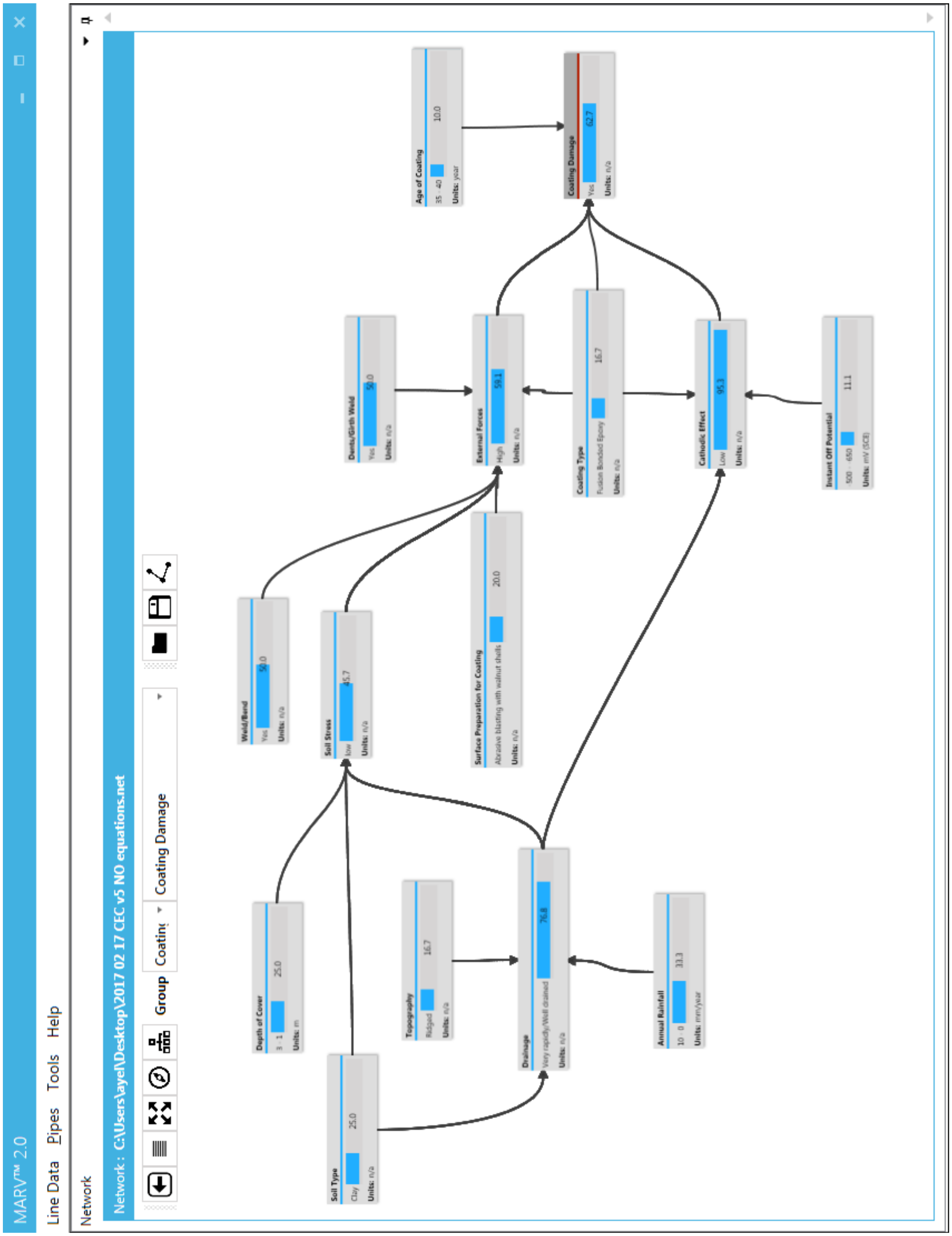
Source: DNV GL

Figure 21: MARV™ Threat Model Window: Probability of Failure Module



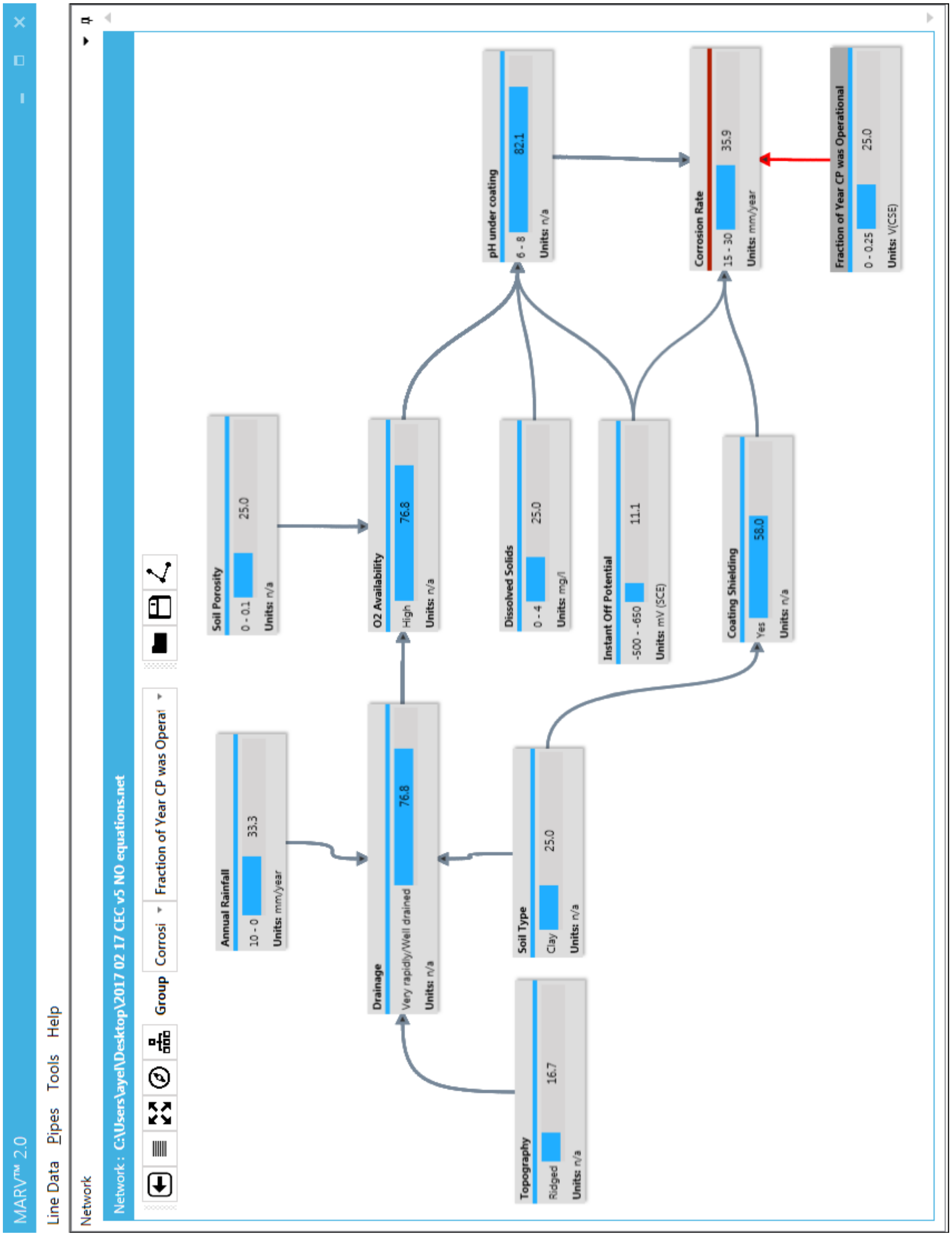
Source: DNV GL

Figure 22: MARV™ Threat Model Window: Coating Damage Module



Source: DNV GL

Figure 23: MARV™ Threat Model Window: External Corrosion Rate Module

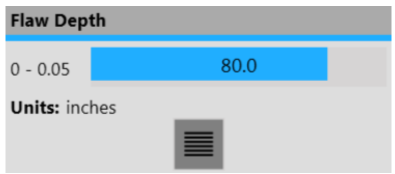


Source: DNV GL

Threat Model Nodes

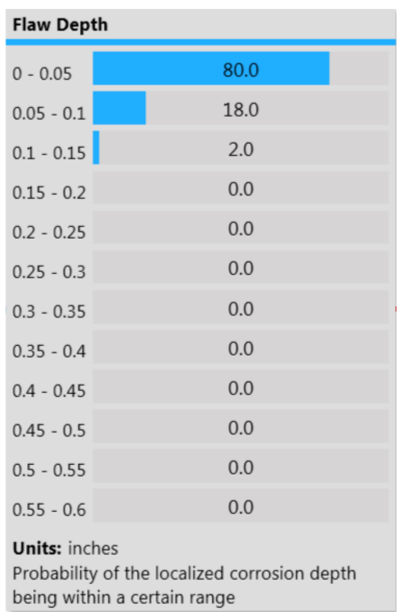
Nodes show the degree of belief in a specific variable. By default, each node shows a summary of the results. For example, "Flaw Depth" (Figure 24) shows that the most probable state for the flaw depth at the specific location (selected on the map) and the specific time (selected in the time slider) is 0 inches to 0.05 inches. The certainty of that prediction is 80 percent. For information about this node, the user can click the "expand" button and see all possible states, units, and brief description of the node (Figure 25). In this example, the flaw depth (for that specific location and time) has to be less than 0.15 inch. The external corrosion flow size could be between 0 and 0.05 inch at 80 percent probability, 0.05 to 0.1 inch at 18 percent probability or even as high as 0.1 to 0.15 inch with a 2 percent probability.

Figure 24: Collapsed Simple View of a Node



Source: DNV GL

Figure 25: Expanded View of a Node



Source: DNV GL

MARV™ Interface: Map and Time Slider

The user is able to change the location of the threat assessment (Figure 26). All data displayed in the threat window is linked to the location highlighted by a yellow circle. If the user moves the yellow circle to another location, results in the threat window are immediately updated.

Figure 26: Moving in Space (Top View Location 11000 / Bottom View Location 11085)

Source: DNV GL

The user is also able to change the date of the threat assessment (Figure 27). All data displayed in the threat window is linked to the time slider displayed on the bottom of the map. If the user moves the time slider to another date, results in the threat window are immediately updated.

Figure 27: Moving in Time (Top View 2013 / Bottom View 2020)

Source: DNV GL

Decision Making

The interface shows what could potentially happen to the pipeline. Green, yellow, and red colors on the map are only a first step to help pipeline engineers focus their attention on relevant pipeline segments. The bulk of the information is shown in the network window, where pipeline engineers can see the data (and associated uncertainties through probability density functions) and the link between events (both causes and consequences). The visual nature of the Bayesian network allows pipeline engineers to follow the effect of an input through a chain of causal relationships. This makes threats clearly visible and easy to anticipate and helps with selecting proper action to mitigate risk.

CHAPTER 3: Pipeline Third Party Damage Threat

Consequences of Third-Party Damage

Third-party activity around pipelines (for example, digging or drilling) can cause damage and pose a large risk to public safety because of the proximity of the persons to the pipeline when these incidents occur.

Between 1993 and 2012, 1630 third-party damage (TPD) incidents onshore were reported to the United States Department of Transportation's Pipeline and Hazardous Materials Safety Administration (PHMSA). These incidents caused 141 deaths and 440 injuries, and incurred $369 million in property losses (Pipeline and Hazardous Material Safety Administration, 2014). Total actual costs including repair, loss of economic production due to energy outages, increased regulatory oversight, insurance, legal settlements, and reputation loss are likely to be orders of magnitude higher than the property damage costs.

TPD is the leading cause of pipeline failure. From 1985 to 1997, 28.1 percent of all pipeline incidents were caused by TPD (Kiefner, Melosh, & Kidfner, 2001), increasing to 45.9 percent during 2002 to 2013. Approximately 26.3 percent of these incidents were caused by third party excavation alone. (Lam & Wengzing, 2016)

Unlike causes of failure like internal and external corrosion, TPD cannot be deterministically modelled. External corrosion is increasingly studied, with incrementally more sophisticated models emerging over time. These models allow an understanding of the failure mechanisms involved, which can identify effective preventive measures such as the application of coating supplemented by cathodic protection (CP) (NACE International, Standard Practice Control of External Corrosion on Underground or Submerged Metallic Piping Systems, 2013).

Understanding TPD is less a hardware reliability problem than a human reliability one. First generation human reliability analysis models used performance shaping factors that drive human error probability calculations, with more sophisticated cognitive models being used for second generation human reliability analysis models (Forester, Kolaczkowski, Lois, & Kelly, 2006). Human reliability analysis requires large amounts of information that is not available for gas and pipeline TPD scenarios. This effectively precludes the majority of human reliability analysis models, so an alternate approach is required.

However, simple empirical data analysis reveals close correlation between TPD occurrence and pipeline characteristics. For example, TPD occurrence increases when the year a pipeline was installed is unknown, (Lam & Wengzing, 2016) suggesting that the recordkeeping associated with that pipeline is inadequate. If the year of installation is unknown, it is also more likely that the exact location of that pipeline will be unknown.

Other potentially misleading trends are also apparent. For example, TPD occurrences decrease as the pipeline wall thickness increases. This makes intuitive sense, but because wall thickness is proportional (in general) to pipeline diameter as is how deep a pipeline is underground, the apparent trend between TPD occurrence and pipeline wall thickness could also be explained (at least in part) by a trend between TPD occurrence and depth of cover. It is not possible now to understand the true relationship.

TDP is also difficult to predict. Prediction requires some deterministic or mechanistic basis. A basic approach to prediction relies on previous empirical data being representative of the future. This approach is uninformative and not useful – save for perhaps calculating insurance premiums. The aim of creating a sophisticated model is to understand causality – what influences the outcome of a process in a way that allows engineers to do something about it.

The majority of literature involves simple statistical analysis of TPD, identifying trends and relationships such as the study conducted by Lam and Zhou (Lam & Wengzing, 2016). This is useful in terms of identifying potential causal relationships which does inform mitigation, but is not sophisticated or analytic. Other studies, which attempt to predict TPD, are simple, such as the 12-events fault tree of Chen et al (Chen, Davis, & Parker, 2006). Of these 12 events, 10 are "undeveloped" and require further modelling. Further, event probabilities are relatively simply drawn from empirical data, which combine with the simplistic modelling to yield little utility for current and ongoing decision making.

Relying on empirical data will never produce an accurate predictive model. The two main publicly available data sources are the PHMSA's mandatory reporting database (Department of Transportation, 2016) and the Common Ground Alliance's Damage Information Reporting Tool (Common Ground Alliance, 2015). Both data sources involve "failure events" only and are discussed in greater detail in the next section. Incidents that have the same preceding events and causes but do not result in pipeline failure never get reported. Empirical data analysis simply reports on a "conditional probabilistic" relationship given failure.

$$\Pr(C|F)$$

where $\Pr(x|y)$ is the way the probability of some event x given event y occurred, and in the expression above C is some causal factor event and F is the failure event.

For predictive modelling, this probabilistic conditionality is required to be reversed or inverted. That is, the team is interested in the probability of failure given a causal factor event.

$$\Pr(F|C)$$

The problem of reversing conditionality can be solved by applying Bayes' Theorem as follows:

$$\Pr(F|C) = \frac{\Pr(C|F)\Pr(F)}{\Pr(C)} = \frac{\Pr(C|F)\Pr(F)}{\Pr(C|F)\Pr(F) + \Pr(C|\bar{F})\Pr(\bar{F})}$$

where $\bar{F}$ is the complement of F, or the event of "not failure."

This makes empirical analysis for creating a predictive model virtually impossible, as there is no data that deals with pipeline failure not occurring when causal factor events occur. For example, it is unknown the number of "unsafe" operating events that occur but do not result in pipeline failure.

However, there remains another very useful information source: expert judgment and opinion. Bayesian analysis allows expert opinion to be incorporated into modeling – which argues for the use of a Bayesian modeling framework such as a Bayesian Network. The approaches used to develop these models are outlined in subsequent sections.

Understanding Third-Party Damage

TPD mechanisms are at this stage impossible to classify and generalize deterministically. Understanding TPD essentially requires combining information from two sources: (empirical) databases and expert judgment.

Data analysis allows trends and relationships to be identified and quantified. Empirical trends can be identified between the apparent propensity for pipeline failure and the underlying parameters. Expert opinion can point us in the right "direction" for identifying what these parameters will likely be, and for developing a causal model that can be subsequently quantified to align with empirical data.

The PHMSA database mentioned earlier is legally mandated.[5] Post-2002 data in the database is much more detailed because the form that pipeline operators were required to fill in became more complete over time. The mileage data (which breaks down pipeline configuration) has only been updated to 2013. Forms were updated in 1984, 2002, and 2010. Operators are required to report incidents to PHMSA under Part 191 of Title 49 of the Code of Federal Regulations (CFR). An incident is reportable if it meets any of the following criteria (United States Office of the Federal Register, 2013):

1. An event that involves a release of gas from a pipeline, or of liquefied natural gas (LNG), liquefied petroleum gas, refrigerant gas, or gas from an LNG facility and that results in one or more of the following consequences:
    i. A death, or personal injury necessitating in-patient hospitalization;
    ii. Estimated property damage of $50,000 or more, including loss to the operator and others, or both, but excluding cost of gas lost;
    iii. Unintentional estimated gas loss of three million cubic feet or more;
2. An event that results in an emergency shutdown of an LNG facility.
3. An event that is significant in the judgment of the operator, even though it does not meet (1) or (2) above.

Not all failure events result in incidents as defined above. It is likely that all *rupture* failure modes meet the criteria and are reported, but not all *leakage* failure modes do. A repeatedly observed shortcoming of PHMSA data is that data can only be broken down by a single attribute, meaning that dependencies are effectively hidden. For example, it is impossible to identify the percentage of pipes that are in a particular location class and have a particular diameter range.

Regarding the first event criterion, the threshold of $50,000 has not changed since 1984. Both time and inflation will increase the number of events satisfying this criterion (if all other variables and parameters remain unchanged).

The effect of these limits is quite marked. Table 6 compares apparent gas pipeline failure rates for different international regions with different reporting criteria. Those with no lower limits in reporting criteria (where every failure needs to be reported) have higher failure rates, on the order of $2.3 - 3.6 \times 10^{-4}$ failures per (km year). Those that have lower limits in reporting

[5] http://www.phmsa.dot.gov/pipeline/library/data-stats.

criteria (where only some failures are reported) have lower failure rates: 1.0 – 1.1 × 10^{-4} failures per (km year). It is conceivable that failure rate estimates based on PHMSA data alone could be an order of two to three lower than actual failure rates.

Table 6: Comparison of Gas Pipeline Failure Rates by International Reporting Regime (da Cunha, 2016)

Country or Region	Period	Failures per (km year)	Database	Reporting Criteria
Western Europe	1970-2010	3.5×10^{-4}	European Gas Pipeline Incident Data Group (EGIG)	No lower limit
United Kingdom	1962-2010	2.3×10^{-4}	United Kingdom's Onshore Pipeline Operators Association (UKOPA) Database	
Brazil	1978-2010	3.6×10^{-4}		
United States	1985-1997	1.1×10^{-4}	PHMSA	Death, injury, damage > $ 50 000
Canada	2000-2008	1.0×10^{-4}	National Energy Board (NEB) Database	Pipelines at 15 bar or more

Source: UCLA

PHMSA data divides failures into two cause categories: "Excavation Damage" and "Other Outside Force Damage." Within the "Excavation Damage" category, from 2002 to 2013 there are four sub-categories of TPD causes (da Cunha, 2016). From 2002, causes that related to TPD as per the PHMSA data base were third party excavation and other external forces (da Cunha, 2016). However, other databases include information for other proximate causes and are included here.

The Common Ground Alliance (CGA) is a member-centric organization with 1,700 members including utilities and pipeline operators. It was established in 2000 to better mitigate pipeline damage. The CGA maintains multiple databases that feed its Damage Information Reporting Tool launched in 2003. Stakeholders can voluntarily and securely submit reports on pipeline damage and near-misses that inform an interactive web page. This allows more database "fields," and by extension parameters, that can be used in model development. However, this is a voluntary endeavor which must be taken into account when interpreting the data.

The other publicly available database is the National Transportation Safety Board (NTSB) Pipeline Accident Reports (PARs). A summary of all TPD PARs is included in Appendix A to this report. The NTSB will only investigate "significant" pipeline failures, such as those that cause fatalities or a large amount of property damage. Consequently, NTSB databases cover a tiny fraction of pipeline failure events. However, PARs contain extensive analysis about preceding events which provide insight into pipeline-risky third-party activities.

Project Role in Assessing Third Party Damage Risk

The main goal of the project discussed in this report is to demonstrate a new risk assessment method. Developing a TPD Bayesian network model allows the MARV™ platform to provide a quantifiable and verifiable way to incorporate the effects of mitigation and monitoring activities on risk associated with third-party activity. Once key risk factors have been identified, their quantitative effect on risk can be calculated to inform any cost-benefit analyses. Key TPD factors identified throughout this project are:

- Pipeline robustness: Increasing the diameter, depth of cover, and wall thickness clearly had an effect in reducing the likelihood of TPD. There is an obvious relationship between the ability for pipeline strength versus typical stresses associated with TPD.
- Culture and behaviors: Public advertising and other awareness campaigns are very useful ways to positively influence third-party behavior. A reduction in TPD prevalence over time has been attributed largely to an increased likelihood for third parties to contact utilities regarding pipeline location.
- Advice and signage: Clear signage regarding the presence of a pipeline has obvious benefit in making third parties aware of pipeline locations. However, because signage typically does not indicate pipeline presence in advance to the third party, business decisions to immediately (perhaps somewhat cautiously) continue with excavation are often made in preference to delays associated with contacting the utilities.
- Physical barriers: Many studies (primarily from Europe) highlight how physical barriers can mitigate or effectively prevent TPD. Two separate studies showed that pipelines with concrete or steel slabs buried with warning tape never experienced TPD (WS Atkins Consultants Ltd, 2001). This issue is discussed in greater detail later in this report.

Modeling Pipeline Third Party Damage with Bayesian Networks

Accidents and incidents involving TPD are typically a sequence of events where each event contributes to the likelihood of or enables the next. These events are generally known based on combined expertise, which allows analysts to theoretically list and potentially model these event sequences.

Many modelling techniques, however, do not incorporate sequencing. For example, fault trees (a top-down, deductive failure analysis) do not consider one event to have occurred before another. Although it is possible for fault trees to be constructed to incorporate sequenced events, diagrammatically these events are independent events regardless of whether they were enabled by previous events. This is true of many popular reliability modelling techniques.

Event Sequence Diagrams

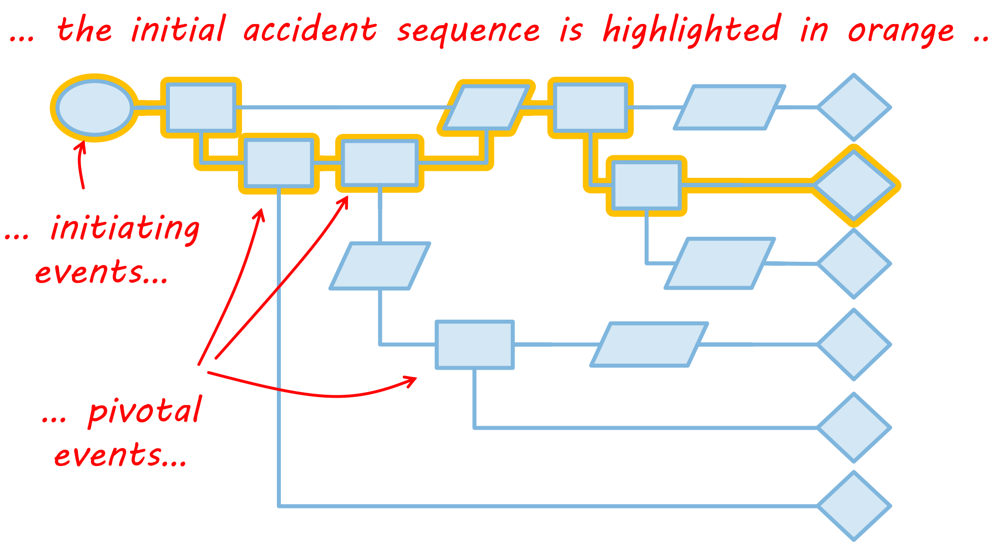
Event Sequence Diagrams (ESDs) have been used extensively in incident and accident investigation. A sequential approach to analysis aligns with human thought processes, which are the predominant root cause of TPD damage failure. The following four step approach was used to generate the TPD model.

1. Cluster Failure Event Scenarios: A literature review was conducted, along with more generic research that involved the professional network, to identify all documented

cases of TPD for which an investigation had been conducted. The NTSB was one valuable source of information.

2. Create Specific Failure Event Scenarios: For each incident identified, a specific event scenario was developed. This involved recreating the incident in terms of preceding events and decisions made by both the third parties and the pipeline operators.
3. Develop Generic Failure Event Scenarios: From the event sequences from the previous step, generic scenarios were compiled that included plausible alternatives in the sequence. This allowed "branching" sequences that in some instances avoided pipeline failure.
4. Develop Single Generic ESDs for Initiating Events: The event sequences in step 3 were combined to create a single ESD for all TPD scenarios. This was then compared with the literature regarding TPD to ensure that all possible event scenarios were included. Generally, comparison with literature confirmed the completeness of the ESD, with branches needing to be added in only a few instances. (Chen, Davis, & Parker, 2006)

Figure 28: Example of Generalized Event Sequence Diagram



Source: UCLA

While the final ESD is broken down into several discrete diagrams, they combine through linking events to create one general ESD for TPD scenarios. This ESD was extensively reviewed by experts from the NTSB and utility organizations.

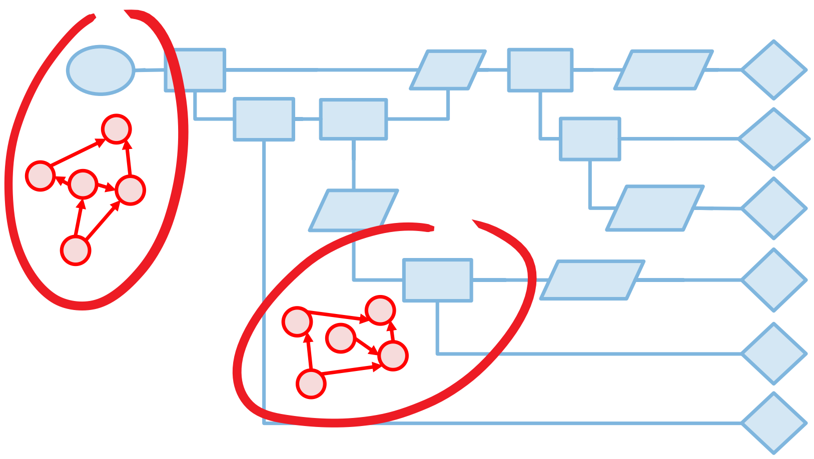
Bayesian Networks

ESDs are somewhat "memoryless" in that the probability that an event will occur at a point in time does not depend on how the sequence got to that point. This characteristic can be overcome by have multiple branches for different scenarios, each with its own set of probabilities. However, this becomes cumbersome even for a moderate number of pivotal events.

Bayesian Networks inherently allow multiple node states to affect conditional probabilities of any node, regardless of how far removed from the initiating event that subsequent event is. Cause and consequence probabilities are linked and quantified using cross probability tables, allowing many different physics models to be combined. The use of several models enables us to capture not only data's uncertainty, but also model's uncertainty.

The Bayesian Network was implemented by industry experts providing judgment on pivotal events in ESDs. Experts were then asked to quantify the estimates by giving a best guess along with a level of certainty on a scale of one through to five. When multiple DNV GL and UCLA experts were engaged for the same point, a beta distribution was used to characterize their uncertainty. Should one expert have a certainty of "5" (the highest), a variance of 0.2 was assumed for their corresponding beta distribution. Likewise, those with the lowest certainty have an assumed variance of 1.0. All intermediate levels of certainty had variances linearly dispersed between the two limits. This allowed subsequent combinations to be weighted according to certainty (through multiplying beta distribution probability density functions, which are conjugate). The process is illustrated in Figure 29.

Figure 29: Event Sequence Diagrams and the Development of Influencing Nodes



Source: UCLA

New Bayesian Network Threat Model for Third Party Damage

The new TPD Bayesian network model for TPD is illustrated Figure 30.

Industry Partner Requirements

The following input nodes, which align with mandatory reporting fields for all oil and gas pipeline operators, are required from any operator or utility:

1. State (location)
2. Year of Installation
3. Diameter
4. Material
5. Depth of Cover (DOC)
6. Commodity
7. Location Class
8. Other Pipelines in the Vicinity

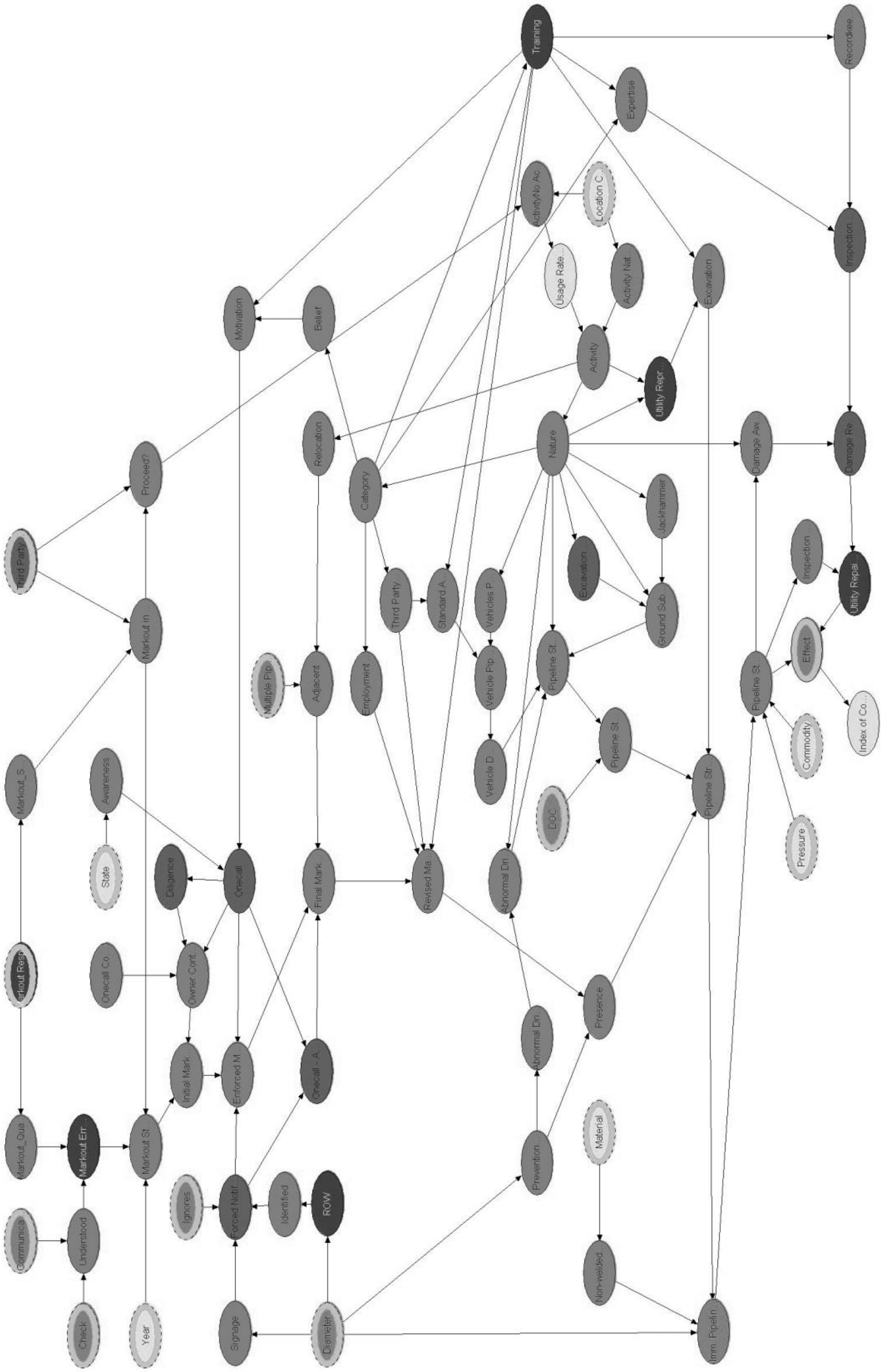
Model Overview

For a sequential (human) failure process, Bayesian networks are inherently difficult to visually appreciate and interpret. The combined ESD-Bayesian network nodes more naturally communicate TPD process and are examined in greater detail below.

Excavation Over Pipeline

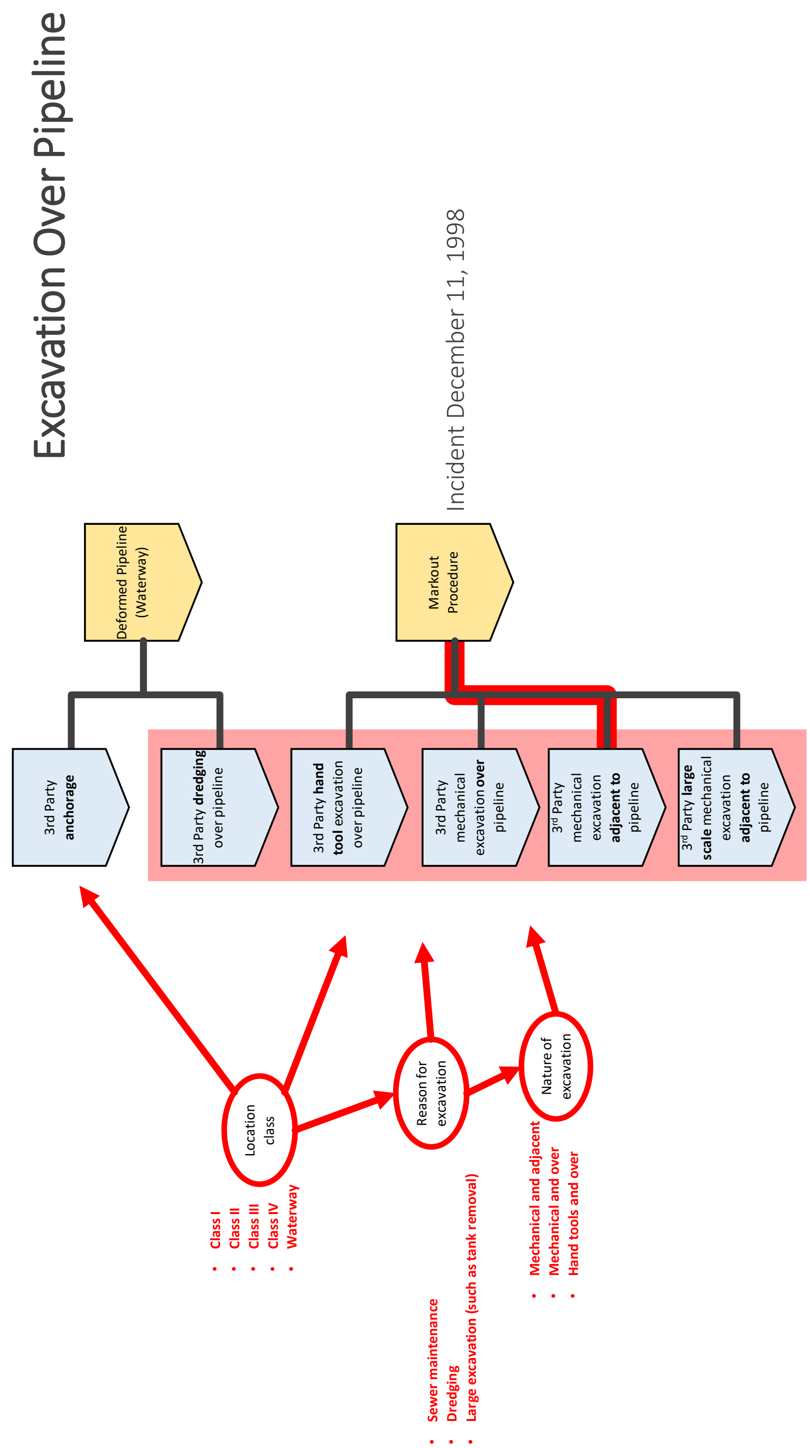
The first event that triggers a TPD causal chain is a decision to conduct some form of third party activity over a pipeline. This event does not necessarily involve the third party starting to investigate the presence of the pipeline. Subsequent ESD elements deal with the decision-making process to investigate the location further (Figure 31).

Figure 30: Complete Bayesian Network of Third Party Damage Threat



Source: UCLA

Figure 31: Excavation Over Pipeline Event Sequence Diagram Element

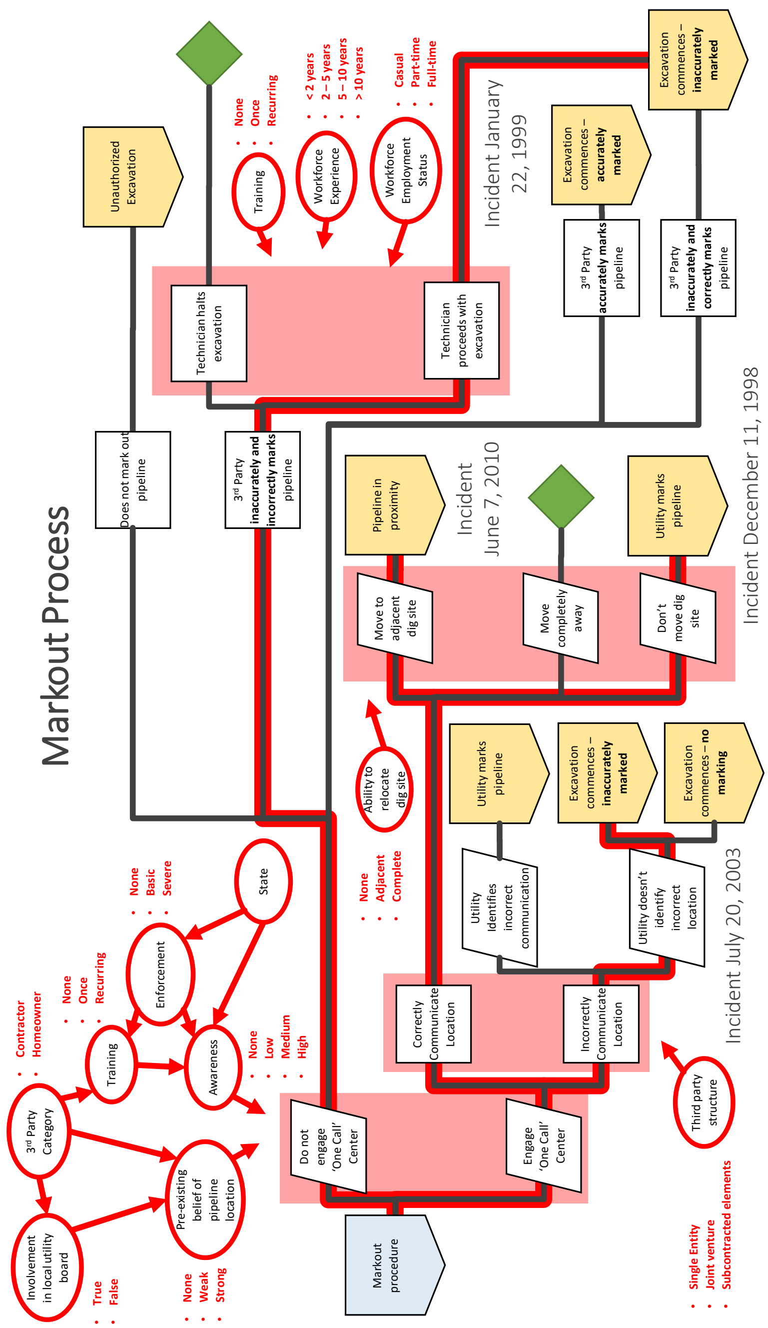


Source: UCLA

Markout Process

Once the activity is planned, third parties may take steps to investigate the presence of the pipeline. If they do, there is a chance that the ensuing "markout" process will be done accurately and timely (Figure 32). Inaccuracy and delays will introduce risk that the activity may commence without the third party being aware of the pipeline presence.

Figure 32: Markout Process Event Sequence Diagram Element

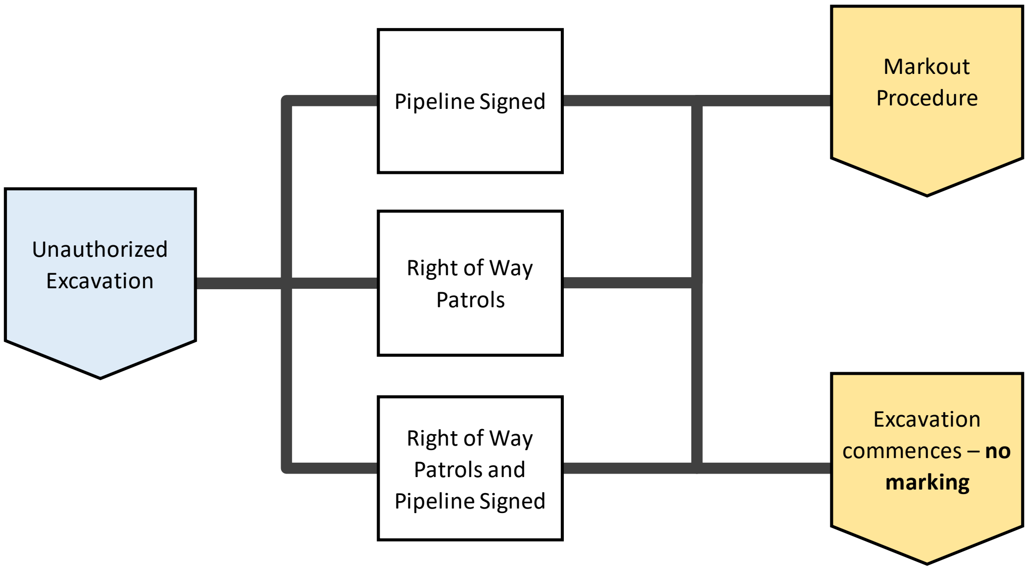


Source: UCLA

Unauthorized Activity

If a third party decides to undertake an activity without seeking authorization or guidance, there are still mechanisms to ensure that they do not damage pipelines. This includes "right of way" patrols that can detect unauthorized patrols and signage (Figure 33).

Figure 33: Unauthorized Activity

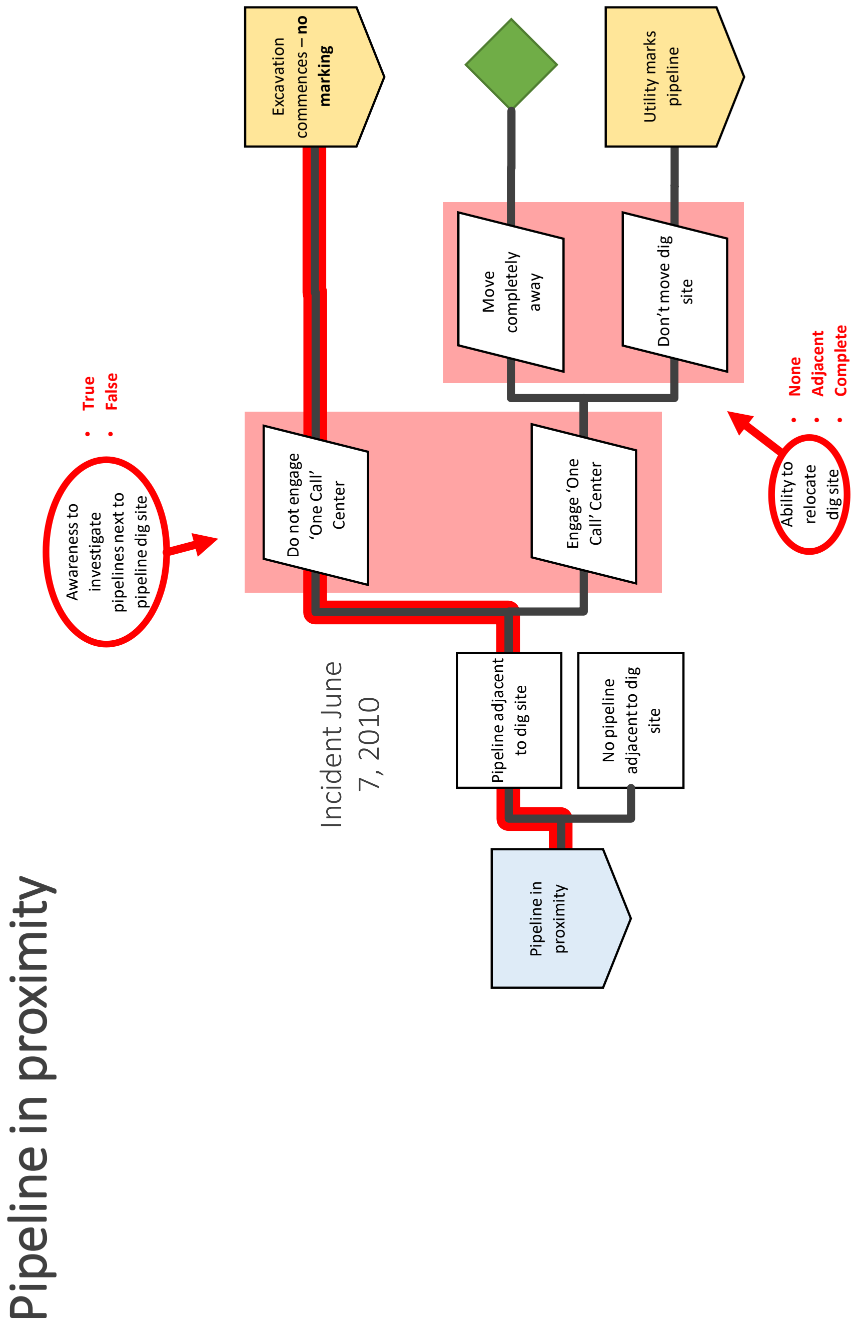


Source: UCLA

Pipelines in Proximity

Multiple pipelines in the same vicinity are particularly problematic. Third parties who become aware of a pipeline in the original activity location can often move their activity nearby without rechecking the presence of pipelines (Figure 34).

Figure 34: Pipelines in Proximity

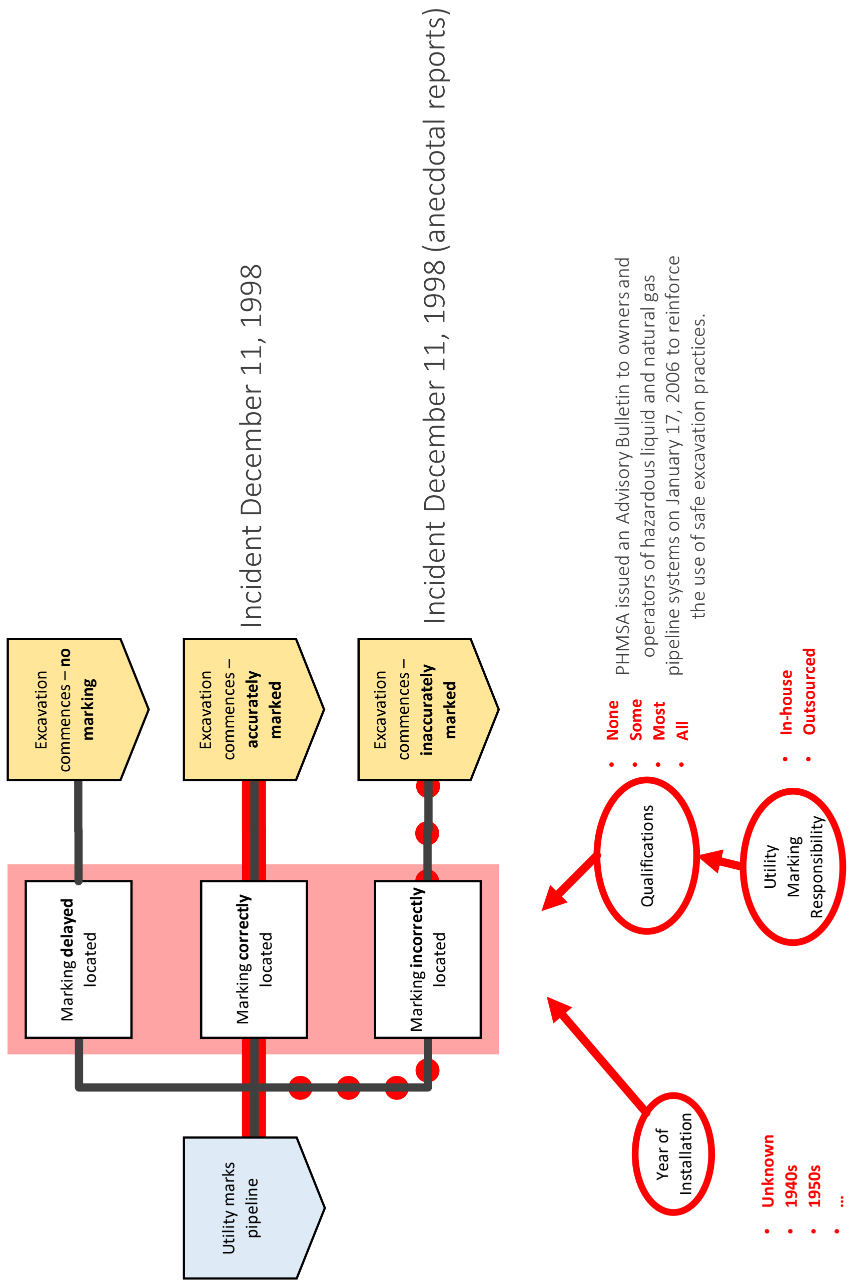


Source: UCLA

Utility Marks Pipeline

Once aware of the intent of a third party, the utility can indicate through "markout" where their pipelines are (Figure 35).

Figure 35: Utility Marks Pipeline

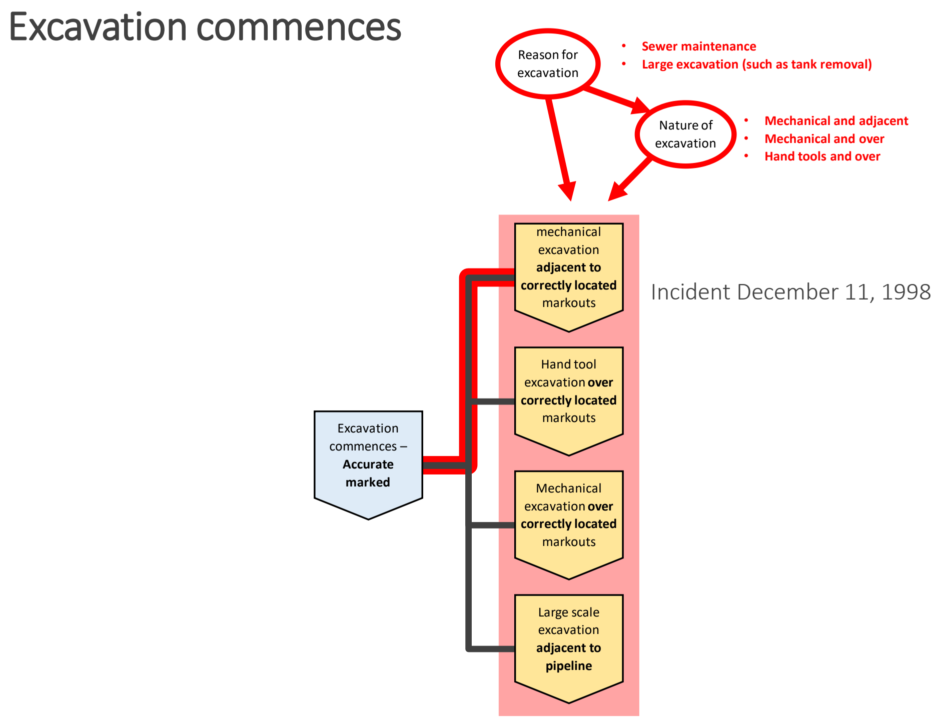


Source: UCLA

Excavation Commences

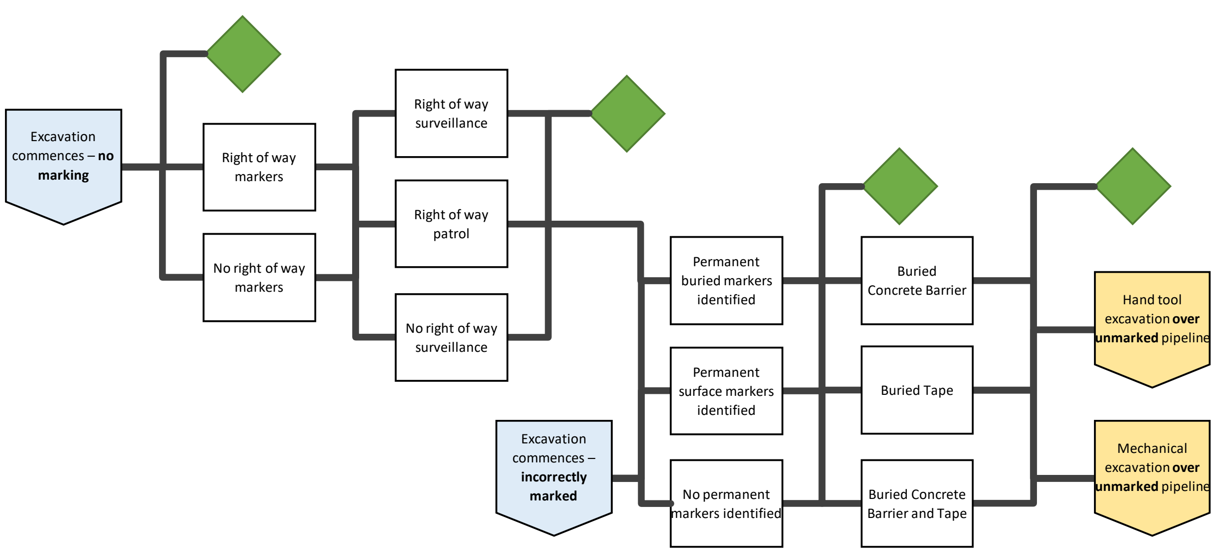
When excavation commences, many events or decisions can influence TPD risk. These include whether or not the third party uses correct procedures, and the nature of excavation (Figure 36 and Figure 37).

Figure 36: Excavation Commences (Part One)



Source: UCLA

Figure 37: Excavation Commences (Part Two)

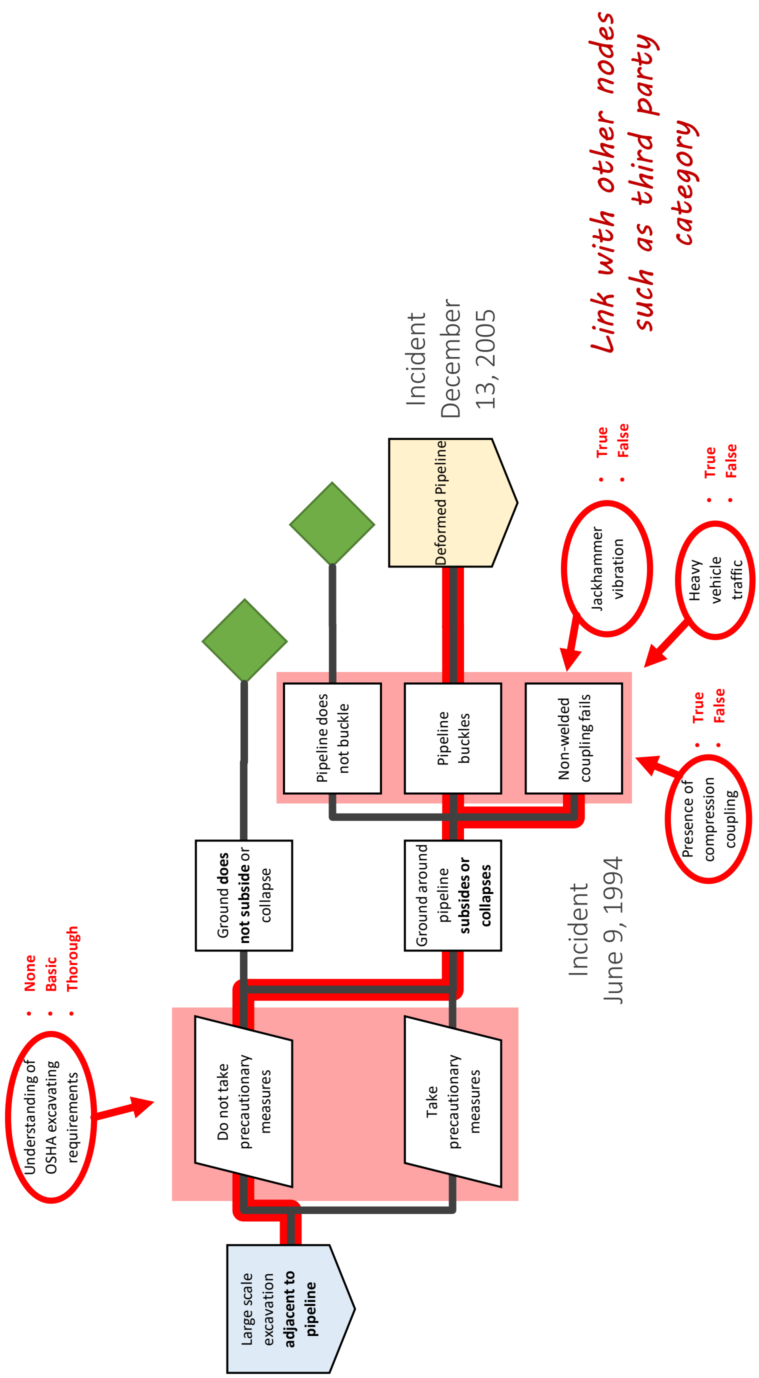


Source: UCLA

Large Scale Excavation Adjacent to Pipeline

Third party activity does not have to occur over a pipeline for TPD to occur. Large scale excavation in the vicinity of pipelines can increase the risk of subsidence, which may in turn put stresses on the pipeline that was originally in the collapsed dirt (Figure 38).

Figure 38: Large Scale Excavation Adjacent to Pipeline

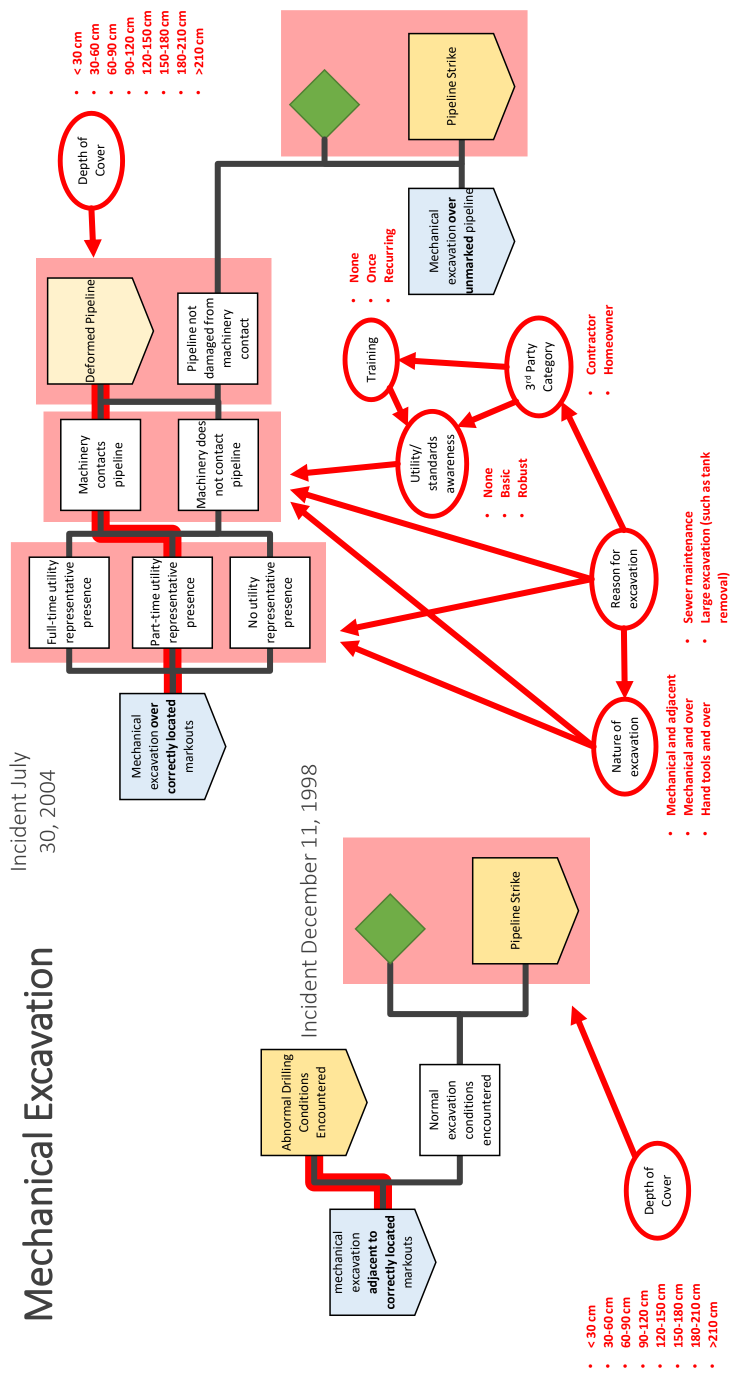


Source: UCLA

Mechanical Excavation

Most TPD happens from mechanical excavation techniques. These include machine-based excavation involving diggers (Figure 39).

Figure 39: Mechanical Excavation

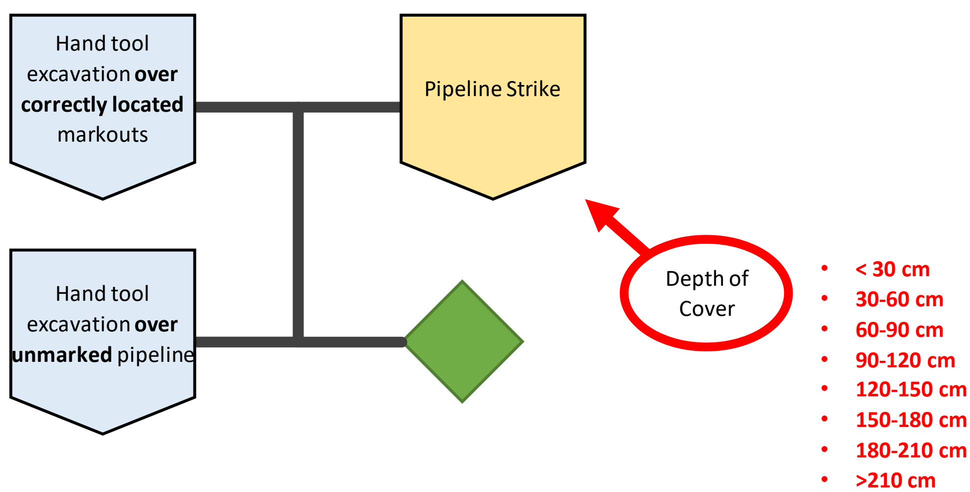


Source: UCLA

Hand Tool Excavation

Excavation using hand tools is a less likely source of third party damage incidents, but is more likely to occur in and around residential areas. Residential areas have smaller supply pipelines running to individual structures and buildings, so when hand tools do cause damage, it can be significant due to the smaller size of the pipelines. (Figure 40).

Figure 40: Hand Tool Excavation

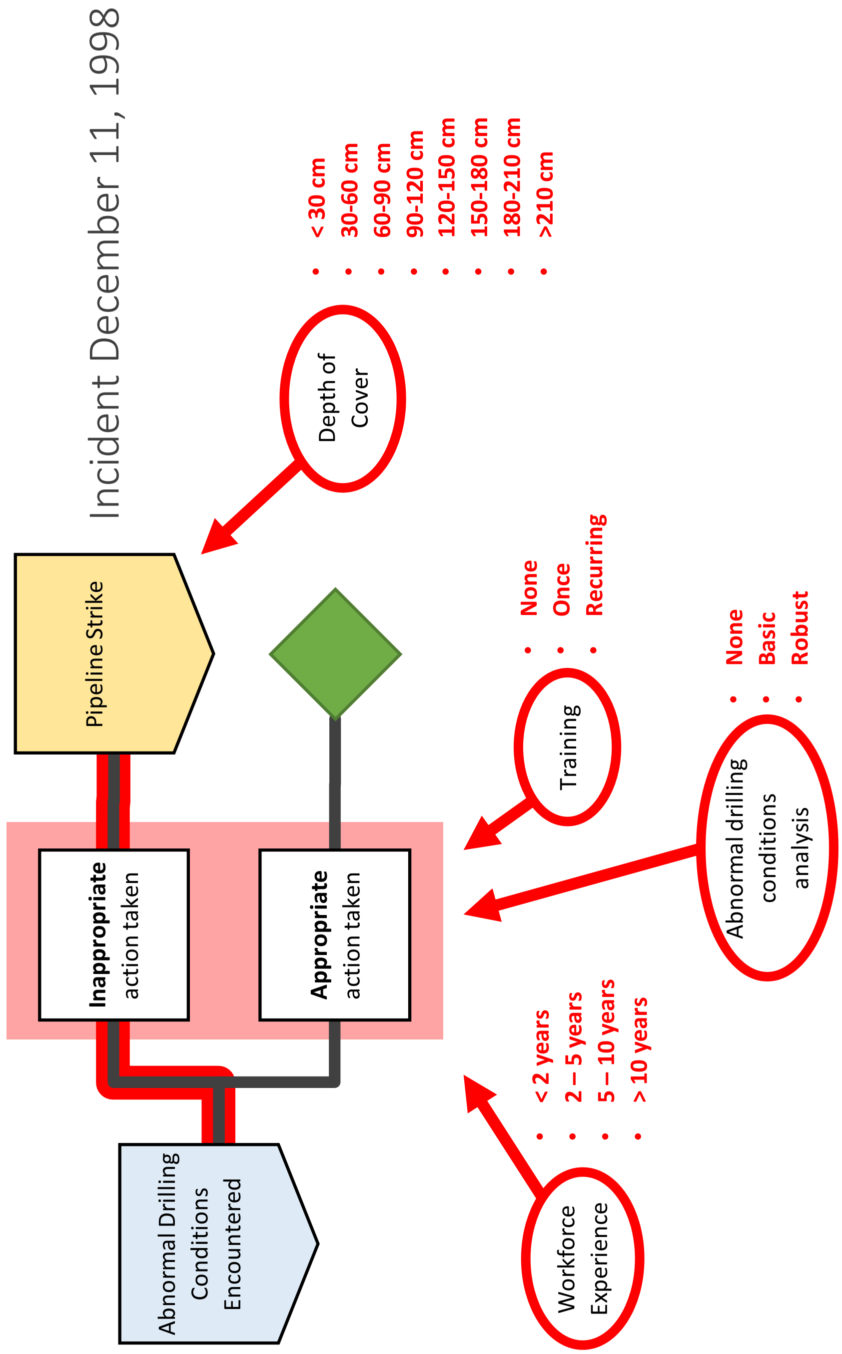


Source: UCLA

Abnormal Drilling Conditions

Many third-party activities involve drilling. Abnormal drilling conditions can increase the likelihood of TPD (Figure 41). For example, stone bedrock and other geological phenomena can make drill bits deviate from their intended course, damaging nearby pipelines. Third parties who are properly trained can typically identify abnormal drilling conditions.

Figure 41: Abnormal Drilling Conditions

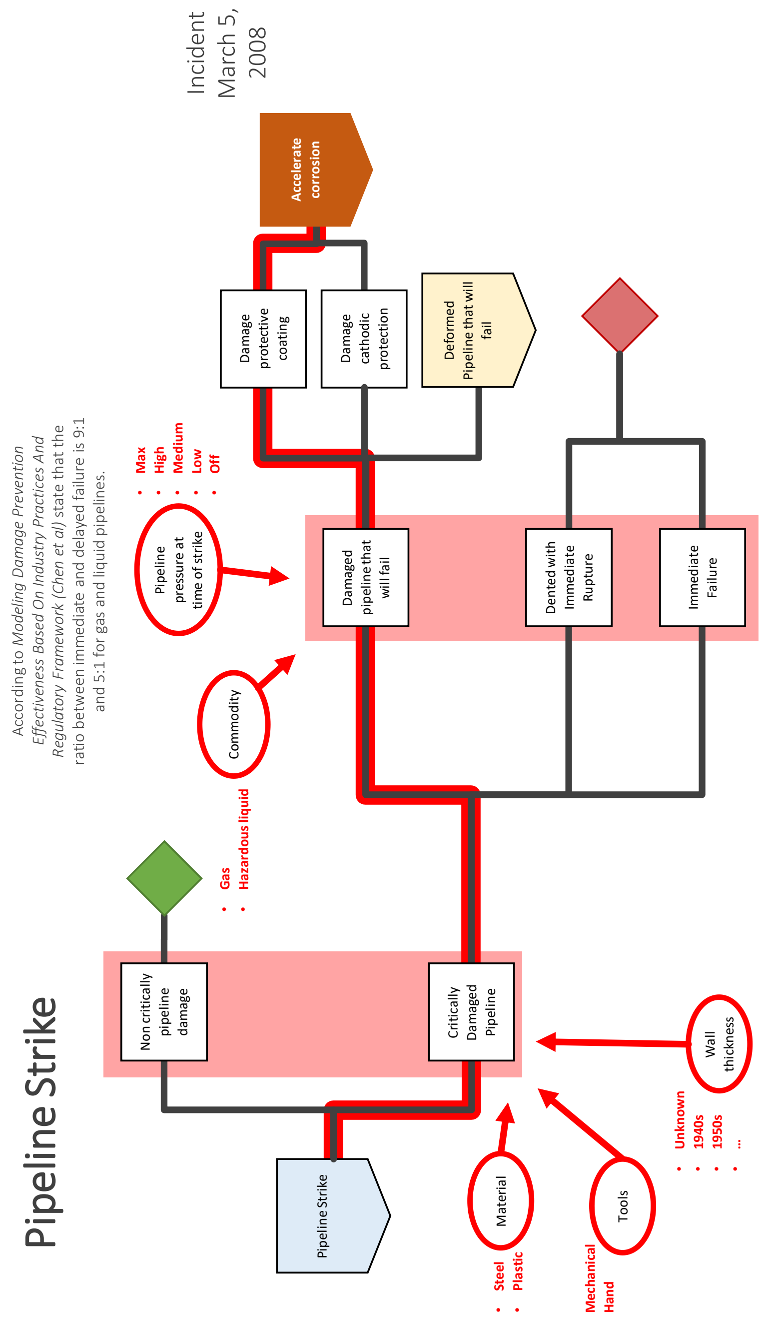


Source: UCLA

Pipeline Strike

Once a pipeline is struck, damage can happen in many ways (Figure 42). Cathodic protection or coating can be damaged, increasing the prevalence of corrosion. Pipelines can also be dented, punctured or ruptured. Each failure mode occurs at different rates in different conditions.

Figure 42: Pipeline Strike

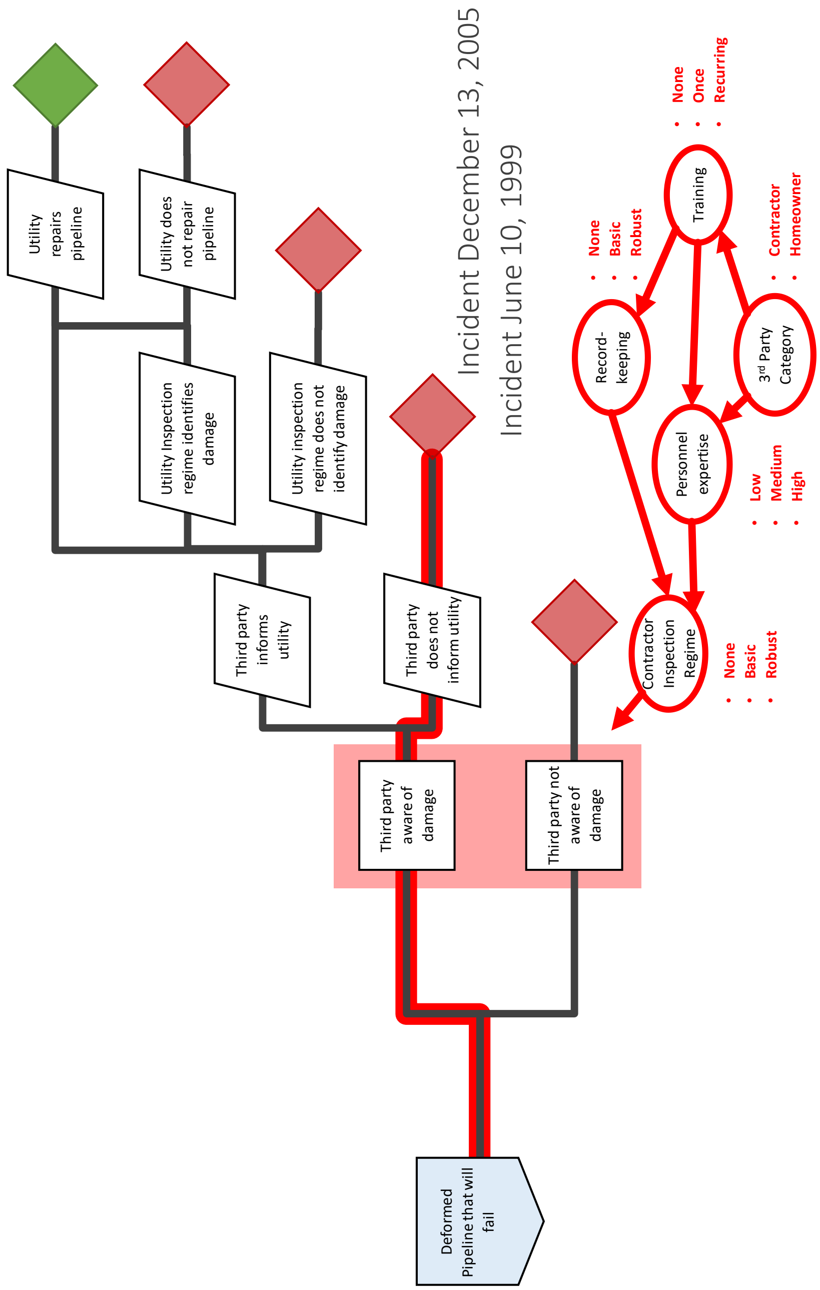


Source: UCLA

Deformed Pipeline

A deformed pipeline may not fail immediately (Figure 43). Reducing pressure at the time of the third-party activity reduces this likelihood. It also allows inspection to identify the deformation before full pressure is restored, allowing repair if necessary.

Figure 43: Deformed Pipeline

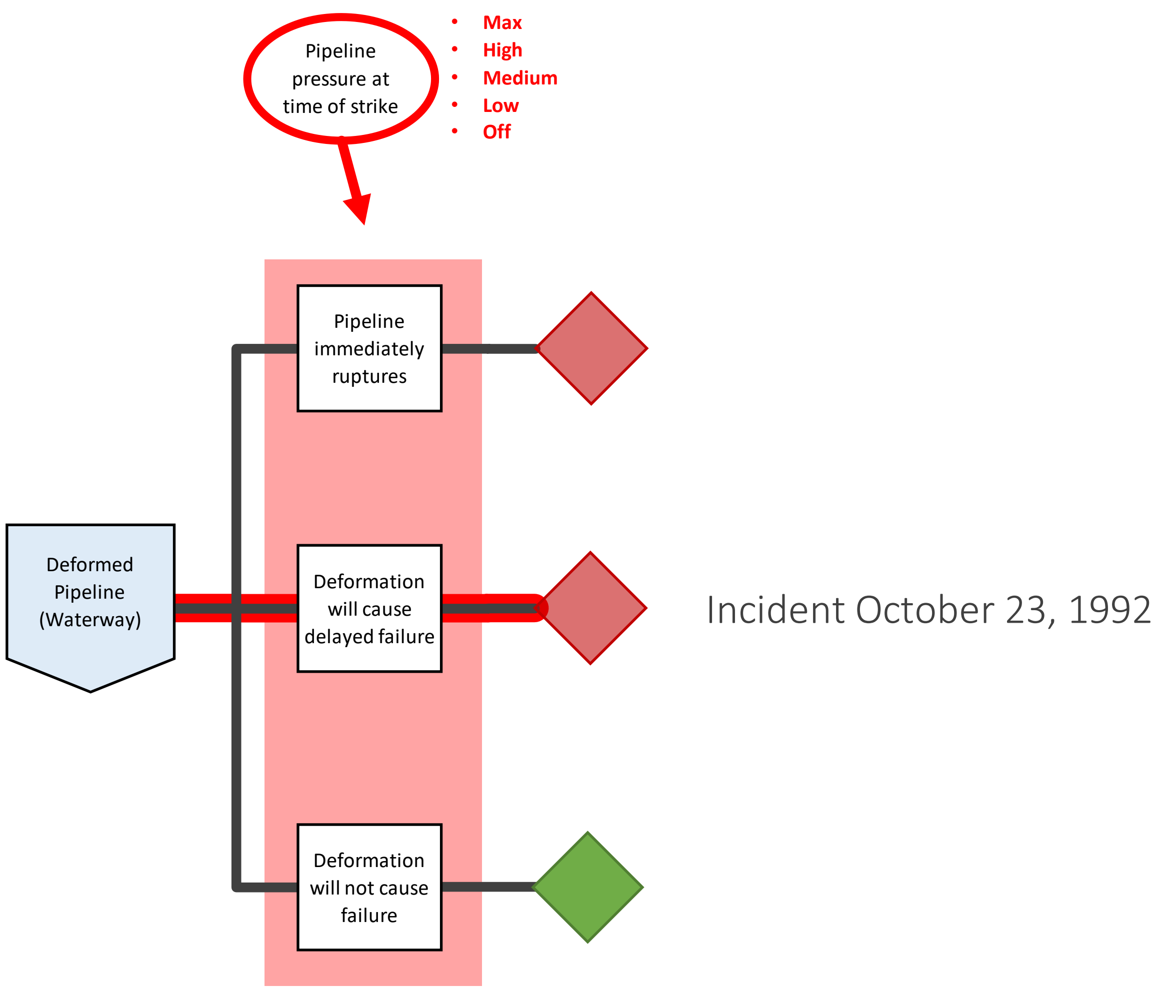


Source: UCLA

Deformed Pipeline (Waterway)

Deformed pipelines have different failure characteristics when they occur in waterways (Figure 44).

Figure 44: Deformed Pipeline (Waterway)



Source: UCLA

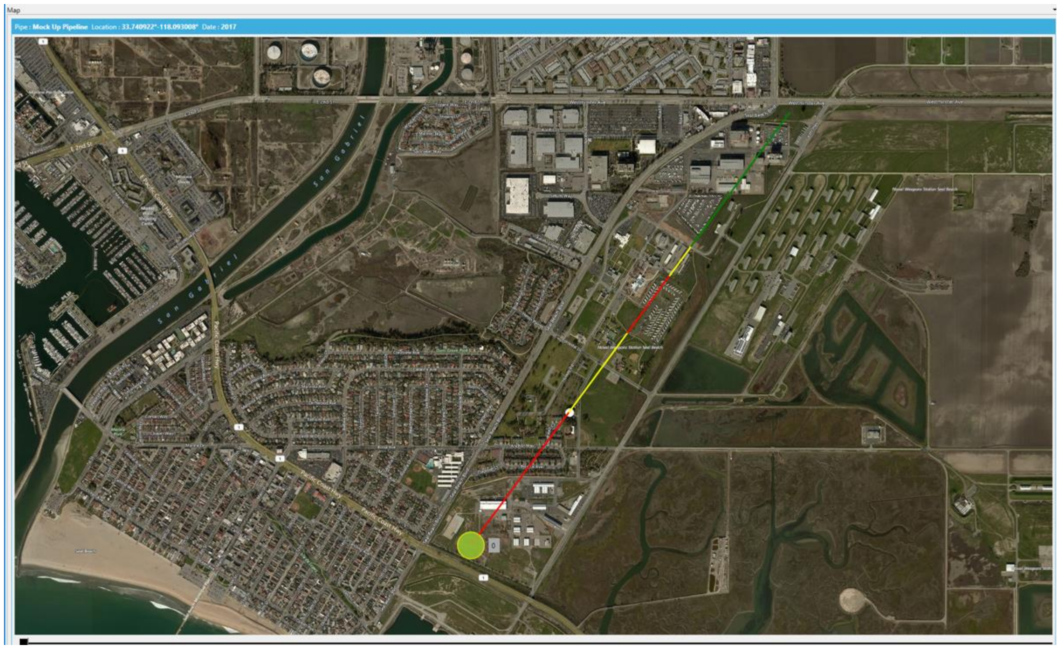
Pipeline Third Party Damage Results and Decision Making

This section presents the MARV™ implementation of the TPD model and highlights some of the benefits to pipeline operators and decision makers.

MARV™ Implementation of the Third Party Damage Model

Graphical layers allow users of software to easily visualize the cause-consequence relationships between various factors that impact a threat's likelihood, and to use a drill down-approach to access information at the desired level of detail. Model inputs and outputs are clearly shown using an intuitive graphical user interface. Figure 45 shows the graphical user interface that color codes the various levels of TPD threat likelihood for a pipe segment selected by the user on the map.

Figure 45: MARV™ Graphical User Interface Shows Pipeline Threat Results on a Map for Third Party Damage



Source: UCLA

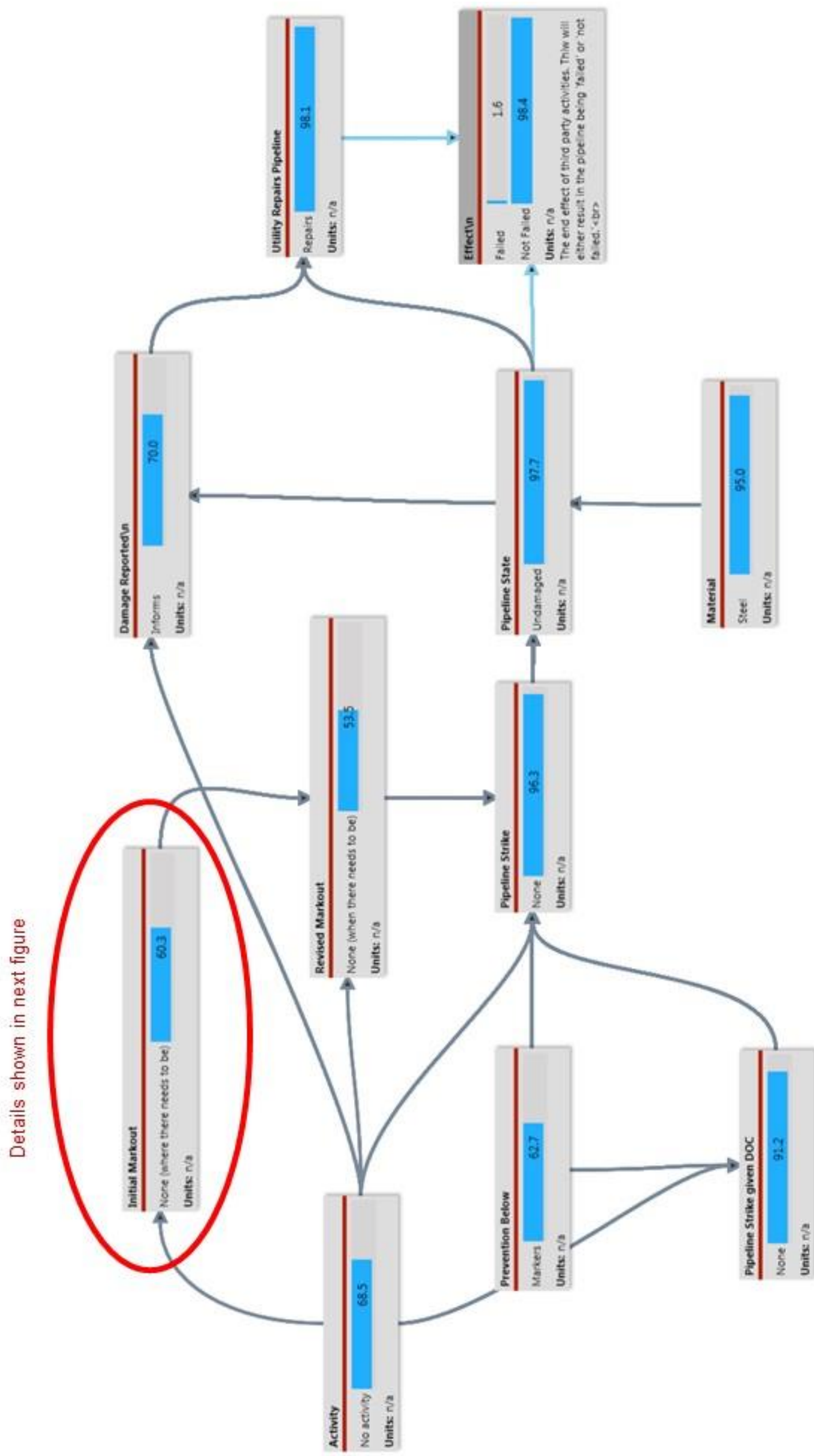
In the example illustrated in the figure, the pipeline was divided into thousands of segments defined by global positioning satellite coordinates (the pipeline was also moved to a different location). For each segment, pipeline characteristics where entered as defined in section 3.2.3.1. The example includes some "actual" data and some "synthesized" data so pipeline characteristics cannot be inferred from Figure 45.

The pipeline diameter, material, year of installation, and commodity class were either identical are very similar for all pipeline segments (as would be the case for most pipelines). The key factor for pipeline failure risk was largely based on depth of cover and location class.

The colors in Figure 45 are relative. That is, "red" represents pipeline segments with the highest risk relative to other pipeline segments. Overall, the example had relatively low risk of TPD failure when compared to indicative pipeline failure characteristics for continental United States.

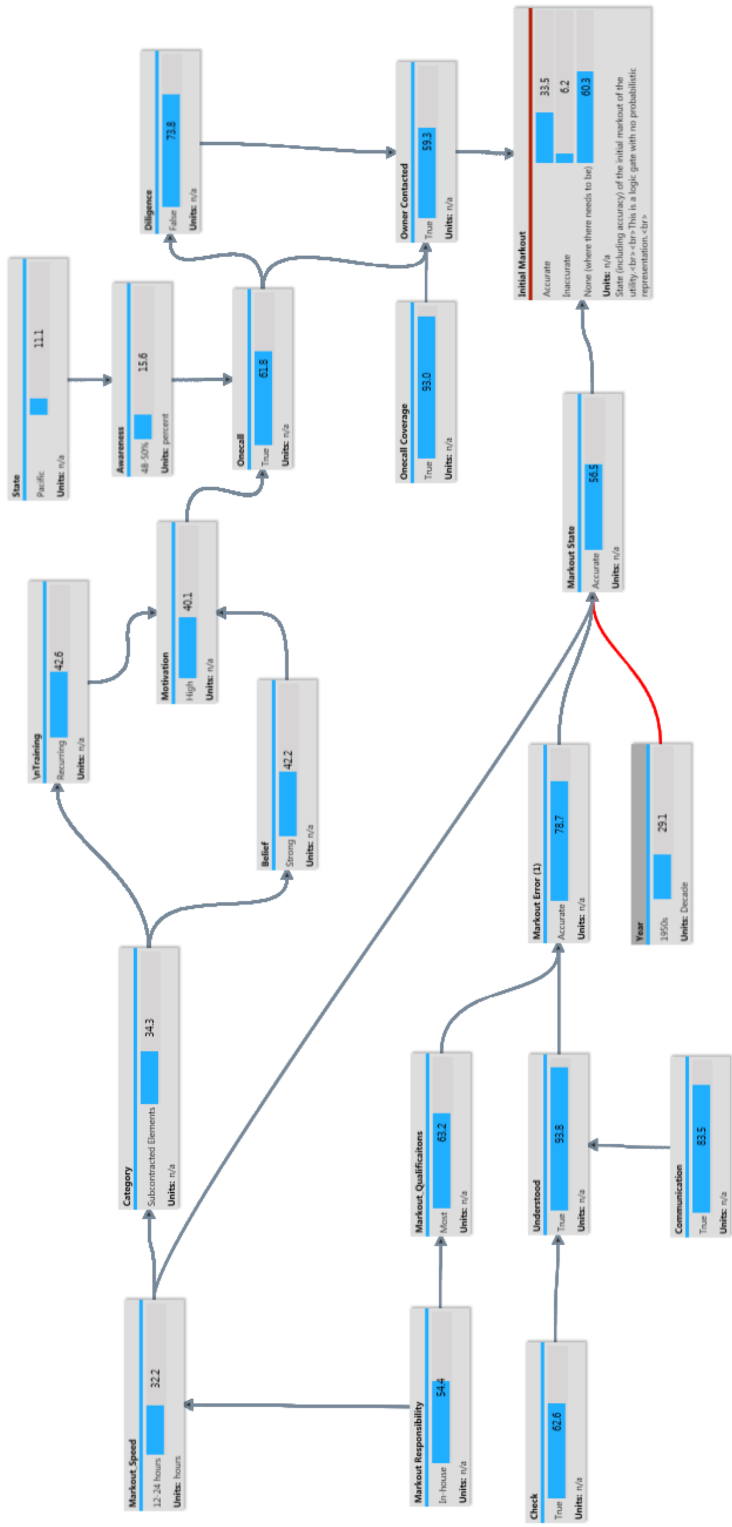
A series of screenshots of the MARV™ TPD model modules is shown below (Figure 46 and Figure 47). These images correspond to various segments of the Bayesian Belief Network the models developed.

Figure 46: Picture of Overall Threat Model Window



Source: UCLA

Figure 47: Picture of a Subsection of the Threat Model: Initial Markout Group



Source: UCLA

The model has been quantified in the sense that it can provide the relative likelihood of damage due to third party activities. The quantification is based on generic information, but it is a property of Bayesian Networks; the model can be specialized with site or operation specific information, and queried to provide any case- or situation-specific assessment.

Model Benefits

Fundamentally the TPD model provides substantially more information than has previously existed for decision makers regarding oil and gas pipeline failures emanating from third party activity. The model allows a much more thorough understanding of the causal factors that influence pipeline failures. With the model, the risks can be traced back to their roots, in terms of human activities, and effectiveness of the mitigating or aggravating factors.

Using a quantitative model, the pipeline owner/operator can rank risks by their corresponding cause and in terms of their relative likelihoods. Also, with the method introduced in Chapter 4, a decision maker can identify and rank "leading risk indicators" for more proactive risk management of the pipeline.

The generic TPD Bayesian Network in MARV™ can be extended easily at the root cause level, and with some effort also in terms of consequences. Furthermore, the model can be used to explore preventive measures (actions and/or barriers) that can be more effective in reducing TPD risk. Until now there has been limited basis to understand what effect each will have and whether it represents value for the necessary investment.

For example, consider a primarily residential scenario in which the main TPD revolves around homeowners and their contractors striking the relatively small gas supply lines to houses. It is reasonable to assume that television and radio advertising for a single call center would have more effect on homeowners than on excavating companies who should reasonably be expected to be aware of notification procedures. Some basic assumptions could be made about the expected increases in awareness for this situation, and (along with pipeline characteristics) the TPD model could estimate the likely positive impact such a campaign would have on TPD risk.

From a pipeline owner's perspective, the TPD model can be used to identify the benefits of modifying pipeline characteristics that are known to influence TPD frequency (like depth of cover or pipeline diameter). The TPD model can also be used to inform procedures associated with third party activity, such as turning off supplies to reduce the risk of immediate failure should a pipeline be deformed. Turning off a supply is a costly exercise, and the TPD model can go some way to risk-inform the decision-making process associated with it.

Finally, the TPD model can also inform urban planning considerations. Pipelines originally installed in more rural areas can be subject to ongoing urban expansion. This means that planning considerations for a new subdivision or suburb can be based on this TPD model and existing pipeline infrastructure. The extent to which mitigating activities such as cages, signs and so on impact risk can inform planning considerations and caveats that local governments impose on developers.

CHAPTER 4:
Leading Indicators

Method of Identifying the Risk Leading Factors

Introduction

Model-based risk leading indicators are among the effective tools for proactive risk-informed assessment and monitoring of a system's operational parameters and maintaining a desired level of reliability. Measuring and trending values of leading risk indictors can be used to estimate risk margins and time trend of total risk.

In the context of a Bayesian Network-based risk model of a system of process, and in principle, any node representing observable or measurable states of a physical parameter or human activity can be viewed as a risk indicator of the system or process. This can be carried out by conducting a sensitivity analysis in the system Bayesian Network to determine the degree to which variation in the probabilistic inference of the system node is influenced by variation of other nodes.

In the proposed method, the sensitivity analysis is performed in two steps. The first phase is designed to determine and rank the influence of the nodes on the system node uncertainty. In this step, each node is considered as a whole, and a ranking metric that can aggregate the influence of all the states of a node in one scalar number is developed and applied. In contrast, in the second step each node is segregated into its states and a second metric is developed to rank the node-state pair's influence on the system node.

The two-step approach addresses two categories of problems. The first category is when the objective of identifying the risk leading indicators is to prioritize some system factors for monitoring. For example, assume that the goal of a study is to choose between monitoring the temperature or the pressure. In this case, the effect of all the states must be aggregated and then the most critical node chosen, since monitoring a node provides information about all the states. The second category is when the objective of identifying the risk leading indicators is to mitigate the most adverse effect on the system. As an example, consider the case with the option to reduce the adverse effect of high temperature or the adverse effect of high pressure. In this case, considering the effects of other states, such as low temperature and low pressure, might yield misleading results.

The two-step approach is also a good strategy to address the problem of identifying risk leading indicators in the Bayesian Networks with a large number of nodes, since a large Bayesian Network might have up to a thousand node-state pairs. Therefore, it is preferred to rank the nodes first, and then pick some of the top nodes and rank the node-state pairs of just those selected top nodes. More importantly, the node ranking step can be extended to the continuous Bayesian Network in future work.

While a model-based mathematical procedure such as the method presented here is an effective way for identifying elements of the causal risk model that could be good candidates as risk indicator, there are other important factors that must be considered in the final selection.

Node Ranking Based on Conditional Entropy

The first step is to rank the nodes based on a metric that can aggregate the effect of all states of a node on the "system" node in a single scalar. The proposed metric is named node metric and derived on the basis of entropy. Entropy is a metric for measuring the average uncertainty (or amount of information) about the value of a variable. Let *i* be a variable with discrete probability distribution *P*, where *P (i = j)* is the probability of *i* being in state *j*. Let *Si* be the set of the states associated with the random variable *i*. Entropy of *i* is defined as (Gray, 2013) (Okafor, 2005).

$$H(i) = -\sum_{k \in S_i} P(i = j)\, log_2[P(i = j)]. \qquad (1)$$

When there is no uncertainty about the states of variable *i*, for example *P (i = w) = 1*, the entropy of *i* is zero.

In Bayesian Networks, the determination of a subset of nodes (evidence) is used to calculate the posterior probability of unobservable nodes. The nodes representing the risk indicators must have higher influence on the posterior probability of the system node, denoting the underlying health state of a system (such as, failed or functional). Therefore, it is expected that obtaining information from such nodes reduces the average uncertainty of the system node more than other nodes in the Bayesian Network model of the system. The average uncertainty of the system node can be computed by employing Equation (1), and the uncertainty after obtaining some evidence can be formulated as conditional entropy.

Let *System node* | *i* be the conditional entropy of system node given node *i*. Then, the node metric can be expressed as the following

$$node_{metric(i)} = H(system\, node) - H(system\, node\ |i). \qquad (2)$$

The conditional entropy of the system node given node *i* is the average uncertainty about the value of the system node after obtaining the findings from node, and it can be measured by

$$H(system\, \mathrm{node} \mid i) = \Big[\sum_{k \in S_{sys}} \sum_{j \in S_i} - P(sys = k \mid i = j) \times P(i = j) \times \log [P(sys = state\ k\ |node\ i = j)] \Big]. \qquad (3)$$

The final expression for the node metric can be derived by substituting (1) and (3) in (2). The first risk leading indicator, denoted by I^1, is the node that obtaining information from that node reduces the average uncertainty of the system node more than other nodes. Therefore, it can be identified as follows

$$I^1 = \arg\max_i [node\_metric(i)]. \qquad (4)$$

Besides, all the rest of the nodes in the Bayesian Network under study can be ranked based on their value of the node metric. However, often it is not useful nor cost-effective to consider all the nodes in the ranking, for example, when the purpose of the study is to identify the risk leading indicators among the environmental factors, it is sensible to exclude non-environmental factors. Hence, it is well advised to consult with the expert who has developed the Bayesian Network to choose the most relevant nodes for the study.

Node-State Ranking Based on Conditional Probability

The goal of the second step is to evaluate and rank the influence of the various states of the critical nodes on the system node. A second metric based on conditional probability is defined to carry out this task.

Node *i* in state *j* can be a potential leading risk indicator if obtaining the information that node *i* is in state *j* increases the failure probability of the system node. Besides, if node *l* in state *k* rises the failure probability more than node *i* in state *j*, then the node-state pair (*l, k)* should get a higher ranking than (*i, j)*. Therefore, the node-state metric should encompass the following incremental effect on the failure probability:

$$incremental\ failure\ probability = P(sys = fail\ |i = j) - P(sys = fail), \qquad (5)$$

Where *P (sys = fail* | *I = j)* is the conditional probability of system node failure given node *i* is in state *j.* In the Bayesian Networks where the system node has several failure states, the weighted sum of the incremental failure probabilities should be employed.

$$\begin{aligned} &weighted\ incremental\ failure\ probability \\ &= \sum_{k \in S_{sys}^{f}} weight(k) \times [\,p(sys = k \mid i = j) - P(sys = k)]. \end{aligned}$$

(6)

In the above expression, S_{sys}^{f} is the set of failure states of the system node, and the user must specify the weights. It should be noted that the weights must add up to one and they must be assigned in a way that reflects the importance of each failure state, that is, more critical failure states must have larger weights.

Another factor that must be included in the node-state metric is the probability of the node-state occurrence. If the chance of node *i* being in state *j* is too low, which is known as a rare event, there might be a loss interest in studying and monitoring that node state pair. Therefore, the probability of the event of node *i* being in state *j* into the node-state metric must be factored. The following expression is the proposed method for taking into account the probability of the event.

$$\begin{aligned} &node\_state\_metric\ (node\ i\ at\ state\ j) \\ &= \sum_{k \in S_{sys}^{f}} Weight(k) \times [\frac{[\,p(sys = state\ k\ |node\ i = j) - P(sys = state\ k)]}{1 - P(node\ i = j)}] \end{aligned}$$

(7)

An analysis tool called "RiskLI" has been developed in MATLAB™ to execute the above risk indicator algorithms. The tool takes the Bayesian Network model and input data and returns the leading indicators according to the two-step method described above. Junction Tree Engine in Bayes Net Toolbox (BNT) (Murphy) is used to propagate the evidence.

The tool takes the ".oobn" file of the Bayesian Network as input and returns the ranking results in an excel spreadsheet. RiskLI has three preparation steps that require user input:

1. Define the system state node in the Bayesian Network model

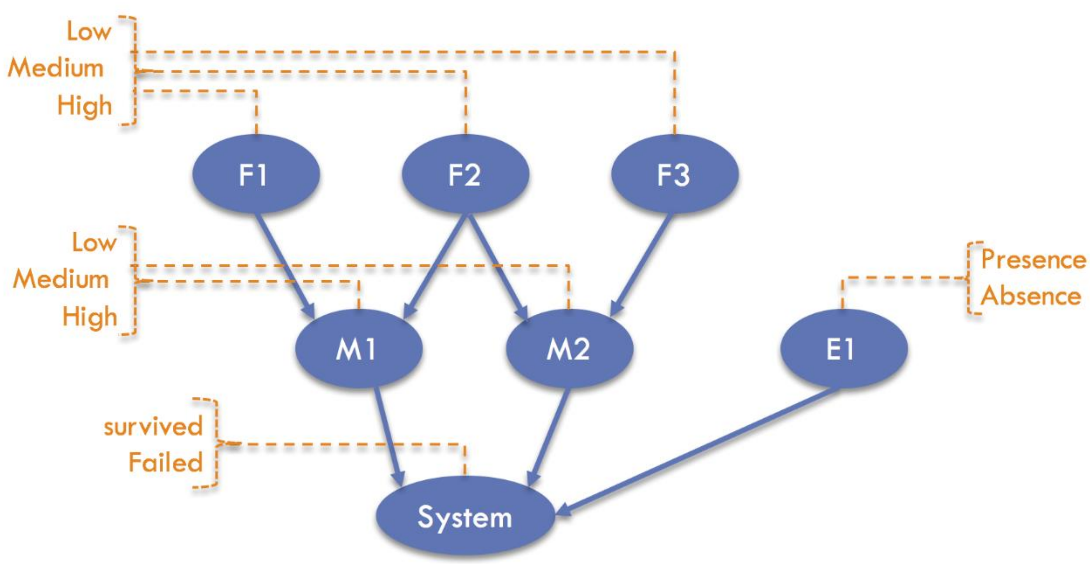
2. Assign weights to the system node states. The weights must add up to one, and the more critical failure states must have larger weights. Besides, success states must be assigned zero weight.
3. The user has the choice of eliminating some nodes from the study, at her/his discretion based on other criteria such as technical feasibility, regulatory requirement, and cost.

Instructions on how to use "RiskLI" are presented in the appendix.

Illustrative Examples

To demonstrate using the method, a numerical example is presented. A simple Bayesian Network is considered, modeling the interaction of three different factors (such as, temperature, humidity), three different failure mechanisms (such as internal corrosion, external corrosion, and drilling), and a system node. Factors *F1, F2,* and *F3* and the failure mechanisms and *M1* and M2 are assumed to have three discrete states each (low, medium, and high. Failure mechanism *E1* is considered to have two states (presence or absence of the mechanism *E1.* The system node states are considered to be "failed" or "survived/functioning." The Bayesian Network model is shown in Figure 48.

Figure 48: Bayesian Network of the Illustrative Example



Source: UCLA

Example 1

Leading indicators can be identified among factors and mechanisms. Prior state probabilities are shown in Table 7. The conditional probabilities defining the Bayesian Network are assigned in such a way that factor node *F1* has the highest influence on failure mechanism *M1,* and *M1* has the highest influence on the system node. Besides, E1 has the second highest influence on the system node. These conditional probabilities are shown in Table 8, Table 9, and Table 10.

Table 7: Prior State Probabilities for Example 1

State	F1	F2	F3	E1
State 1	0.2	0.1	0.7	0.5
State 2	0.4	0.2	0.1	0.5
State 3	0.4	0.7	0.2	-

Source: UCLA

Table 8: M1 Conditional Probability Table for Example 1

F2	State1			State2			State3		
F1	State1	State2	State3	State1	State2	State3	State1	State2	State3
State 1	0.4	0.1	0.05	0.3	0.09	0.05	0.3	0.05	0.005
State 2	0.3	0.1	0.15	0.4	0.09	0.05	0.3	0.05	0.005
State 3	0.3	0.8	0.8	0.3	0.82	0.9	0.4	0.9	0.99

Source: UCLA

Table 9: M2 Conditional Probability Table for Example 1

	State1			State2			State3		
F3	**State1**	**State2**	**State3**	**State1**	**State2**	**State3**	**State1**	**State2**	**State3**
State 1	0.85	0.7	0.6	0.75	0.6	0.25	0.1	0.1	0.1
State 2	0.1	0.25	0.3	0.2	0.3	0.25	0.3	0.2	0.1
State 3	0.05	0.05	0.1	0.05	0.1	0.5	0.6	0.7	0.8

Source: UCLA

Table 10: System Node Conditional Probability Table for Example 1

E1	State1									State2								
M2	State1			State2			State3			State1			State2			State3		
M1	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3
State 1	0.6	0.7	0.1	0.91	0.8	0.15	0.95	0.9	0.005	0.1	0.15	0.1	0.1	0.15	0.15	0.05	0.1	0.005
State 2	0.4	0.3	0.9	0.09	0.2	0.85	0.05	0.1	0.995	0.9	0.85	0.9	0.9	0.85	0.85	0.95	0.9	0.995

Source: UCLA

The conditional probabilities are assigned such that that F1 in States 2 and 3 “excites” M1 to go to State 3 (Table 8), and M1 at State 3 forces the system node to go to State 2 (Table 9). Also, E1 at State 2 triggers the system node to go to State 2 (Table 10). With these numbers, E1, M1, and F1 are expected to be identified as leading indicators.

Table 11 presents the results of the first step, that is the ranking according to the node metric. As expected, nodes M1, F1, and E1 rank higher than others, making them good candidates as leading indicators.

Table 11: Node Ranking of the Illustrative Example 1

Rank	Node name	Node_Metric Value
1	M1	0.0869
2	F1	0.0289
3	E1	0.0225
4	M2	0.0095
5	F3	0.0018
6	F2	0.0017

Source: UCLA

In the second step (node-state ranking), only the top three leading indicators (M1, F1, and E1) are considered. Table 12 presents the results of the node-state ranking. The results show that M1 in State 3, E1 in State 2, and F1 in States 2 and 3 are the most appropriate risk leading factors.

Table 12: Node-State Ranking of the Illustrative Example 1

Node name	State	Node-State Metric
M1	3	0.3507
E1	2	0.1269
F1	3	0.0869
F1	2	0.0406
E1	1	-0.1269
F1	1	-0.1913
M1	1	-0.2936
M1	2	-0.3309

Source: UCLA

The negative values of node-state metric in the 5th to 8th rows mean that the realization of corresponding node-states decreases the failure probability of the system node. For example, the evidence that E1 is in State 1, reduces the system failure probability. Since the objective of the procedure developed in this study is to identify risk indicators, node-states with negative metrics would not be proper risk indictors.

Example 2

To further explore the performance of the method, the prior probability of E1 being in State 2 is changed in a way that makes it a rare event. The updated prior probabilities are shown in Table 13.

Table 13: Modified Prior Probabilities for Example 2

	F1	F2	F3	E1
State 1	0.2	0.1	0.7	0.95
State 2	0.4	0.2	0.1	0.05
State 3	0.4	0.7	0.2	-

Source: UCLA

In this scenario, E1 is expected to receive a lower ranking since the probability of E1 being in an adverse state has been decreased by a factor of ten. The results of the node ranking procedure is shown in Table 14.

Table 14: Node Ranking for Illustrative Example 2

Rank	Node name	Node_Metric
1	M1	0.3074
2	F1	0.1512
3	M2	0.0078
4	F2	0.0050
5	E1	0.0046
6	F3	0.0019

Source: UCLA

The results of the node-state ranking procedure is shown in Table 15.

Table 15: Node-State Ranking for Illustrative Example 2

Node name	State	Node-State
M1	3	0.7699
F1	3	0.1805
E1	2	0.1392
M2	3	0.0930
F2	3	0.0741
F1	2	0.0714
F3	3	0.0508
F3	2	0.0104

Source: UCLA

The results show that the E1 ranking has dropped in the node table from the second most important risk leading indicator to the second least important factor. Also, E1 in State 2 has dropped to the third critical node-state pair in the node-state table. These results confirm that the proposed algorithms produce intuitively expected results.

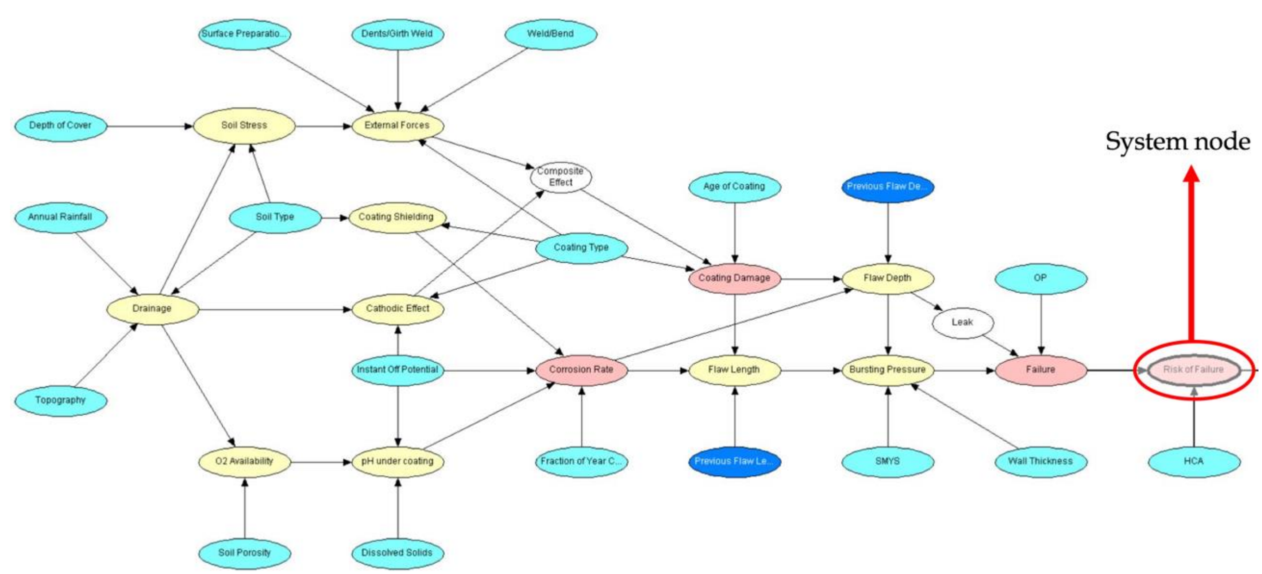
Application to Pipeline Risk Models

The ultimate objective of Task 5 of the project was to show how one would identify the leading risk indicators based on the Bayesian Network risk models developed and implemented in MARV™. This section summarizes the results of applying the procedure to Bayesian Network models of corrosion and TPD developed under Tasks 3 and 4.

Risk Leading Indicators of the Corrosion Model

The corrosion Bayesian Network risk model is described in the report section on Task 3. The Bayesian Network built in Hugin software is shown in Figure 49. The Bayesian Network node names and descriptions are provided in Table 16. The system node of the corrosion model is "Risk of Failure", which has three states. Only the first state is assumed to be the failure state. Hence, the weights are [1,0,0].

Figure 49: Bayesian Network of the Corrosion Model



Source: DNV GL

The model has 36 nodes. In consultation with the expert who developed the corrosion Bayesian Network model, only the nodes marked in purple in Table 16 were deemed appropriate for inclusion in the risk indicator determination process.

Table 16: Listing of Corrosion Bayesian Network Model Nodes

Name	Description
Age of Coating	Probability of age of the coating since construction or repair
Bursting Pressure	Probability of bursting pressure being in a certain range
External Forces	Probability that the external forces are high, medium or low to pipeline surface
O2 Availability	Probability of oxygen availability in the drainage water within a certain range
SMYS	Specified Minimum Yield Strength (psi)
HCA	Probability of High Consequence Area
Composite Effect	Probability of the combined effect of external forces and cathodic effect
Risk of Failure	*Not in Scope of Model*
Coating Damage	Probability of coating damage
Coating Type	Probability of the type of coating
Index for Color Coding	Index for color coding
Fraction of Year CP Operational	Probability of fraction of year CP was operational
Instant Off Potential	Probability of effective surface potential being in a certain range
Corrosion Rate	Probability of the corrosion rate. Pitting rates are based on NACE classification SP0775-2013 “Qualitative categorization of carbon steel corrosion rates” and NIST database for external corrosion.
Dents/Girth Weld	The probability of a dent or girth weld being present
Depth of Cover	Probability of the depth of the pipeline being at a certain range
Failure	Probability of failure (pipeline burst or leak)
Flaw Depth	Probability of the localized corrosion depth being within a certain range
Flaw Length	Probability of the localized corrosion length being within a certain range
Leak	
OP	Probability of the operating pressure being in a certain range

Name	Description
pH under coating	Probability of pH at the damaged coating being within a certain range
Soil Porosity	Probability of the soil porosity being within a certain range
Annual Rainfall	Probability of the average annual rainfall in the year
Coating Shielding	Probability that the coating is susceptible to shielding
Soil Stress	Probability that the soil stress is high, medium or low
Soil Type	Probability of type of soil
Surface Preparation for Coating	Probability of the type surface preparation was used during construction before coating application
Dissolved Solids	Probability of concentration of total dissolved solids in the groundwater being within a certain range
Topography	Probability of the type of topography above the pipeline
Wall Thickness	Probability of the wall thickness value (inches)
Weld/Bend	Probability of having the presence of a weld or bend

Source: UCLA

The results of the node ranking are shown in Table 17.

Table 17: Node Ranking for the Corrosion Model

Node Rank	Node Label	Node Metric Value
1	HCA	0.0449
2	OP	0.0422
3	Wall Thickness	0.0137
4	SMYS	0.0002
5	Coat Type	0.0001
6	Instant of Potential	8.5659E-05
7	Age of Coating	4.9521E-05
8	Fraction of Year	1.9923E-05
9	Dents/Girth Weld	6.8184E-07
10	Soil Type	3.1804E-07
11	Dissolved Solids	2.0299E-07
12	Weld/Bend	1.3881E-07
13	Depth of Cover	9.1092E-08
14	Topography	4.4305E-08
15	Surface Preparation for Coating	4.0989E-08
16	Annual Rainfall	1.4737E-08
17	Soil Porosity	0

Source: UCLA

For the node-state ranking, all the nodes marked in purple in Table 16 were taken into account, without eliminating less important nodes. Table 18 presents the results.

Table 18: Node-State Ranking for the Corrosion Model

Rank	Node Label	State	Metric Value
1	OP	11	0.3563
2	Wall Thickness	1	0.1172
3	HCA	1	0.0802
4	SMYS	1	0.0153
5	OP	10	0.0122
6	Coating Type	6	0.0052
7	Instant Off Potential	2	0.0046
8	Instant Off Potential	1	0.0046
9	Instant Off Potential	4	0.0044
10	Instant Off Potential	3	0.0044
11	Coating Type	2	0.0042
12	Age of Coating	10	0.0035
13	Fraction of Year CP was Operational	1	0.0034
14	Instant Off Potential	5	0.0032
15	Age of Coating	9	0.0030
16	Coating Type	5	0.0027
17	Age of Coating	8	0.0026
18	Coating Type	4	0.0023
19	Age of Coating	7	0.0022
20	Age of Coating	6	0.0018
21	Fraction of Year CP was Operational	2	0.0015
22	Age of Coating	5	0.0014
23	Dents/Girth Weld	1	0.0007
24	Dissolved Solids	1	0.0004
25	Soil Type	4	0.0004
26	Weld/Bend	1	0.0003
27	Age of Coating	4	0.0003
28	Surface Preparation for Coating	5	0.0002
29	Topography	4	0.0002
30	Soil Type	3	0.0002
31	Depth of Cover	3	0.0001
32	Depth of Cover	2	0.0001
33	Annual Rainfall	2	5.9012E-05
34	Annual Rainfall	1	5.9012E-05

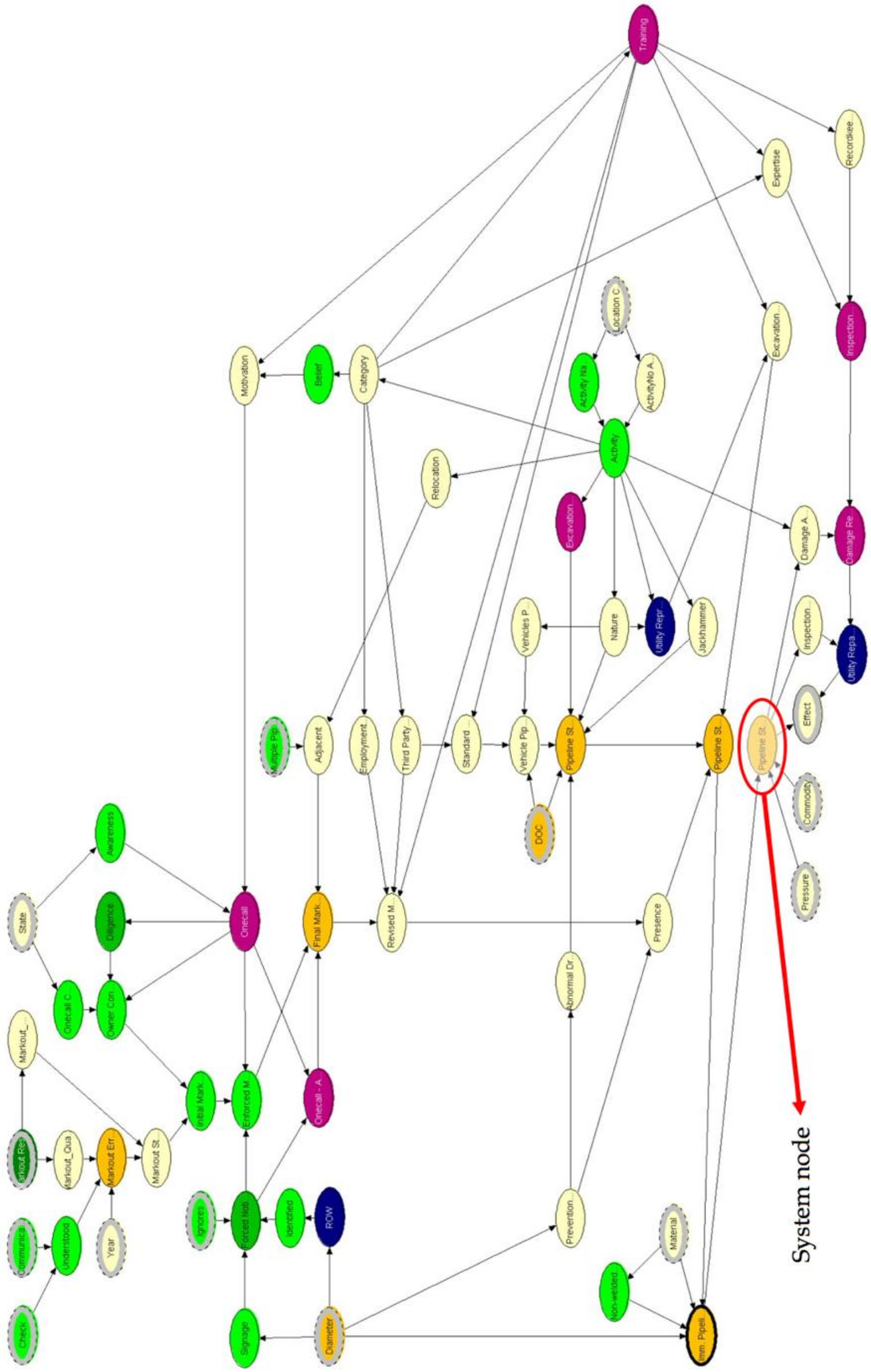
Rank	Node Label	State	Metric Value
35	Depth of Cover	1	5.5488E-05
36	Topography	3	4.8697E-05
37	Dissolved Solids	2	1.7795E-05
38	Soil Porosity	4	0
39	Soil Porosity	3	0
40	Soil Porosity	2	0
41	Soil Porosity	1	0

Source: UCLA

Risk Leading Indicators of the Third Party Damage Model

The Hugin model of the Third-Party Damage is shown in Figure 50. The model has 68 nodes a listed in Table 19. The system node of the TPD model is "Pipeline Effect" which has two states, failure, and success. Therefore, the weight vector is [1,0].

Figure 50: Bayesian Network of the Third Party Damage



Source: UCLA

Table 19: Nodes of the Third Party Damage Model

Name	Label	Description
Abnormal_Drilling_Conditions_2	Abnormal Drilling Conditions	This node indicates when abnormal drilling conditions are encountered for Third Party Activity adjacent to a pipeline
Activity	Activity	Activity undertaken near a "per mile" of the pipeline.
Activity_1	Activity Nature	Activity undertaken near a "per mile" of the pipeline.
Activity_2	Activity No Activity	Activity undertaken near a "per mile" of the pipeline.
Adjacent	Adjacent	The dig site is moved to an adjacent site, and it has a pipeline present.
Awareness	Awareness	Third Party awareness of One Call center.
Belief	Belief	Perceived strength of belief that the third party has in regard to pipeline location.
Category_2	Category	The category of the third party
Check	Check	The event that when incorrect locations are presented to the utility, they will identify it.
Commodity_2	Commodity	Commodity that the pipeline is transporting
Communication	Communication	The event that the third party correctly communicates to the One Call Center the location of the activity.
Damage_Awareness_2	Damage Awareness	For damaged but not failed pipeline, this node describes the probability that the third party is aware of pipeline damage.
Damage_Reported_2	Damage Reported	
Diameter	Diameter	Pipe Diameter
Diligence	Diligence	Event where the third party will contact other pipeline operators beyond simply calling the One Call Center.
DOC_2	DOC	Depth of Cover (DOC) of Pipeline

Name	Label	Description
Employment_Status_2	Employment_Status	Employment status of Third Party personnel
Enforced Markout	Enforced Markout	Accuracy of markout
Excavation Error	Excavation Error	The nature in which the pipeline is struck
Excavation_Nature_2	Nature	The nature of the excavation
Excavation_Precautions_2	Excavation Precautions	Probability that Third Party undertakes precautions when conducting large scale excavations.
Expertise	Expertise_2	The expertise of the Third Party organization's personnel
Final_Markout_2	Final Markout	Markout accuracy at the point where excavation starts
Forced Notification	Forced Notification	The event that a third party contacts the One Call Center if they become aware of pipeline presence due to above ground preventive measures (signage).
Identified	Identified	The event where a third party who had not made an attempt to contact the One Call center is discovered by a right of way (ROW) patrol.
Ignores	Ignores	The event that when faced with preventive measures (signage), the third party will ignore the warnings and continue with the excavation.
Immediate_Pipeline__State_2	Imm. Pipeline State	
Initial_Markout	Initial_Markout	State (including accuracy) of their initial markout of the utility.
Inspection_Detects_Damage_2	Inspection Detects Damage	This node represents the probability that a utility inspection regime will detect damage.

Name	Label	Description
Inspection_Regime_2	Inspection Regime	The extent to which the third party inspects its work, where it may identify damage incurred on pipelines.
Jackhammer_2	Jackhammer	Presence of Jackhammers at Third party Activity
Location_Class_2	Location Class	Location Class of the pipeline.
Markout State	Markout State	Initial markout of the utility
Markout_Error_1	Markout Error (1)	Initial markout of the utility
Markout_Qualifications	Markout_ Qualifications	Qualifications of the personnel marking out the pipeline
Markout_Responsibility	Markout_ Responsibility	Responsibility for utility markout responsibility
Markout_Speed	Markout_Speed	Qualifications of the personnel marking out the pipeline.
Material_2	Material	Pipeline Material
Motivation	Motivation	Propensity for Third Party to engage One Call Center beyond geographic awareness characteristics
Multiple Pipelines	Multiple Pipelines	The event that there are pipelines in the vicinity of the first pipeline in an original third party activity site.
Nonwelded_Coupling_2	Non-welded Coupling	Presence of non-welded coupling, which only occurs on plastic pipes
Onecall	Onecall	Third party engages One Call center (or “811” phone number)
Onecall - Adjacent	Onecall - Adjacent	The event that the third party engages One Call center after relocating in the immediate vicinity
Onecall Coverage	Onecall Coverage	The probability that a pipeline exists within the One Call System remit

Name	Label	Description
Owner_Contacted	Owner_ Contacted	Event that the pipeline owner is contacted
Pipeline__State_2	Pipeline State	
Pipeline_Effect_2	Effect	The end effect of third party activities. This will either result in the pipeline being "failed" or "not failed."
Pipeline_Strike	Pipeline Strike	The nature in which the pipeline is struck
Pipeline_Strike_2	Pipeline Strike W/O Awareness	The nature in which the pipeline is struck
Presence_2	Presence	Pipeline presence correctly identified to Third Party.
Pressure_2	Pressure	
Prevention_ Below_2	Prevention Below	Below ground prevention
Recordkeeping_2	Recordkeeping	The extent to which the third party keeps and maintains records.
Relocation_2	Relocation	Ability for Third Party to relocate to a nearby location but within the vicinity of the original markout.
Revised_ Markout_2	Revised Markout	Third Party technicians identify improper markouts. This then prompts the third party to identify correct markout procedures.
Right_of_Way_Patrolling	ROW	The extent to which the utility undertakes right of way patrolling.
Signage	Signage	Any preventive measures of pipeline above ground.
Standard_Awareness_2	Standard Awareness	Extent to which the Third Party is aware of utility guidance and standards.
State	State	State in the United States where the pipeline is located.

Name	Label	Description
Third_Party_Workforce_Experience_2	Third Party Workforce Experience	This node indicates probabilities associated with Third Party Workforce Experience
Training	Training	The training that the Third Party Organization internally undertakes.
Uitility_Repairs_Pipeline_2	Utility Repairs Pipeline	This node describes whether the utility, on learning that the pipeline has been damaged, initiates repair
Understood	Understood	The state where the utility has correctly understood the location of the third-party activity site given that the third party has tried to communicate it prior to its activity.
Utility_Representation_2	Utility Representation	This node describes the extent to which a utility representative is present at the third-party activity.
Vehicle_Pipeline_Contact_2	Vehicle Pipeline Contact	This node represents the probabilities associated with the nature of vehicle contact with pipelines.
Vehicles_Present_2	Vehicles Present	This node identifies the probability of construction vehicles being present for the Third-Party Activity
Year_2	Year	Year of Installation

Source: UCLA

According to the expert who developed the corrosion model, the nodes marked purple in Table 19 are the only ones required to be considered in the study.

The node ranking results are presented in Table 20. The results for node-state ranking are shown Table 21. All the nodes marked by purple in Table 19 are included in the study for the node-state ranking.

Table 20: Node Ranking of the Third Party Damage Model

Node Rank	Node Label	Metric Value
1	DOC	0.0171
2	Utility Representation	0.0079
3	Diameter	0.0073
4	Inspection Detects Damage	0.0062
5	Utility Repairs Pipeline	0.0017
6	Prevention Below	0.0010
7	Signage	0.0009
8	ROW	0.00089
9	Location Class	0.00060
10	Pressure	0.00019
11	Markout_Speed	0.00012
12	Awareness	4.75E-05
13	Commodity	1.69E-06
14	Material	1.136E-06
15	Year	1.643E-07

Source: UCLA

Table 21: Node State Ranking of the Third Party Damage Model

Rank	Node label	State	Metric Value
1	Inspection Detects Damage	2	0.3652
2	Utility Repairs Pipeline	2	0.0705
3	DOC	1	0.0698
4	Diameter	1	0.0372
5	Utility Representation	1	0.0317
6	Utility Representation	2	0.0261
7	DOC_2	2	0.0237
8	Prevention Below	1	0.0157
9	Diameter	2	0.0149
10	ROW	9	0.0139
11	Signage	2	0.0132
12	Location Class	3	0.0112
13	Location Class	4	0.0110
14	Location Class	2	0.0055
15	Markout Speed	5	0.0052
16	Pressure	1	0.0036
17	Pressure	2	0.0033
18	Markout Speed	4	0.0032
19	Awareness	1	0.0022
20	Awareness	2	0.0021
21	Material	3	0.0020
22	Awareness	3	0.0014
23	ROW	1	0.0009
24	Awareness	4	0.0008
25	Pressure	3	0.0006
26	Commodity	1	0.0004
27	Awareness	5	0.0003
28	Year	1	0.0002
29	Mark out Speed	3	0.0002
30	Year	2	6.9429E-05

Source: UCLA

Conclusions

This section describes a method and tool developed for identifying leading risk indicators of a system or a process that is modeled by a Bayesian Network-based risk model. A two-step method was developed based on the concepts of conditional entropy and conditional probability.

In the first step, the nodes of the Bayesian Network were ranked based on a metric that was formulated around the idea of conditional entropy. This metric is named node metric and can rank the risk model nodes based on their overall impact on probability of the systems level risk metric. The metric is very useful in selecting a subset of the model elements for a more detail analysis and ranking based on the states of each node and corresponding prior likelihood as described below.

The second step was the node-state ranking based on a defined node-state metric. The node-state metric is formulated on the concept of conditional probability and is able to rate the states separately.

The method was implemented in a MATLAB™ package named RiskLI, and applied to the Bayesian Network models developed for corrosion risk and third party damage risk.

While a model-based mathematical procedure such as the method presented here is an effective way to identify elements of the causal risk model that could be good candidates as a risk indicator, there are other important factors that must be considered in the final selection. Some of the basic guidelines in applying the method are:

- Disregard the nodes with negative value. If the value for a node or a node-state pair is negative, it means that "evidencing" that node doesn't decrease the target node (failure) uncertainty, and therefore, there is no gain in monitoring that node.
- Exclude the non-physical nodes or nodes that cannot be monitored. Some of the nodes in the system are not accessible, observable, or not of interest for the study. It is recommended to exclude those nodes from the study before running the ranking algorithm.
- Additional factors such as cost, industry standards, or regulatory requirements may be considered in ranking and selection of risk indicators.

CHAPTER 5: Synthesis

Introduction

The previous chapters in this report present work on modeling two major pipeline threats: external corrosion and third-party damage (TPD). The threats were modeled using a Bayesian network method called MARV™, which stands for Multi-Analytic Risk Visualization. The results are presented in Chapter 2 for the external corrosion threat and Chapter 3 for the TPD threat. Additionally, Chapter 4 shows the use of entropy calculations to quantify the impact of individual events on the overall pipeline threat probability. The benefits of the MARV™ method demonstrated in the previous chapters include:

- MARV™ is a mechanistic threat assessment method that is based the mechanism of failure rather than empirical correlations and thus is applicable for wider conditions without sacrificing the accuracy of the model. This is the opposite of empirical models and works reasonably well in the conditions for which those models have been developed, but also provides results with inputs with greater uncertainty outside of these conditions.
- MARV™ is capable of integrating different types of knowledge (for example, subject matter expertise, mechanistic models, statistical databases, and sensor data) into a centralized system. All types of information are treated the same using conditional probability tables relating the likelihood of an event knowing other events are true.
- MARV™ overcomes the problems generated by uncertain and unknown data. MARV™ uses probability density functions that describe the relative likelihoods for each variable to take on any given value, and takes every possible state into consideration. Even if the state is very unlikely, it is considered. This unique property gives engineers the flexibility to use several values with paired probability for inputs instead of using single deterministic values, thus eliminating the necessity to use conservative values to replace unknown data.
- MARV™ predicts the desired results in a distribution format with clear uncertainty (that is generates all possible outcome with corresponding probability). This is different from conventional modeling approach that use deterministic values for all inputs, thus producing a defined set of results, which could lead to overlooking other possible scenarios. Understanding the uncertainty of the outcome is very helpful on selecting proper action towards the risk mitigation.
- The final benefit of the Bayesian method was identified as most useful by the project's industry partner and is the focus of this chapter. The discussion shows how the MARV™-based decision making approach is different from conventional approaches, and how MARV™-based data prioritization process uses data uncertainty to help pipeline operators determine what data is most useful and help answer questions such as "What data would reduce uncertainty of threats the most? What data should we gather first? And when do we have enough data?"

Decision Making Process

Conventional Process

When there is a need to evaluate the threat or risk associated with a pipeline, a series of questions arise. What is the major threat to the system? Will that threat cause pipeline failure? What is the best solution to reduce the likelihood of such undesired events or potential adverse impacts?

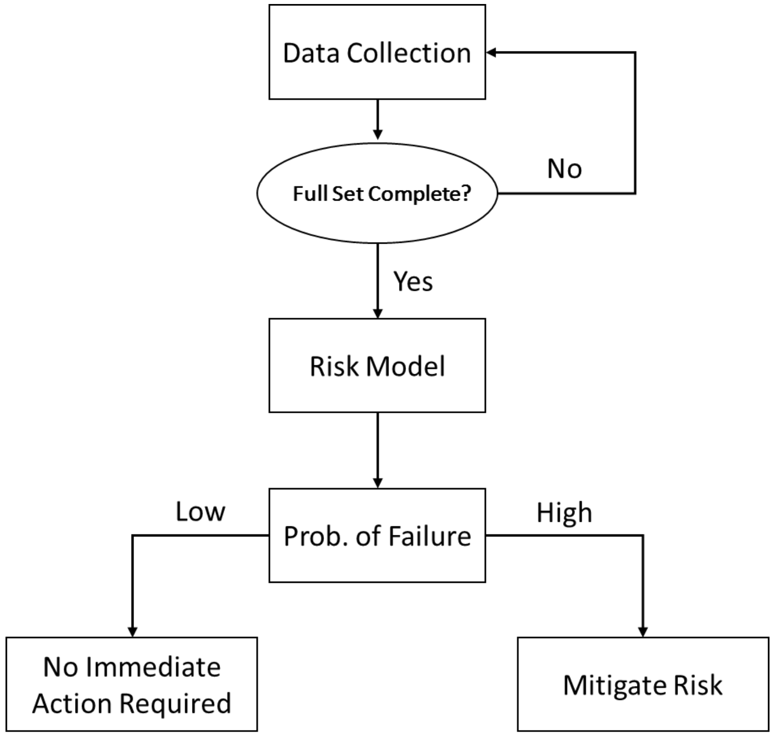
The decision-making process affects the ability to answer these questions. Decision-making for typical pipeline risk assessment and integrity threat assessments (like external corrosion direct assessment [ECDA] and internal corrosion direct assessment [ICDA]) generally follows a linear approach. The first step is to gather relevant data. The next step is to analyze the data and interpret results. Finally, a determination is made of the required follow-up actions based on the results (for example, calculate the next reassessment interval or identify proper mitigation actions). These steps are repeated over time as the actions taken change the threats and new data are acquired. The sections below introduce the decision-making processes and discusses their deficiencies for conventional risk assessment and threat assessment.

Risk Assessment Decision Making Process

The Pipeline and Hazardous Materials Safety Administration (PHMSA) defines pipeline risk assessment as a process "used to evaluate unwanted consequences and the likelihood of those consequences occurring," and defines the purpose of risk assessment as "to develop information that allows organizations to make decisions that reduce or eliminate unwanted consequences by changing their likelihood, their adverse impacts, or both" (PHMSA, 2017). Any risk assessment must include two components: failure probability assessment and consequence assessment. Since this report focuses on external corrosion and third party damage (TPD) threat assessment, only the failure probability part of risk assessment is discussed here.

Figure 51 is a typical flow chart of decision-making process for pipeline risk assessment for the failure probability portion of a risk model. The first step in assessing risk is to identify the threats and collect all relevant data. In this step, all relevant data needed as inputs to the risk model must be clearly defined. If some inputs are unknown or cannot be obtained, the risk model will not work until the specific values or, at least best guesses, are provided for these inputs. For example, unknown inputs could be assigned with clear values based on industry statistics or subject matter expertise. Next, all data collected that has specific values are put into the risk model, which generates a defined set of results, such as the probability of failure, based on the collected specified inputs and the model logic. Depending on regulatory requirements, industry standards, or company policies, the generated risk results will be compared with certain threshold values. The outcome is either that the chance of failure is low (meaning it is not necessary to conduct any immediate action), or the potential of failure occurrence is high (so actions must be taken to mitigate the risk). Of course, the risk model should be re-run to determine proper actions if any new data is provided and fed into risk model.

Figure 51: Typical Decision Making Process for Risk Model



Source: DNV GL

This typical decision-making process leads to some inefficiencies. For example, the subsequent steps can only be executed after the completion of prior steps, no step can be skipped, and it is impossible to run the risk model with only part of the available data.

Data collection is the first and probably most important step of pipeline risk assessment. This seemingly reasonable approach, however, has two major problems. First, pipeline engineers tend to assign conservative values to unknown inputs. Consequently, when there are too many unknowns, the final results can be too conservative and not provide credible information. Moreover, one of the objectives of the risk assessment is to prioritize pipeline locations that must be investigated (or mitigated) first. By using conservative values, the entire pipeline appears to be at risk. In such conditions, it becomes difficult for pipeline engineers to decide where the pipeline should be inspected, leading to critical locations being missed or unnoticed.

Another problem is that the conservatism level is hard to define, especially when a factor has effects on multiple threats. A so-called conservative assumption may not hold the same level of conservatism in relation to the same threat, let alone throughout all threats. For example, when considering internal corrosion threat of liquid pipelines, an assumed high flow rate is a conservative assumption for erosion-corrosion (because a higher flow rate will cause severe erosion), but it is not a conservative assumption for microbially induced corrosion (because a higher flow rate will decrease the microbial accumulation, thus the corrosion rate). Another example is a high cathodic protection (CP) value, which is considered helpful for preventing external corrosion of the pipeline due to soil chemistry or nearby alternating current. On the other hand, a high CP value will increase the deterioration rate of pipeline coating layers, leading to corrosion over the long term. These examples show that assuming defined conservative values is not easy, and it is difficult to control the level of conservatism.

Threat Assessment Decision Making Process

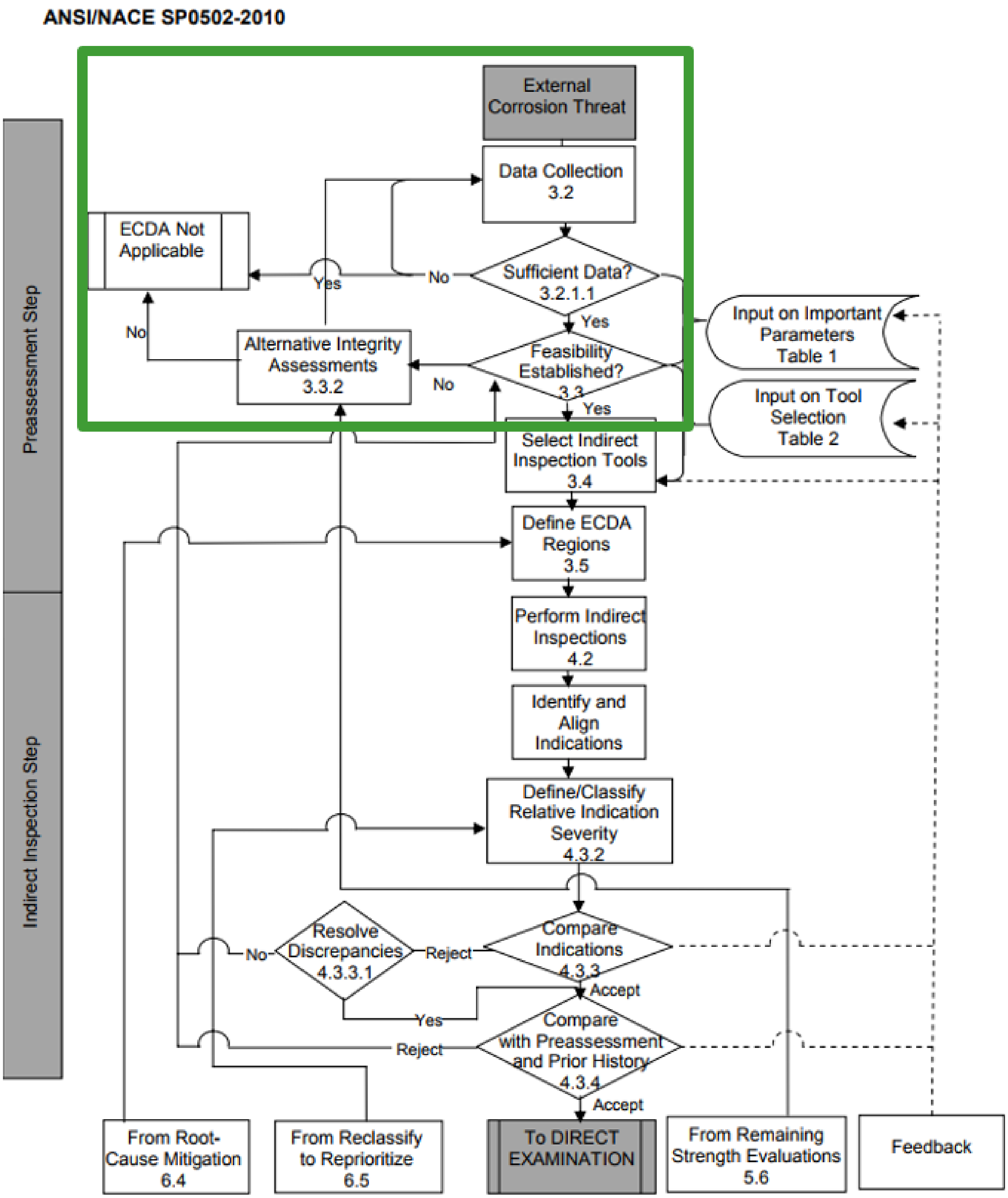
Direct Assessment is identified by the Gas Pipeline Integrity Management Rule as one of three acceptable methods to evaluate time-dependent threats to the integrity of a pipeline segment: external corrosion, internal corrosion, and stress corrosion cracking. Pipeline operators are required to act on the findings from direct assessment studies (PHMSA, 2017). The steps in ECDA, ICDA, and stress corrosion cracking direct assessment (SCCDA) are similar:

- Pre-assessment step: Gather and integrate data to determine feasibility of direct assessment.
- Indirect examination step: Based on findings in pre-assessment step, analyze the gathered data, find the possible indications of corresponding threats, and prioritize the excavation locations for direct examinations.
- Direct examination step: Based on findings in indirect examination step, check the excavated pipe segments, determine the severity of defects induced by corresponding threats, and remediate or address the threats.
- Post-assessment step: Based on the first three steps, evaluate the effectiveness of direct assessment and determine the reassessment interval.

NACE defines the standard practice for ECDA (NACE 2010), ICDA (NACE 2016) and SSCDA (NACE 2015). Figure 52 shows a flow chart of ECDA with only the pre-assessment step and indirect examination step due to the size of chart. The green box highlights a typical linear part of the logic process. Similar to the data collection step in a risk assessment logic loop, the data gathering in threat assessment must continue until sufficient data are gathered, otherwise the following steps cannot be executed. Once sufficient data are collected, they are integrated and analyzed to judge the feasibility of applying indirect examination/inspection tools. Should any of these steps fail (if it is impossible to obtain sufficient data or infeasible to apply indirect examination/inspection tools), the logic process would stop and ECDA could not be applied.

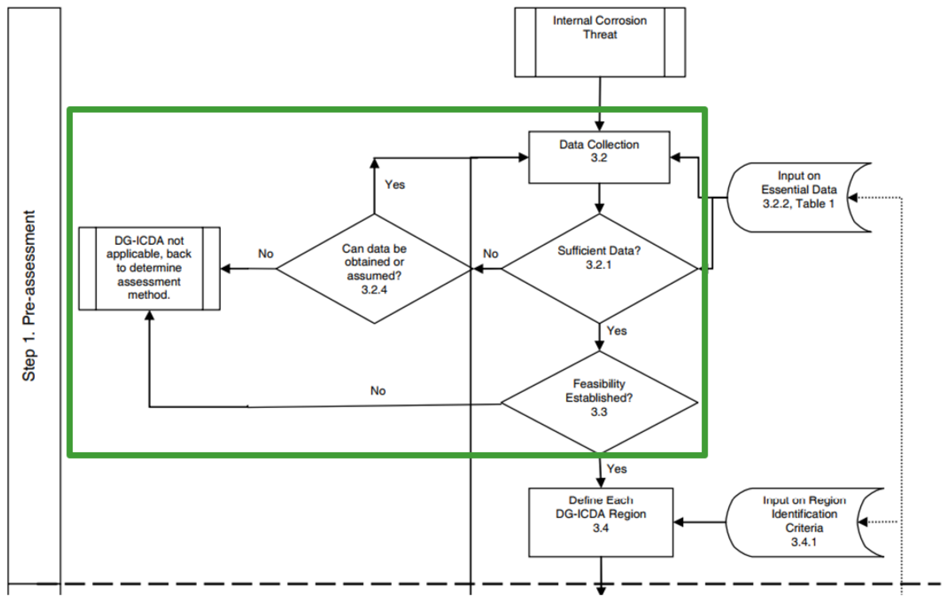
Due to these characteristics, the process of ECDA exhibits a very linear pattern. Obvious linear patterns are also observed in ICDA and SCCDA, as shown in Figure 53 and Figure 54 respectively. Across ECDA, ICDA and SCCDA processes, the succeeding steps always rely on the completion of prior steps and the order of steps must be followed. Similar to conventional risk assessment approach, there inevitably is a waiting stage for gathering sufficient input data in the beginning. Moreover, not all input data are equally important to the final results. The variation of some inputs may have minor impact, but the collection effort to get these inputs defined may not be trivial. Thus, waiting and collecting sufficient/or all relevant data (especially those data having little impact) could be a significant waste of limited resources, which could have been allocated to the sections where resource is urgently required.

Figure 52: External Corrosion Direct Assessment Flow Chart



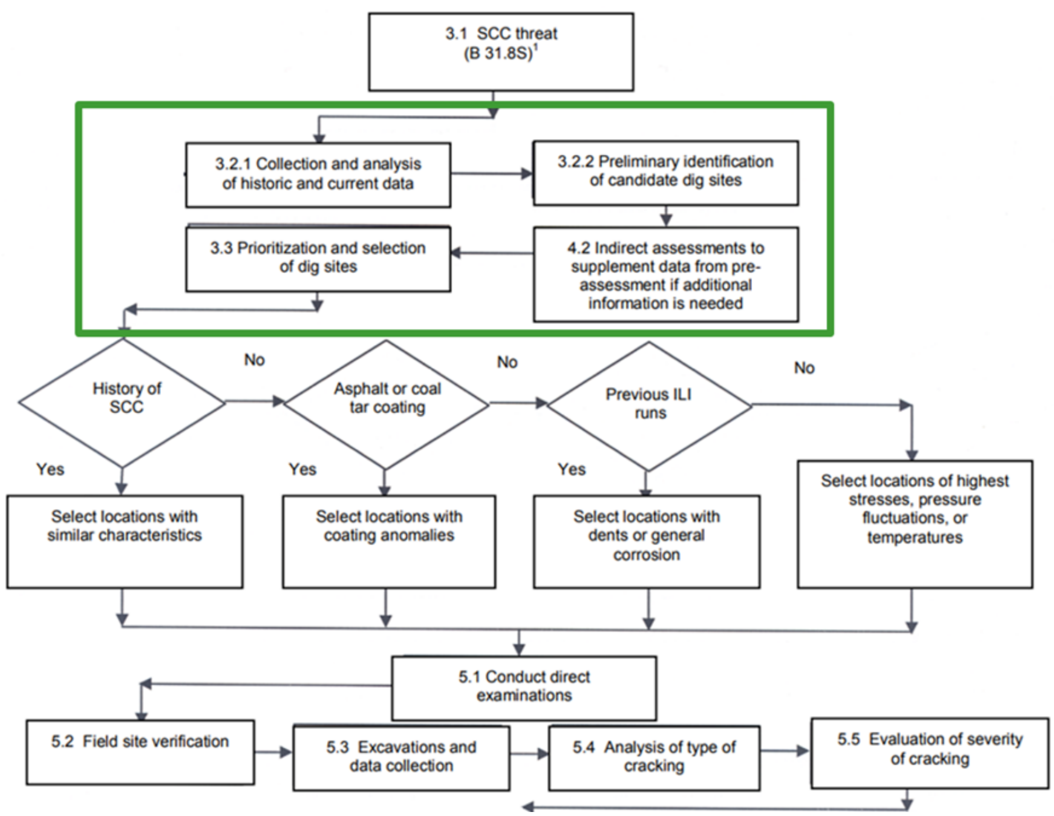
Source: NACE, Reproduced from ANSI/NACE SP0502-2010

Figure 53: Internal Corrosion Direct Assessment Flow Chart



Source: NACE, Reproduced from NACE SP0206-2006

Figure 54: Stress Corrosion Cracking Direct Assessment Flow Chart



Source: NACE, Reproduced from NACE SP0204-2008

MARV™ Decision Making Process

Understanding Where the Uncertainty Comes From

Due to time limitations, pipeline engineers cannot afford to wait for complete data sets to perform risk assessments. Therefore, risk assessment must be done with incomplete and often uncertain data, which creates barriers for conventional assessment approaches. However, in the MARV™ approach, data uncertainty (including missing data) is not a problem. Missing data is simply another source of uncertainty in the final risk results. In some cases, the variability or uncertainty of an input does not change the probability of failure; in other cases, small variability in one input can lead to catastrophic events. The importance of a variable can be determined using the methods discussed in Chapter 4 (leading indicators).

The demonstrated MARV™ method considers all three sources of data uncertainty:

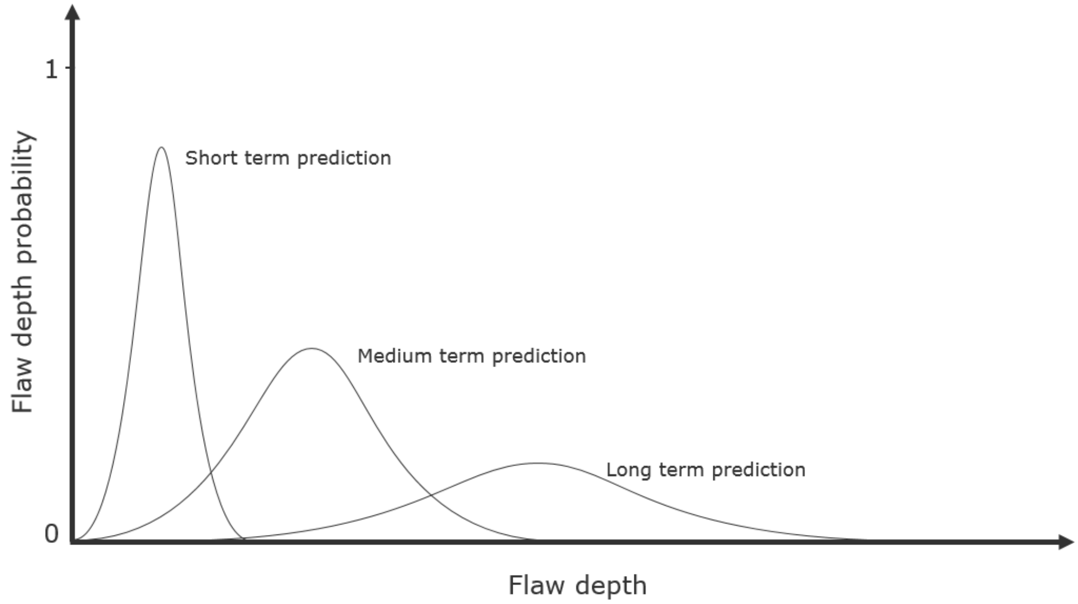
- The use of average values instead of a time series
- The lack of precision or accuracy in recording equipment
- Missing data

Furthermore, MARV™ accounts for knowledge uncertainty by incorporating different models or expert judgements in developing the conditional probability tables.

Understanding where the uncertainty comes from is useful for the decision-making process. Take the prediction of flaw depth growth with time as an example. Since it is not possible to predict future pipeline flaw depth with absolute certainty, MARV™ instead predicts a pipeline flaw depth probability density function, which is a range of flaw depths paired with corresponding probabilities (for example, 50 percent chance to have a flaw depth of 0.05 inch, 25 percent chance to have a flaw depth of 0.1 inch, and so on).

Figure 55 depicts three hypothetical examples showing the predictions of growth in flaw depth in the short term (one year), medium term (five year) and long term (ten year). A flaw can grow without being treated, so the average value of flaw depth will increase from short term to medium term to long term (the position of curve peak on horizontal axis moves towards right from near future to far future). The uncertain input data makes the prediction of near future easier than the prediction of far future, as the uncertainty grows with time.

Figure 55: Evolution of Predicted Pipeline Flaw Depth in Time

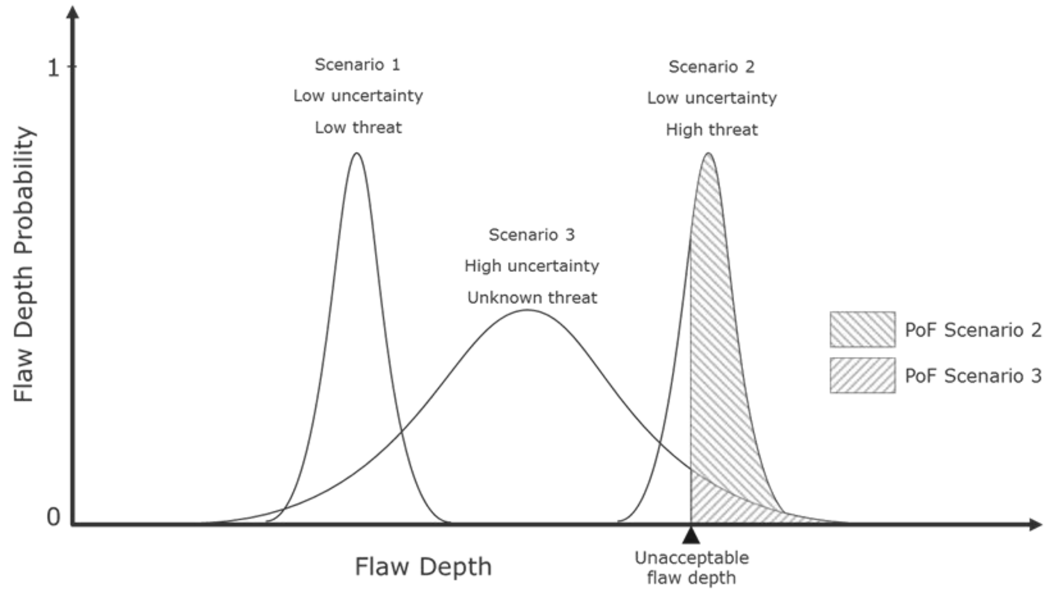


Source: DNV GL

Uncertainty Drives the Decision Making Process

The increase of flaw depth eventually leads to three different failure scenarios, as shown in Figure 56. In the first scenario, the probability of failure (POF, the area of curve above the unacceptable flaw depth) is within an acceptable range and there is no need for immediate action. In the second scenario, the POF is high, and because the uncertainty is low, the team is confident that the pipe section is going to fail. This scenario requires mitigation actions and it is not necessary to collect more data since the uncertainty is already low (results are confident). In the third scenario, the probability of failure is not as high as in the second scenario (that is, the shading area is smaller) but is still unacceptable. However, because of the high uncertainty of the prediction, it is unclear if the pipe section will fail or not. In this scenario, the uncertainty of the prediction must be reduced by collecting more data to be able to make a more confident decision.

Figure 56: Three Types of Distributions



Source: DNV GL

Understanding the uncertainty of a prediction leads to different decisions – no action, immediate mitigation, or gather more data. The flaw depth prediction and corresponding responses in Scenario 1 and Scenario 2 are very clear, but the flaw depth data in Scenario 3 are quite scattered, so no targeted actions could be determined except gathering more data to refine the flaw depth. With more data, Scenario 3 could transform into Scenario 1 or Scenario 2 as shown in the examples below.

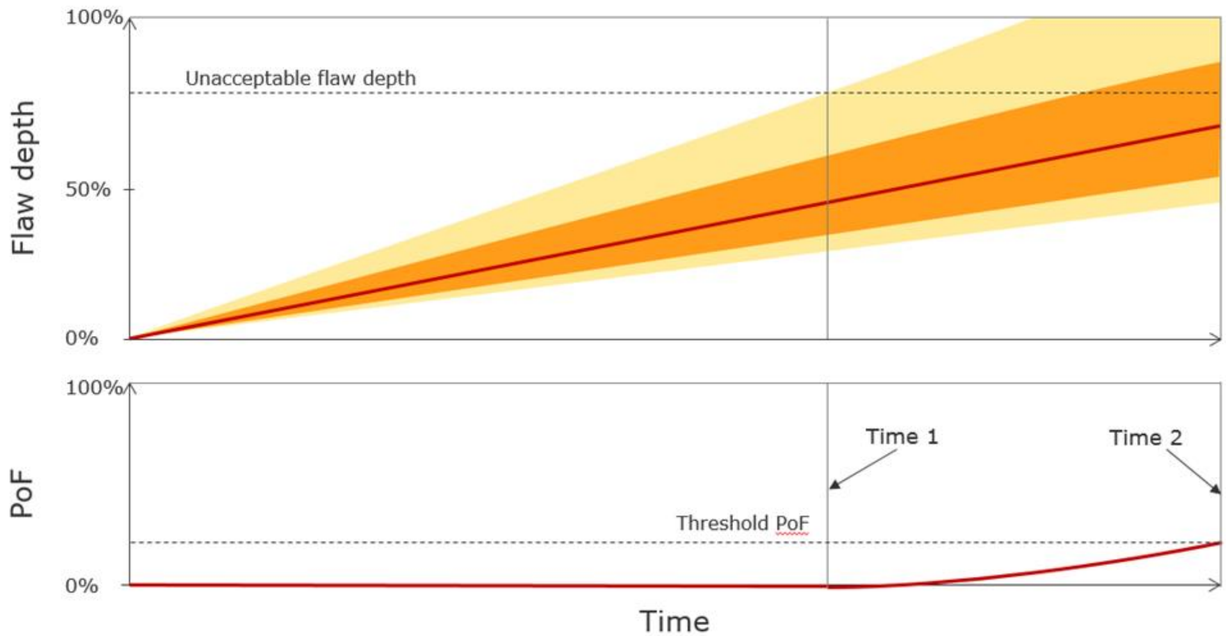
Scenario 3: Uncertain Prediction Due to Lack of Data

The MARV™ method predicts the flaw depth as a range of values with associated confidence level. As shown in Figure 56, the short-term prediction of flaw depth is more certain than prediction further into the future. The more data that is collected, the more confident is the prediction. Figure 57 shows the same concept with time on the x-axis. The red line represents the median flaw depth, the orange band represents the 90 percent confidence interval, and the yellow band represents the 99 percent confidence interval. The associated probability of failure POF is shown below the flaw depth chart. POF is calculated by integrating the portion of the flaw depth probability distribution that is above the unacceptable flaw depth. For example, if the shading area of the curve above the unacceptable flaw depth is 5 percent of the total curve area, there is a 5 percent chance that the flaw depth under study is larger than the unacceptable flaw depth, and thus POF is 0.05.

Figure 57 shows how the prediction of pipeline flaw depth evolves over time. The flaw grows with time (the slope of the red line is the corrosion rate) and the uncertainty also increases with time (the confidence interval orange and yellow bands increase). Once the 99 percent confidence interval (yellow band) crosses the unacceptable flaw depth, there is a 0.5 percent chance that the flaw depth analyses will fail. With time passing, the flaw depth grows and it becomes more and more likely to exceed the unacceptable level, and the probability of failure increases with time.

When the upper boundary of 90 percent confidence interval (orange band) intersects the unacceptable level, it could be 5 percent chance that the flaw is deeper than acceptable threshold, resulting in a 5 percent POF. Eventually, when the red line (the median flaw depth) reach the unacceptable level, it indicates a POF of 50 percent. At Time 1, the uncertainty band is relatively narrow and only upper boundary of 99 percent confidence region cross the unacceptable flaw indicating a POF of 0.5 percent. With time passing, at Time 2, POF reaches threshold value which requires immediate actions. However, the uncertainty bands increase greatly from Time 1 to Time 2, making it difficult to decide whether the actual POF reaches threshold or not. To be more confident, more data must be collected to reduce the uncertainty band/confidence interval. Two possible outcome with more data collected are the median flaw depth keeps the same or reduces (Scenario 1 in Figure 56) or flaw depth increases (Scenario 2 in Figure 56).

Figure 57: Evolution of Flaw Depth Prediction in Time

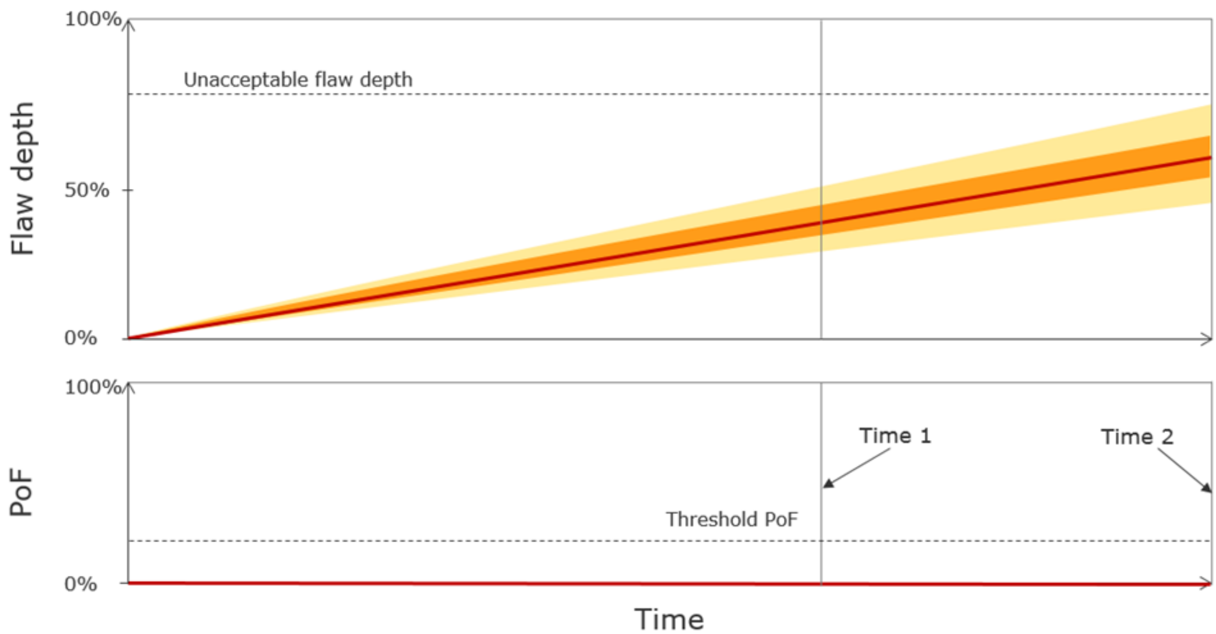


Source: DNV GL

Scenario 3 Transformed to Scenario 1

Gathering more data reduces the uncertainty of the predictions. When the median flaw depth is the same or lower, the predictions made in Scenario 3 might become like those in Scenario 1 after another set of data collection. Figure 58 illustrates the value of collecting more data. In this example, the median flaw depth is the same as in Figure 57. However, the flaw depth predictions have less uncertainty. The reduced uncertainty has great impact on the decision-making process. Although the median flaw depth is the same as the previous example, the range confidence intervals is smaller. Consequently, the 90 percent and 99 percent confidence internal do not reach the unacceptable flaw depth and POF stays below 0.5 percent, way lower than the threshold POF from Time 1 to Time 2. Since the uncertainty band is very narrow in this case, it is confidence that no action is necessary in this period. This example illustrates the benefit of gathering more data. The more data is gathered, the more certain are the predictions (confidence region shrinks) and consequently the next reassessment can be pushed out further in time, as the time point when the boundary of same confidence level intersects with unacceptable level is postponed.

Figure 58: Evolution of Flaw Depth Prediction in Time with Reduced Uncertainty

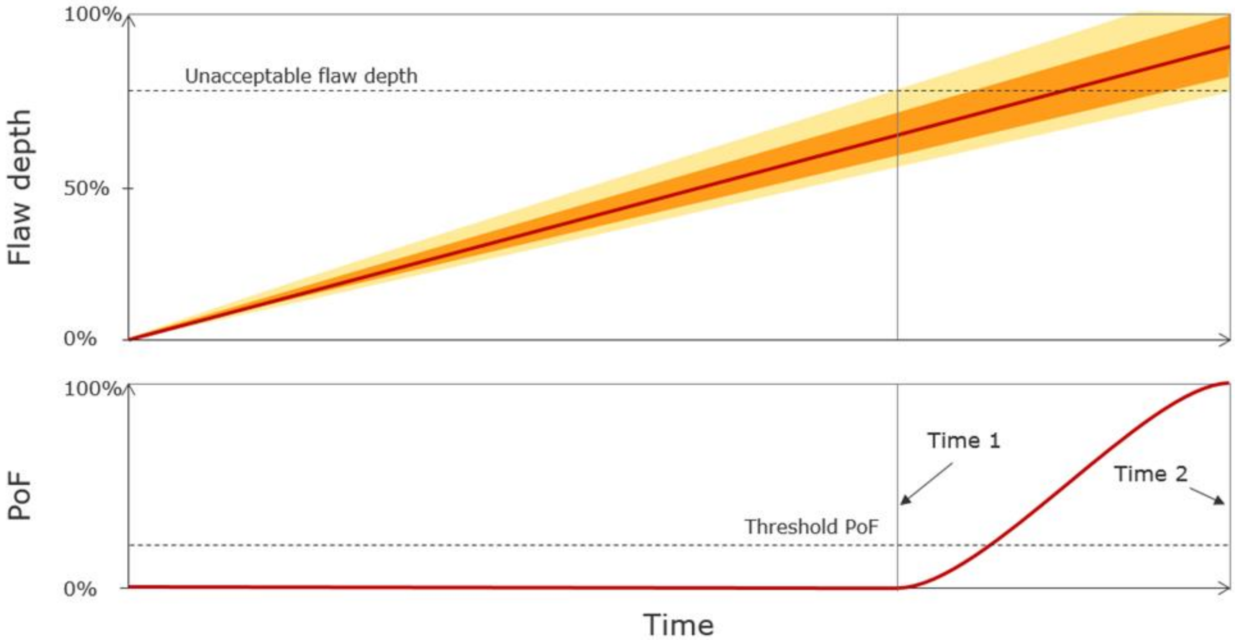


Source: DNV GL

Scenario 3 Transformed to Scenario 2

Although it is preferred to gather more data to reduce both uncertainty and median flaw depth, the practical case does not always go this route. Gathering more data could reduce uncertainty, but it is impossible to know its impact on the predicted median flaw depth – which could keep or reduce (Scenario 3 transformed to Scenario 1 above) or which could increase instead. Figure 59 illustrates an example where the uncertainty is reduced (manifested as narrower confidence intervals) but the median flaw depth is increased (the red line has steeper slope). Consequently, the POF increases greatly from Time 1 to Time 2. From integrity management point of view, this case is not desired, because this situation requires immediate actions (for example, inspections, assessments, mitigations, etc.) which always consume resources (time, staffing, monetary). But from decision making point of view, this case is very helpful, because it is confident that the POF will exceed the threshold shortly from Time 1 and it justifies the necessity of allocating resources to this system to bring down the likelihood of failure. It also indicates more data collection is not helpful for decision making, since the uncertainty is acceptably small enough to draw useful conclusion.

Figure 59: Reduced Uncertainty and Increased Average with Additional Data

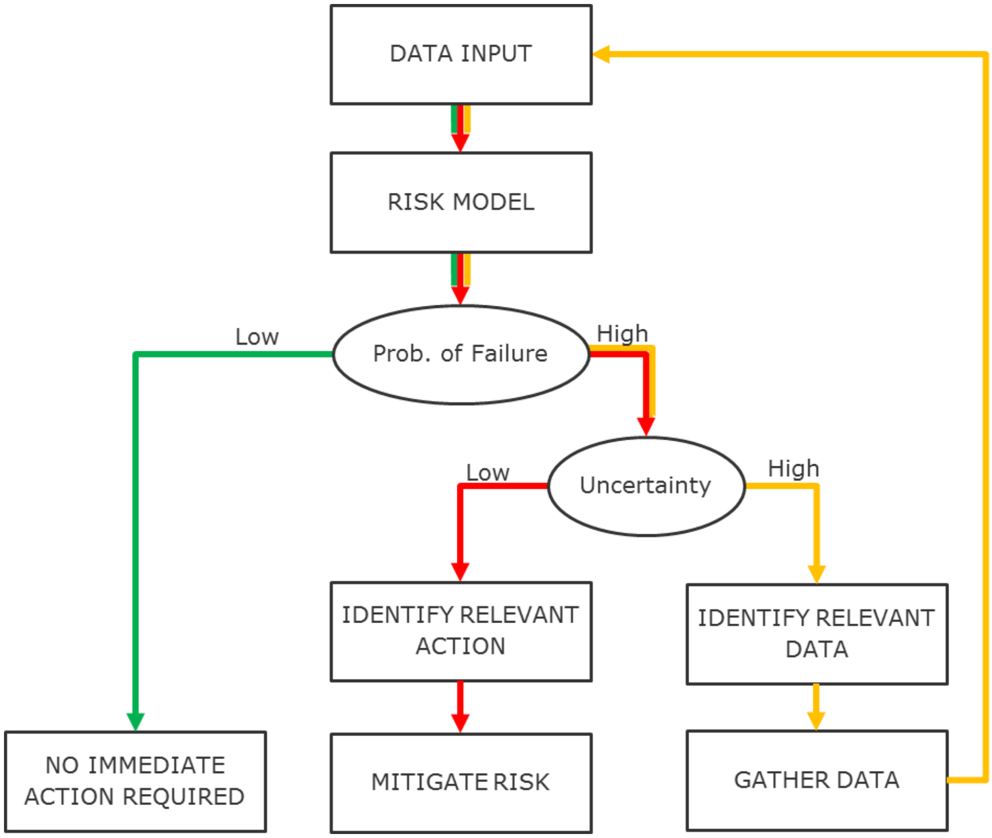


Source: DNV GL

MARV™ Logic Process

When data is certain, the MARV™ decision-making approach should be similar to conventional decision making approach, because the team can be confident that the outcome is either no action necessary for low POF case or immediate actions required for high POF case. But when uncertainty is high, there is a distinct difference setting MARV™ aside from conventional approaches. As discussed earlier, uncertain data is a great barrier for conventional decision making processes because they follow a linear approach. In contrast, the MARV™ method allows educated decision making based on understanding the uncertainties in different scenarios. Therefore, the MARV™-based decision-making logic loop is quite different from the conventional approach (Figure 60).

Figure 60: MARV™ Logic Loop for Decision Making Process



Source: DNV GL

When performing the risk assessment, some data may already be present. Instead of waiting for all relevant data to be collected, the risk model in MARV™ approach can use all currently available data input to generate the probability of failure (leak or rupture). The MARV™ model generates an average failure probability and a clear uncertainty associated with the average failure probability, based on the uncertainty of all inputs. Following this step, there are three pathways, shown in green, red, and orange. The green pathway is the shortest (having the least steps). Similar to the conventional approach, if the probably of failure is low, no immediate action is required at this moment (this corresponds to Scenario 1), although long-term monitoring is still necessary to ensure the studied targets are within an acceptable range.

However, if the probability of failure is higher than the threshold values, it has two scenarios depending on the uncertainty level: the uncertainty of failure probability is low (red pathway) or the uncertainty of failure probability is high (yellow pathway).

The red pathway shows the uncertainty on whether the POF is high is low. This means that the pipe segments have a high chance of failure, thus it is essential to identify the relevant actions to reduce the failure probability or mitigate the consequences due to failure.

The orange pathway indicates that the average probability of failure is high, but because of insufficient data it is uncertain whether the pipe segments truly have a high probability of failure. Therefore, more data must be gathered to provide conclude whether or not further actions are required to mitigate the risk. Once more data is input into the risk model, the decision-making process would go through the logic loop again and the outcome could be either affirmative (green and red pathways) or still informative (orange pathway). If the conclusion is still not affirmative, the decision-making process will keep moving along the orange pathway in the logic loop. Thus, the MARV™ decision making is an iterative process until an affirmative conclusion is reached.

However, collecting data requires allocation of resources like staffing, time, and money, and the more data that is needed, the more resources will be required. Also, it may be infeasible to collect some types of data under some circumstances. Moreover, for some instances at some time points, gathering more data does not help achieve more favorable or desired results, especially when the types of data have minor impact on final results. Therefore, there should be a stopping point for gathering more data, as discussed below.

MARV™-Based Data Prioritization

As discussed above, data gathering can be resource intensive and resources are not unlimited. In many cases, processes are slowed or stopped by limited resources such as short time frames, limited monetary budgets, and lack of relevant experience. How to allocate these limited resources more efficiently becomes an urgent need. For data gathering, it means determining what data to collect, how much to collect, and when to stop collecting. Prioritizing different types of data for gathering efforts involves two aspects – benefits and costs.

Benefits are what data gathering can provide for decision making. More data mean fewer assumptions, more affirmative information for decision making, and more confident following actions. However, these benefits come at the expense of resource consumption, that is, costs of human resources, time, and monetary budgets. To prioritize data gathering, it is essential to have a clear understanding of all associated costs (labor, equipment, time, monetary, and so on) to find the optimal point at which the costs of further data gathering outweigh the benefits of the additional data. Since conventional approaches rely on sufficient data or even a complete dataset, the costs of spending limited resources may have already outweighed the benefits of gathering some trivial data.

The unique feature of the MARV™ method allows the possibility of data prioritization based on insufficient or even no data, which overcomes this barrier. By using the MARV™ method, it is possible to achieve a win-win situation where the operations become safer and costs are saved.

Data prioritization could help avoid of spending resources on gathering unnecessary or unimportant data. It could save the costs for data gathering efforts because less data must be collected. Moreover, it could also make assessments easier by reducing the amount of data that must be processed and analyzed in the subsequent steps, in which it also reduces human resources and time.

Data prioritization could also help the important data get more focused without the interference by trivial or unimportant data (specifically, the “right” data get collected and analyzed), which facilitates a better understanding of the corresponding threats. In this sense, it helps to make operations safer. Finally, data prioritization could help allocate the limited resources to the parts of the process that require resources.

The MARV™ method could save resources spent on unnecessary data and subsequent steps of using these trivial data, and it also could facilitate the understanding of the threats to the pipeline operations. These saved resources and better knowledge could be applied to other segments and systems, leading to safer overall operating performance (system-wide or company-wide) with cost effective solutions.

The next section provides a hypothetical case study of how MARV™ driven data prioritization is performed based on cost-benefit analysis.

MARV™-Based Data Prioritization Case Study

To better explain how the MARV™ method drives decision making, this section will use a hypothetical case with very limited data to illustrate a generic MARV™-based data prioritization to guide what data should be collected and when should data gathering stop. External corrosion was selected as the example threat. The in-line inspection (ILI) data (previous flaw depth) is assumed as the only known data for a pipeline segment, since ILI tools such as magnetic flux leakage, transverse flux inspection, and ultrasonic testing are widely used by pipeline operators to measure and record anomalies like corrosion, cracks, laminations, dents, gouges, or other defects along the pipelines to manage pipeline integrity. Moreover, code 49 CFR 192.939 requires pipeline operators to perform Internal Inspection Tool, Pressure Test or Direct Assessment every certain number of years, the maximum allowable interval of which is based on the percent specified minimum yield strength level where the pipeline operates (Code of Federal Regulations, 2016). The hypothetical base case and two sensitivity tests below will demonstrate the generic process of data prioritization starting with knowing only the previous flaw depth and the impact on decision making on handling the external corrosion threat.

Hypothetical Base Case

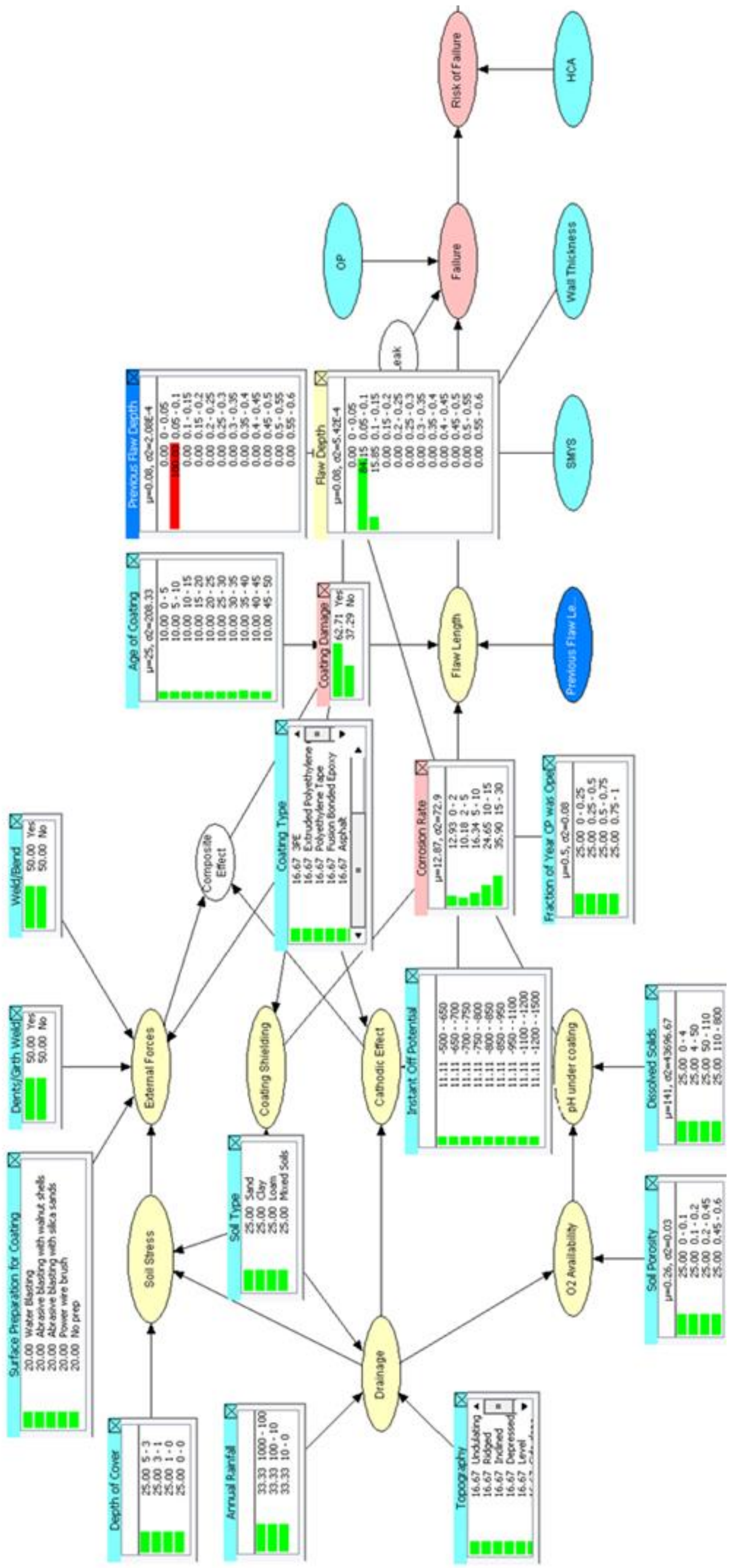
ILI data (feature depth) is assumed to be the only data known for the base case. More specifically, the base case assumes that ILI was run in 2014 and at that time the recorded flaw depth in the pipe segment was 0.09 inch ± 0.01 inch (99 percent confident). Based on the external corrosion model discussed in Chapter 2, the MARV™-based external corrosion model with inputs is shown in Figure 61.

All input nodes except the Previous Flaw Depth node (the value identified by ILI) have an even distribution of data categories, since they are assumed unknown at this stage (that is, it is equally likely for each possibility for each type of data). Only the Previous Flaw Depth node has a known input as 100 percent chance in 0.05-0.1 inch (highlighted as a red bar as shown in the figure).

If ILI data is the only known data, one cannot proceed with conventional assessments – especially risk assessments – without gathering further data. Thanks to the unique capability of the MARV™ method of using distribution values for inputs, the assessment model is not required to have all inputs specified with definite values. Subsequently, the probability of failure could be produced from the assessment model. The flow chart of this process following the MARV™ method is shown as the three highlighted steps in Figure 60.

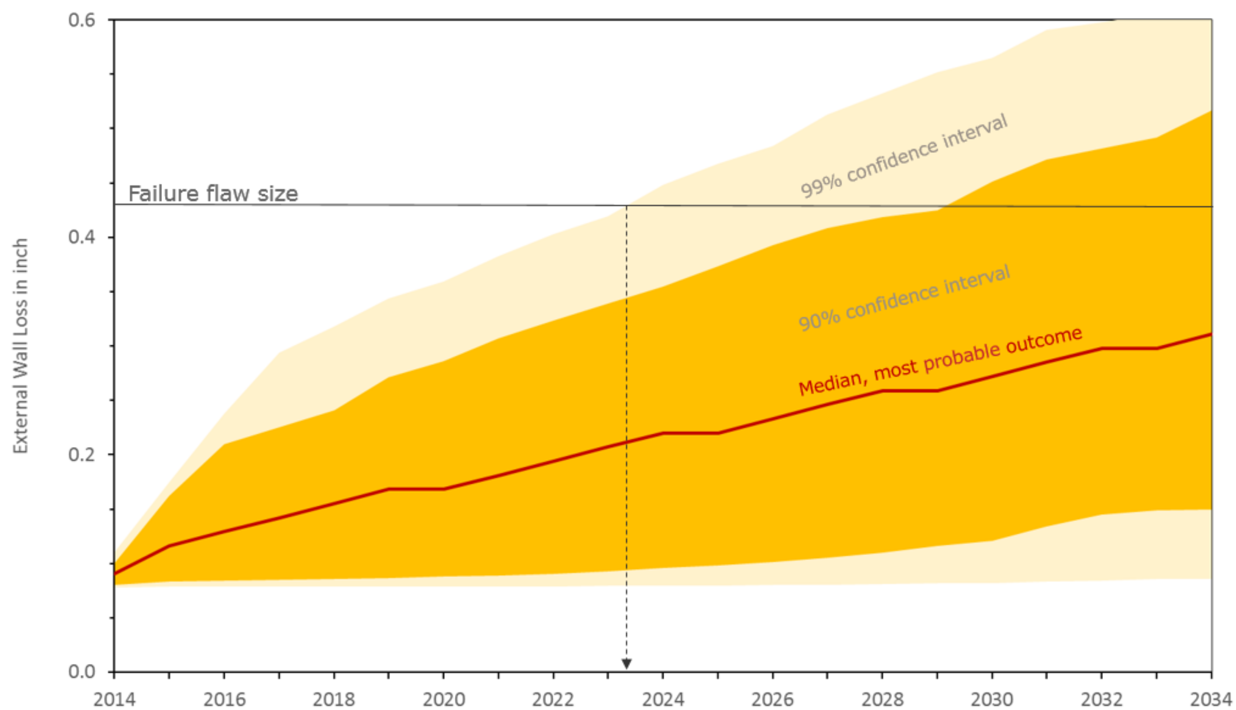
With all inputs being unknown except previous flaw depth, the projection of evolving flaw depth in the near 20 years (from 2014) is shown in Figure 62. The curve in the middle reflects the median flaw depth changing with time. The darker region at the two sides of median flaw depth curve represents the 90 percent confidence level of flaw depth, while the lighter region further outside represents the 99 percent confidence level of flaw depth. In 2014, the flaw depth is 0.09 inch ± 0.01 inch (99 percent confident). With time passing, the flaw depth grows and the uncertainty also increases, as demonstrated by wider regions at the same confidence level. For example, in 2014, it is 99 percent confident that the flaw depth is between 0.08-0.1 inch with a median of 0.09 inch and a span of 0.02 inch. Ten years later, in 2024, the flaw depth range increases to 0.09-0.45 inch with a much large median size of 0.23 inch and a much larger span of 0.36 inch to reach the same confidence level. If the upper boundary of 99 percent confidence region intersecting with the failure flaw depth is used as threshold (assuming POF is large enough at this point to require some mitigation actions), it can be found that the first time when the flaw size goes beyond the failure depth occurs between 2023 and 2024. However, although the POF is large at this point, given the uncertainty is high, it is very difficult to draw a useful definite conclusion on whether actions are required by that time, because of the scattered flaw size.

Figure 61: Hypothetical Base Case



Source: DNV GL

Figure 62: Base Case Projection of Flaw Depth Evolution



Source: DNV GL

According to the MARV™ approach shown in Figure 62, the situation of high POF and high uncertainty (yellow pathway) requires additional data to be gathered for more effective decision making. The ensuing question is which data should be collected next.

First Sensitivity Test

Benefits and costs should be analyzed to prioritize the data gathering effort. For example, the benefit of cover data could be defined as how much a clear value for depth of cover (how deep the pipeline is buried) can reduce the uncertainty around flaw depth. The cost of cover data can be defined as the expenses, including indirect costs like time and human resources and direct costs like monetary budgets associated with a depth of cover survey. The ratio of benefit to cost represents the benefits brought to decision making per unit of resource (for example, per dollar), and can be used to prioritize the effort to gather each type of data.

Reducing the uncertainty was determined using a series of "what if" scenarios:

- What if:
    - Depth of cover was 0 meters (pipe is above ground)?
    - Depth of cover was 0-1 meters?
    - Depth of cover was 1-2 meters?
    - Depth of cover was 2-3 meters?

By assuming a defined value category for all input nodes (with other inputs remaining unchanged) and using the average change of the uncertainty of flaw depth, one can calculate the change in uncertainty (such as how much that data would help reduce overall uncertainty). Results of the sensitivity analyses are the same as in the previous chapter for the first round (when there is no data). In the following rounds, results will be different because the sensitivity analyses take into account data that has already been collected.

To decide what data should be collected next, the usefulness of the data (specifically reducing the uncertainty in the benefit column of the Table) is compared to the cost of gathering that data. Results are shown in Table 22.

Table 22: Benefit Cost Analysis from Sensitivity Test

Node Label	Node Description	Benefit	Data Cost	Benefit/ Cost Ratio
Coating Type	Probability of the type of coating	1.1E-04	$500	2.3E-07
Instant off Potential	Probability of effective surface potential	8.6E-05	$500	1.7E-07
Age of Coating	Probability of age of the coating since construction or repair	5.0E-05	$500	9.9E-08
Fraction of Year	Probability of fraction of year CP was operational	2.0E-05	$500	4.0E-08
Dents	The probability of dent or girth weld being present	6.8E-07	$250,000	2.7E-12
Soil Type	Probability of type of soil	3.2E-07	$25,000	1.3E-11
Dissolved Solids	Probability of concentration of total dissolved solids in the groundwater within a certain range	2.0E-07	$25,000	8.1E-12
Weld/Bend	Probability of having the presence of a weld or bend	1.4E-07	$500	2.8E-10
Depth of Cover	Probability of the depth of the pipeline	9.1E-08	$21,000	4.3E-12
Topography	Probability of the type of topography above the pipeline	4.4E-08	$25,000	1.8E-12
Surface Preparation for Coating	Probability of type surface preparation was used during construction before coating application	4.1E-08	$1,000	4.1E-11
Annual Rainfall	Probability of average annual rainfall in the year	1.5E-08	$1,000	1.5E-11
Soil Porosity	Probability of soil porosity	0	$25,000	0

Source: DNV GL

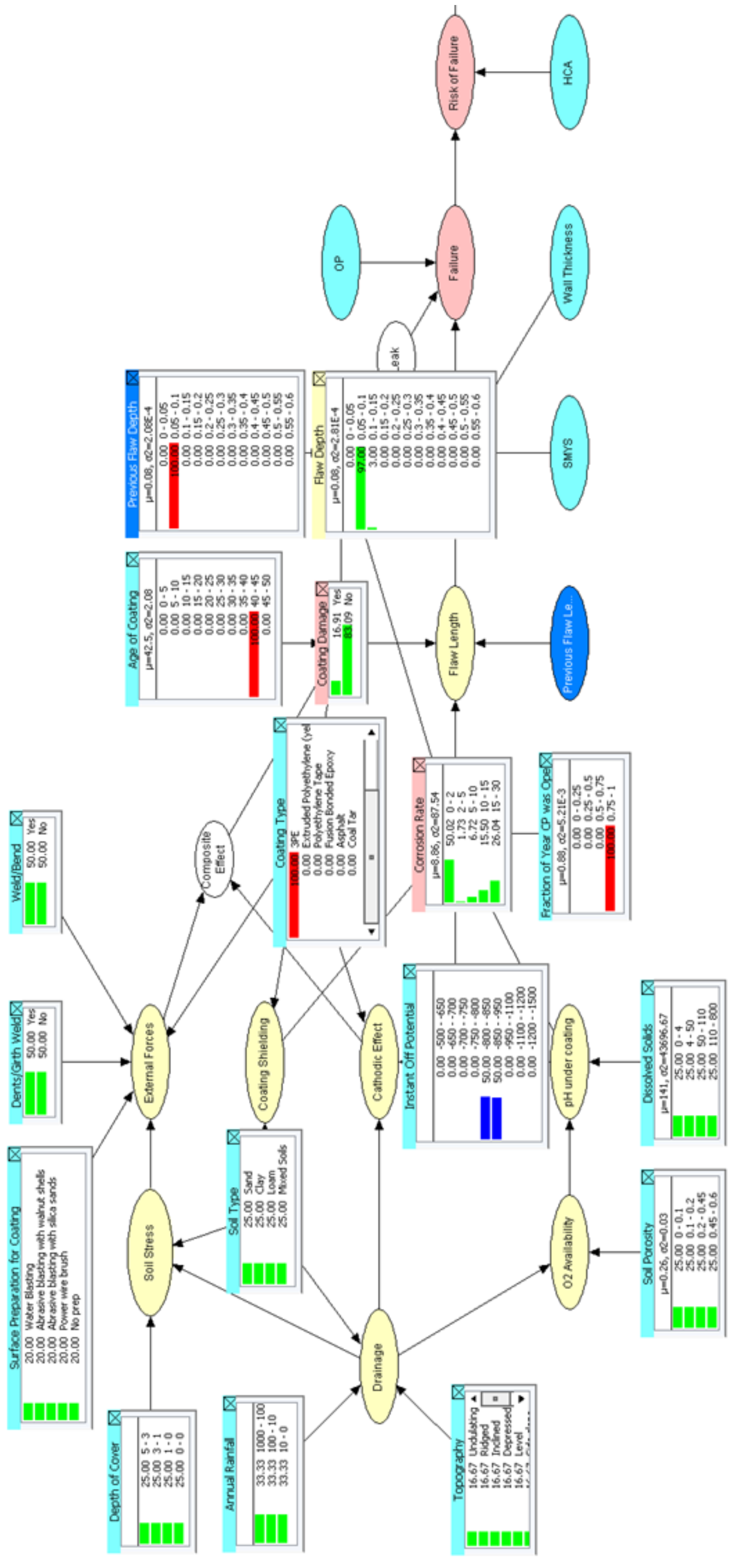
In this hypothetical example, data gathering efforts are executed according to the benefit/cost ratio in Table 22. The data collection provides the following values:

- Coating age is 42 years
- Coating type is 3PE

- Fraction of CP operation since pipe installment 99 percent
- CP potential in the range of -800millivolts~-950 millivolts (mV)

These data are fed into the MARV™ model as shown in Figure 63. The Age of Coating node, Coating Type node, and Fraction of Year CP node now change from multiple green bars to a single red bar, representing a 100 percent fixed range, and the Instant Off Potential node changes from green to two blue bars (as it is still a distribution).

Figure 63: Base Case with Identified Coating Age, Coating Type, Cathodic Protection Potential and Cathodic Protection History

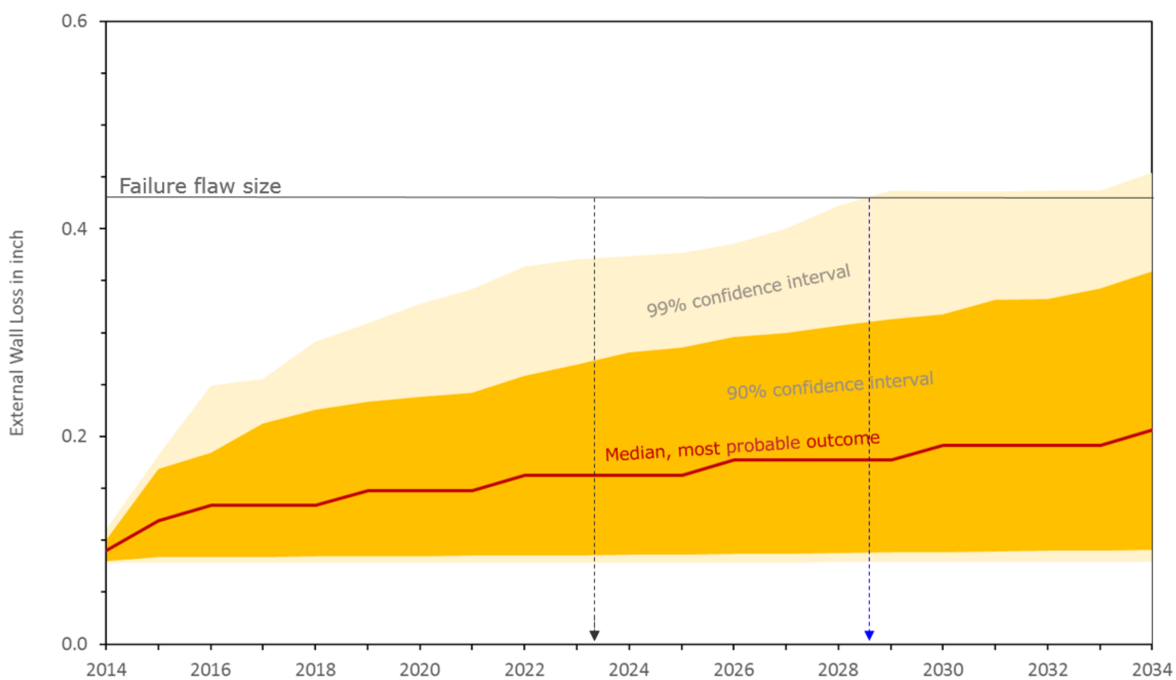


Source: DNV GL

An iteration process (running the assessment model and generating probability of failure) is executed again as shown in Figure 60. With these additional data (coating age, coating type, CP potential and CP history), the evolution of flaw depth is projected as shown in Figure 64. The median flaw depth found with the gathering of additional coating and CP data grows more slowly than under the base case with only the previous flaw depth knowledge. The associated 90 percent confidence and 99 percent confidence regions also become narrower, indicating that the generated flaw size from assessment model is more centralized around the median value and it is no longer a rough guess of flaw size. In 2024, the flaw size range changes to 0.09 inch to 0.37 inch. Compared with base case, the median value reduces from 0.23 inch to 0.16 inch and the span shrinks from 0.36 inch to 0.28 inch. Similar to the base case, if the intersection between failure flaw size and the upper boundary of 99 percent confidence region is used as the threshold, the time point when flaw size exceeds the failure flaw size is postponed by five years from 2023-2024 (blacked dashed line in Figure 64) to 2028-2029 (blue dashed line in Figure 64).

This indicates a possibility of postponing some physical inspection efforts (like ILI or a pressure test) to a later time, which could lead to reduced operating costs since the inspections themselves are costly. Moreover, these inspections require temporary shutdown of corresponding pipelines, which stops delivering products to consumers and could lead to business losses. If these refined results are still not satisfactory for decision making, another sensitivity test may be required to determine what other data could help reduce the uncertainty of results.

Figure 64: Projection for Flaw Depth Evolution with Additional Coating and Cathodic Protection Data



Source: DNV GL

Second Sensitivity Test

Another round of sensitivity testing is performed to analyze which type of data is most helpful to reduce the uncertainty. Knowing the previous flaw depth (0.09 inch ± 0.01 inch), coating age (40-45 years), coating type (3PE), fraction of CP operation (0.75-1.0) and CP potential (50 percent in the range of -800mV~-850mV and 50 percent in the range of -850mV~-950mV), the benefit/cost ratio is summarized in Table 23 below. A data usefulness index combining different value categories under the same input type is also used for easy eye guidance.

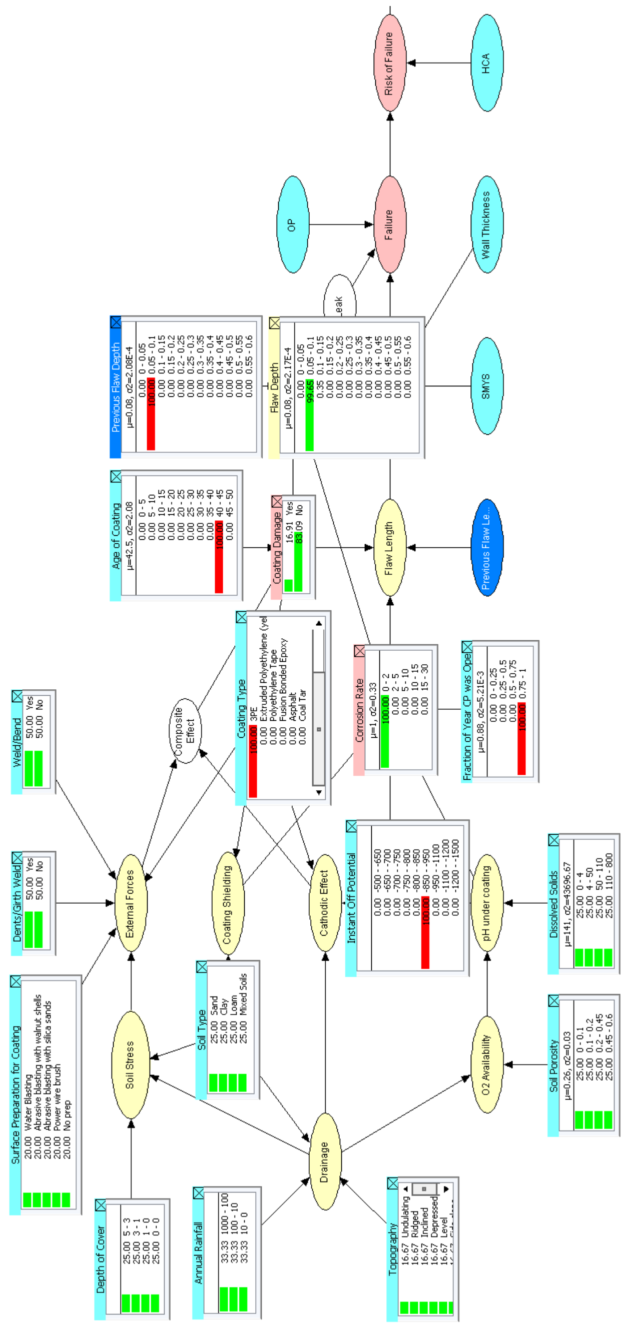
Table 23. Usefulness of Data with Knowing Coating and Cathodic Protection Information in Addition to Previous Flaw Depth

			Flaw Depth (inch)		Benefit	Data Cost	Benefit/Cost Ratio	Usefulness Index
Input Type	Input Name	Input Value	0.03	0.017	-			
Depth of Cover	5-3	25%	0.03	0.017	0.0E+00	$21,000	0.0E+00	0
Depth of Cover	3-1	25%	0.03	0.017	-3.0E-05	$21,000	0.0E+00	
Depth of Cover	1-0	25%	0.03	0.017	-3.0E-05	$21,000	0.0E+00	
Depth of Cover	0-0	25%	0.03	0.017	-3.0E-05	$21,000	0.0E+00	
Surface Prepartion for Coating	Water blasting	20%	0.03	0.017	0.0E+00	$1,000	0.0E+00	0
Surface Prepartion for Coating	Abrasive blasting with walnut shells	20%	0.03	0.017	0.0E+00	$1,000	0.0E+00	
Surface Prepartion for Coating	Abrasive blasting with silica sands	20%	0.03	0.017	0.0E+00	$1,000	0.0E+00	
Surface Prepartion for Coating	Power wire brush	20%	0.03	0.017	0.0E+00	$1,000	0.0E+00	
Surface Prepartion for Coating	No prep	20%	0.03	0.017	-3.0E-05	$1,000	0.0E+00	
Rainfall (mm/year)	1000-100	33%	0.03	0.017	-3.0E-05	$1,000	0.0E+00	2
Rainfall (mm/year)	100-10	33%	0.03	0.017	-3.0E-05	$1,000	0.0E+00	
Rainfall (mm/year)	10-0	33%	0.03	0.017	3.0E-05	$1,000	3.0E-08	
Topography	Undulating	17%	0.03	0.017	3.0E-05	$25,500	1.2E-09	1
Topography	Ridged	17%	0.03	0.017	3.0E-05	$25,500	1.2E-09	
Topography	Inclined	17%	0.03	0.017	-3.0E-05	$25,500	0.0E+00	
Topography	Depressed	17%	0.03	0.017	-8.9E-05	$25,500	0.0E+00	
Topography	Level	17%	0.03	0.017	0.0E+00	$25,500	0.0E+00	
Topography	Side slope	17%	0.03	0.017	3.0E-05	$25,500	1.2E-09	
Soil Type	Sand	25%	0.03	0.017	3.0E-05	$25,500	1.2E-09	0
Soil Type	Clay	25%	0.03	0.017	-3.0E-05	$25,500	0.0E+00	
Soil Type	Loam	25%	0.03	0.017	0.0E+00	$25,500	0.0E+00	
Soil Type	Mixed Soils	25%	0.03	0.017	-3.0E-05	$25,500	0.0E+00	
Soil Porosity	0-0.1	13%	0.03	0.017	-3.0E-05	$25,500	0.0E+00	0
Soil Porosity	0.1-0.2	13%	0.03	0.017	-3.0E-05	$25,500	0.0E+00	
Soil Porosity	0.2-0.45	35%	0.03	0.017	0.0E+00	$25,500	0.0E+00	
Soil Porosity	0.45-0.6	40%	0.03	0.017	0.0E+00	$25,500	0.0E+00	
Coating Type	3PE	100%	0.03	0.017	0.0E+00	$500	0.0E+00	0
Coating Type	Extruded Polyethylene (yellow jacket	0%	0.03	0.018	-1.1E-03	$500	0.0E+00	
Coating Type	Polyethylene Tape	0%	0.03	0.018	-1.1E-03	$500	0.0E+00	
Coating Type	Fusion Bonded Epoxy	0%	0.03	0.018	-1.4E-03	$500	0.0E+00	
Coating Type	Asphalt	0%	0.03	0.018	-1.2E-03	$500	0.0E+00	
Coating Type	Coal Tar	0%	0.03	0.018	-1.2E-03	$500	0.0E+00	
Dent	Yes	50%	0.03	0.017	-8.9E-05	$250,500	0.0E+00	0
Dent	No	50%	0.03	0.017	6.0E-05	$250,500	2.4E-10	
Bend	Yes	50%	0.03	0.017	-3.0E-05	$500	0.0E+00	2
Bend	No	50%	0.03	0.017	3.0E-05	$500	6.0E-08	
Instant Off Potential (mV)	-500 ~ -650	0%	0.03	0.019	-2.0E-03	$500	0.0E+00	4
Instant Off Potential (mV)	-650 ~ -700	0%	0.03	0.019	-2.0E-03	$500	0.0E+00	
Instant Off Potential (mV)	-700 ~ -750	0%	0.03	0.019	-1.9E-03	$500	0.0E+00	
Instant Off Potential (mV)	-750 ~ -800	0%	0.03	0.019	-1.9E-03	$500	0.0E+00	
Instant Off Potential (mV)	-800 ~ -850	50%	0.03	0.018	-1.7E-03	$500	0.0E+00	
Instant Off Potential (mV)	-850 ~ -950	50%	0.03	0.015	2.0E-03	$500	4.1E-06	
Instant Off Potential (mV)	-950 ~ -1100	0%	0.03	0.015	2.0E-03	$500	4.1E-06	
Instant Off Potential (mV)	-1100 ~ -1200	0%	0.03	0.015	2.0E-03	$500	4.1E-06	
Instant Off Potential (mV)	-1200 ~ -1500	0%	0.03	0.015	2.0E-03	$500	4.1E-06	
Dissolved Solids (mg/L)	0-4	25%	0.03	0.017	-1.5E-04	$25,500	0.0E+00	2
Dissolved Solids (mg/L)	4-50	25%	0.03	0.017	-6.0E-05	$25,500	0.0E+00	
Dissolved Solids (mg/L)	50-110	25%	0.03	0.017	9.0E-05	$25,500	3.5E-09	
Dissolved Solids (mg/L)	110-800	25%	0.03	0.017	9.0E-05	$25,500	3.5E-09	
Fraction of Year CP was Operatio	0-0.25	0%	0.03	0.018	-1.5E-03	$500	0.0E+00	0
Fraction of Year CP was Operatio	0.25-0.5	0%	0.03	0.018	-1.1E-03	$500	0.0E+00	
Fraction of Year CP was Operatio	0.5-0.75	0%	0.03	0.017	-5.6E-04	$500	0.0E+00	
Fraction of Year CP was Operatio	0.75-1	100%	0.03	0.017	0.0E+00	$500	0.0E+00	
Age of Coating (Years)	0-5	0%	0.03	0.015	2.2E-03	$500	4.3E-06	0
Age of Coating (Years)	5-10	0%	0.03	0.015	1.9E-03	$500	3.7E-06	
Age of Coating (Years)	10-15	0%	0.03	0.015	1.5E-03	$500	3.0E-06	
Age of Coating (Years)	15-20	0%	0.03	0.016	1.2E-03	$500	2.5E-06	
Age of Coating (Years)	20-25	0%	0.03	0.016	8.3E-04	$500	1.7E-06	
Age of Coating (Years)	25-30	0%	0.03	0.016	5.8E-04	$500	1.2E-06	
Age of Coating (Years)	30-35	0%	0.03	0.016	3.6E-04	$500	7.2E-07	
Age of Coating (Years)	35-40	0%	0.03	0.017	1.2E-04	$500	2.4E-07	
Age of Coating (Years)	40-45	100%	0.03	0.017	0.0E+00	$500	0.0E+00	
Age of Coating (Years)	45-60	0%	0.03	0.017	-2.1E-04	$500	0.0E+00	

Source: DNV GL

Based on Table 23, narrowing the range of CP potential is still the most helpful action, although there is a 50 percent chance that the CP potential is in the range of -800mV~-850mV and a 50 percent chance that it is in the range of -850mV~-950mV. Assuming that another data gathering effort is able to identify the CP potential to be 100 percent in the range of -850mV~-950mV instead of the previous bipolar distribution, the MARV™ model changes as shown in Figure 65.

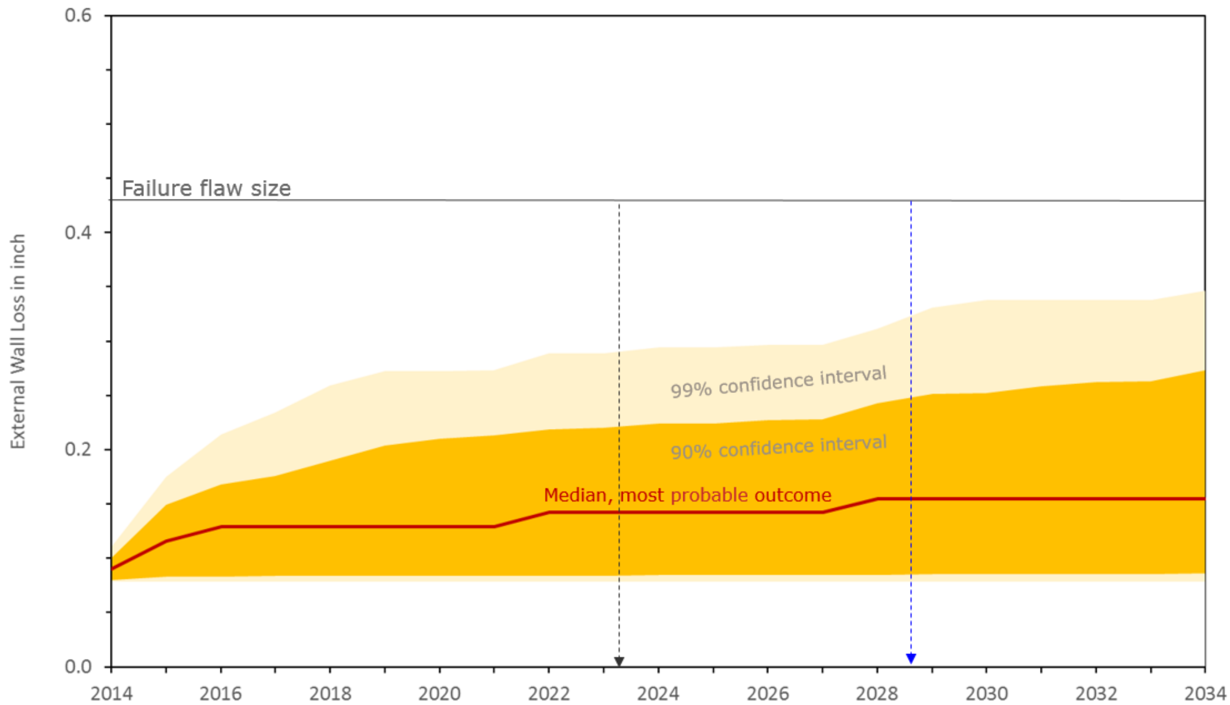
Figure 65: MARV™ Model with Finalized Cathodic Protection Potential



Source: DNV GL

A second iteration process (run assessment model and generate probability of failure) is executed again. With the additional defined CP potential data, together with the data identified in first sensitivity test, the evolution of flaw depth is projected as shown in Figure 66 below.

Figure 66: Projection for Flaw Depth Evolution with Defined Cathodic Protection Potential

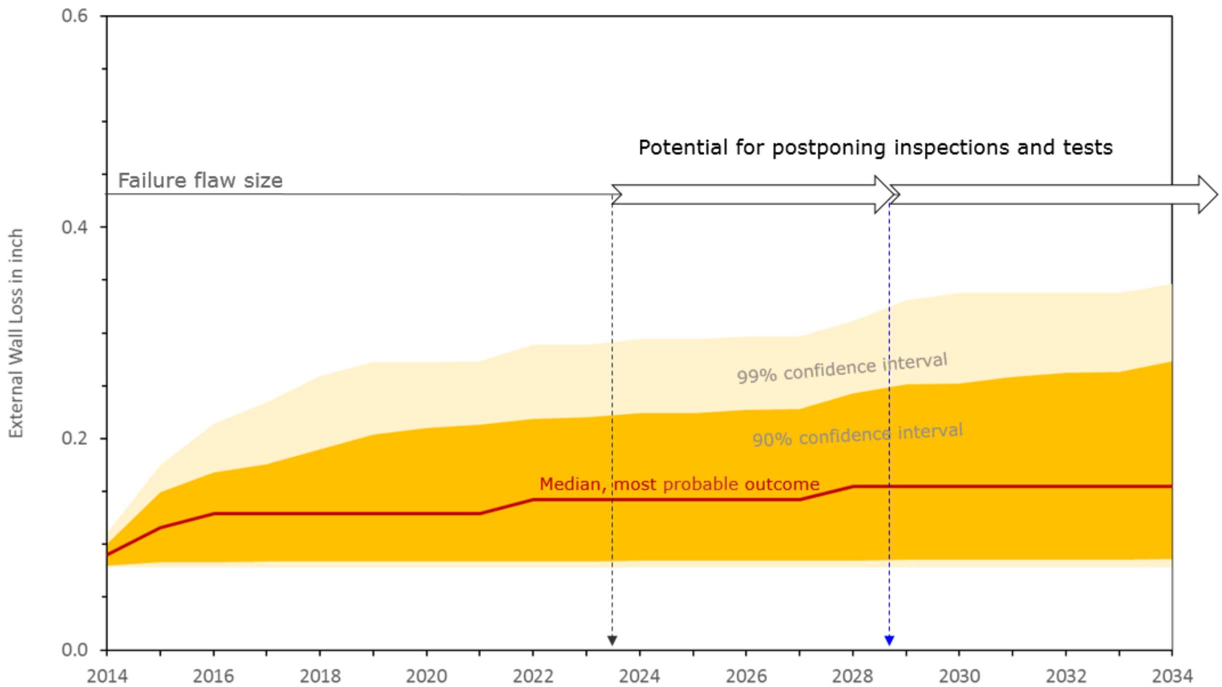


Source: DNV GL

The median flaw depth with the additional coating and CP data grows much more slowly than in the base case that only included the previous flaw depth. The associated 90 percent confidence and 99 percent confidence region also become much narrower, indicating the estimated flaw size is more confident around the median value. In 2024, the flaw size range changes to 0.09 inch - 0.29 inch. Compared with base case, the median value reduces from 0.23 inch to 0.14 inch and the span shrinks greatly from 0.36 inch to 0.20 inch. With the additional information, the flaw depth uncertainty increases with time also slow down much compared with base case. The same as base case, if the intersection between failure flaw size and the upper boundary of 99 percent confidence region is used as the threshold, it can be found in the period 2014-2034, it is very unlikely that flaw size exceeds the failure flaw size, indicating the pipeline is quite safe. If the uncertainty and the median flaw depth value is acceptable at this stage, this could give decision-making a strong confidence without conducting any immediate mitigation actions, as indicated by the green pathway in MARV™ flow chart in Figure 60. From this decision tree, it is not necessary to collect more data (as uncertainty is satisfactory) and unnecessary to conduct immediate actions (as the flaw depth/POF is satisfactorily low).

The benefits of combining the first round of data gathering efforts and the second round of data gathering efforts are shown in Figure 67 below. The time when the flaw depth exceeds the failure depth is postponed by about five years by the first round of data gathering efforts. The second round of data gathering efforts could further postpone the time by more than five years. Postponing inspections and tests should comply with regulatory requirements, industry standards, and the operator’s internal policy; however, postponing of inspections and tests as long as possible could save significant resources without compromising integrity and safe operations of the pipelines. The saved resources could be allocated to other segments/systems for data gathering or mitigation actions, to enhance the overall operating performance of the system.

Figure 67: Benefits of Data Gathering Efforts



Source: DNV GL

Advantages of Bayesian Network Approach

As described in the previous sections the MARV™ method is capable of handling uncertain data to generate meaningful information. This particularity is used to drive the decision-making process. This section will discuss two additional benefits of using the MARV™ method.

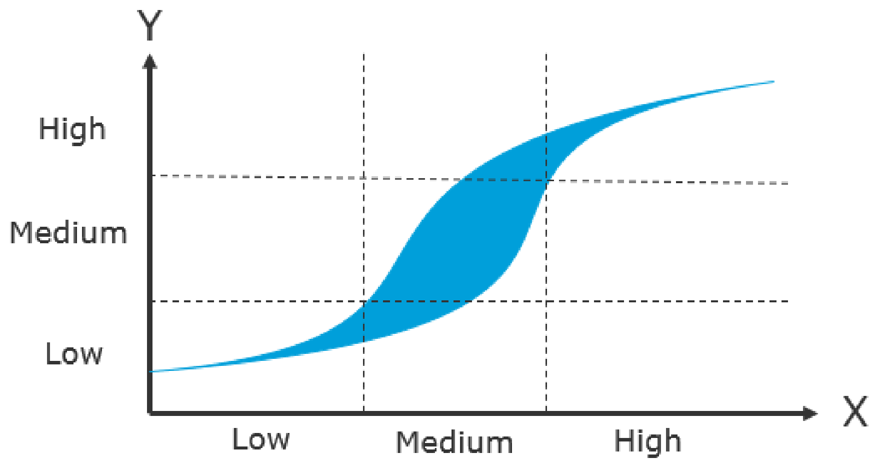
Capability to Use Imperfect Knowledge of Threats in the Assessment

In conventional assessment models, the cause and effect relationship must be clearly defined, specifically the explicit expression for the logic function of converting from input to output must be established. To obtain accurate results, every function from input to outcome should be based on scientific derivations, which requires every step in the threat-failure mechanism to be thoroughly understood. However, in many situations, the cause-effect relationship is obscure for some steps in the threat mechanism, due to limited knowledge of some threats especially threat interactions, impeding the science based establishment of clear functions between input and output. A common workaround is to use empirical correlations to form certain equations such as Y=f(X), where Y is the output and X is the input, because strict scientific derivations are infeasible based on current knowledge.

These empirical correlation works well when a system is fully understood. However, pipeline engineers cannot wait for all knowledge related with threats of interest to be developed (as it may take many years of research to have mature understanding) and they require a reliable tool to build and apply the inferential reasoning in wider conditions.

Bayes rule is the key to inferential reasoning, even in uncertain conditions. Figure 68 represents domain knowledge relating two variables linked by a cause consequence relationship. In this example, when x is low y is also low, when x is high then y is also high. However, the position if the transition between high and low values is uncertain, representing a lack of subject matter expertise.

Figure 68: MARV™ Cause-Effect Relationship



Source: DNV GL

Instead of using a deterministic formula Y=f(X), the MARV™ method presents the relationship as a conditional probability table:

- When X is low, Y is 100 percent low.
- When X is medium, Y is 10 percent low, 80 percent medium, and 10 percent low.
- When X is high, Y is 100 percent high.

Due to this unique property of Bayesian probabilistic approach, the MARV™ method is not limited by specific conditions thus has wider applicability. It is also able to integrate different types of knowledge like subject matter expertise, models, software, databases, and sensor data into a central system, since there is no requirement to fit the data into a deterministic formula. External models could be run multiple times to generate the conditional probability tables. Data could be processed through statistical analysis and then easily compiled into conditional probability tables. Subject matter expert knowledge, though difficult to present in a deterministic formula, could also be easily transformed into conditional probability tables in a Bayesian approach. Moreover, with more knowledge about the cause-effect relationship, the conditional probability tables could be refined and the generated outcome would be closer to the actual situation.

Capability to Analyze "Similar" Segments and Compare Threats

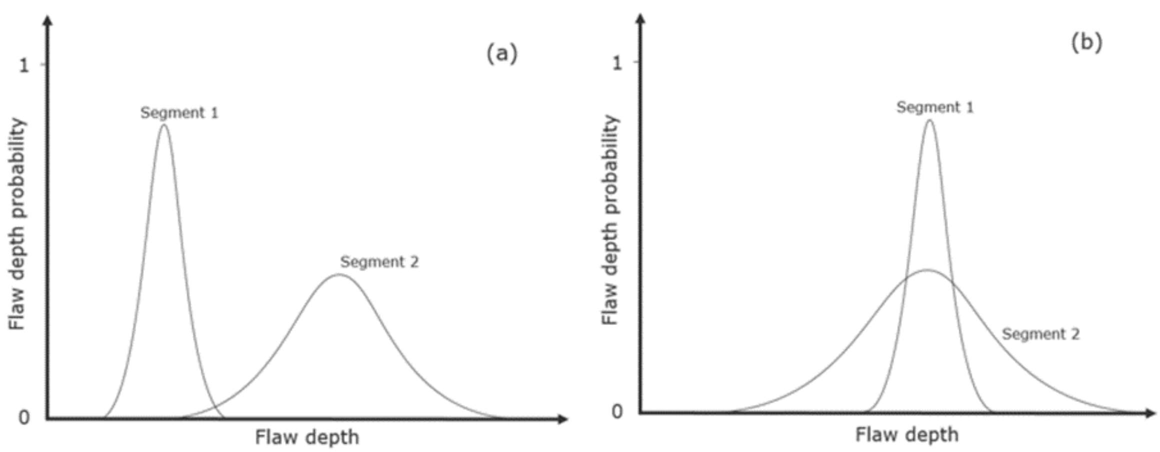
The word "similar" appears multiple times in 49 CFR 192 Subpart O (Code of Federal Regulations, 2016) to refer to segments that are alike. Examples include:

- 192.917(b) mandates "an operator must gather and evaluate the set of data … and consider both on the covered segment and <u>similar</u> non-covered segment…"

- 92.917(e)(5) specifies "… the operator must evaluate and remediate, as necessary, all pipeline segments (both covered and non-covered) with similar material coating and environmental characteristics. An operator must establish a schedule for evaluating and remediating, as necessary, the similar segments…"
- 192.927(c)(3)(iii) requires "Evaluate the potential for internal corrosion in all pipeline segments (both covered and non-covered) in the operator's pipeline system with similar characteristics to the ICDA region containing the covered segment".
- 192.929(a) defines SCCDA as an assessment "by systematically gathering and analyzing excavation data for pipe having similar operational characteristics and residing in a similar physical environment".
- 192.1007(c) states, when evaluating and ranking risk, "An operator may subdivide its pipeline into regions with similar characteristics…and for which similar actions likely would be effective in reducing risk".
-

Although similar pipe segments are required to be evaluated and remediated, the definition of "similar" is qualitative and vague, which makes it difficult for pipeline engineers to group like segments and conduct assessments and remediation for the group. Using external corrosion as an example, the apparently similar pipe specifications, operating conditions, and physical environment does not guarantee similar flaw depth growth or similar uncertainty of the flaw depth, which are the two key parameters for evaluating external corrosion threat. Those apparently similar values may lead to the situations as shown Figure 69 and Figure 70.

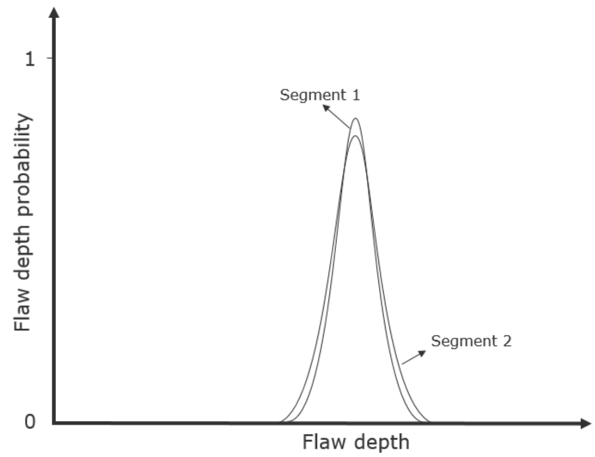
Figure 69: Segments are NOT Similar



Left, Different Flaw Depth. Right, Same Average Flaw Depth but Different Uncertainty Levels.

Source: DNV GL

Figure 70. Pipe Segments That Can be Considered as "Similar"



Such as Same Flaw Depth and Same Uncertainty

Source: DNV GL

Obviously, the segments in Figure 69 (a) cannot be treated as similar because both median flaw depth and the uncertainty is drastically different. Although the median flaw depth is similar in Figure 69(b), the two segments should not be categorized into the same group for evaluation and remediation, since the flaw depth uncertainty between the two segments is very different and it is hard to judge. Only when both median flaw depth and the uncertainty of depth are similar can the segments be considered "similar," as shown in Figure 70. The "similarity" between two segments could be compared with the generated distributions from MARV™ approach. As discussed in previous sections, conventional assessments only generate deterministic results, but only the MARV™ method can produce distribution of result values with paired possibilities. This could allow pipeline engineers to categorize the truly alike segments into the same group, and apply similar analyses and remediation approaches to mitigate the risks in compliance with regulatory requirements, avoiding mistakenly grouping the segments with apparently similar parameters that are actually different.

Conclusions

Two threats were chosen by project's industry partner: external corrosion and third party damage. DNV GL modeled the external corrosion threat and UCLA made a model for the third-party damage threat. Both threats were modeled using Bayesian networks. The causes of the threats were first identified and a network of causal relationship leading to pipeline failure were created.

Results show that it is possible to quantify these threats even though some of the input data maybe uncertain (and sometime unknown). Calculation of the entropy of Bayesian network threat models was used to identify leading indicators (parameters that are the most effect on the probability of pipeline failure). Sensitivity analyses were also used to show what data should be gathered next. Sensitivity analyses differ from the leading indicators because it considers already known data and the cost of data gathering activities. It was shown how the MARV™ method uses uncertainty to drive the decision-making process. The data prioritization based on the method is the answer to questions such as "what data should be gathered first?" and "when is there enough data?"

CHAPTER 6: Project Benefits to the State of California

The Energy Commission's Public Interest Energy Research Natural Gas program has a goal to improve natural gas pipeline integrity and safety. In this project, DNV GL demonstrated that its Multi-Analytic Risk Management (MARV™) tool can improve safety, integrity, and reliability of pipelines in California by enabling operators to better anticipate potential pipeline problems and therefore make timely decisions to prevent failures. The tool uses a Bayesian Network-based risk assessment method to enable effective, systematic, and verifiable decision-making that uses all the knowledge and data available to the pipeline company. The tool also improves the ability of different stakeholders to understand and communicate risks.

Background

There are currently more than 300,000 miles of mainline natural gas transmission pipelines and 1.3 million miles of local distribution pipelines in the United States. California's intrastate natural gas pipeline system consists of approximately 10,500 miles of onshore transmission pipeline in addition to gathering and distribution lines. Recent pipeline failures in California have resulted in injuries, fatalities, and environmental damage. Furthermore, pipeline failures have resulted in shutdowns and increased energy costs.

Pipelines must transport natural gas safely and reliably in a complex environment. Several recent pipeline failures suggest that pipeline companies lack the means to systematically anticipate various threats and make timely decisions. These threats are highly location-specific and likely to increase over time. The current risk assessment practices used by pipeline companies are not sufficiently predictive because they do not quantitatively link the leading indicators to risks. Mechanistic understanding of failure processes is necessary to anticipate failures that have not yet occurred. Further, system data is sparse and knowledge is scattered among different experts. A risk assessment method is required that can integrate diverse sources of knowledge, including the mechanistic understanding of failure processes, and function with sparse data. The method should be capable of being updated using real-time sensor and monitoring data.

In this project, DNV GL demonstrated the Bayesian network risk assessment method for corrosion threat and third-party damage threat. The project also demonstrated how sensitivity analysis on the threat models can drive decision-making; that is, whether to gather more data or to mitigate risk. When the model predicts a high probability of failure with low uncertainty, it would recommend mitigation actions. On the other hand, if the probability of failure is high with high uncertainty, it is possible that gathering more data will reduce risk and therefore expensive mitigation actions might not be required. Pipeline companies can use this tool to make cost-effective decisions on pipeline maintenance and reduce pipeline failure risks while managing maintenance costs.

The MARV™ tool, based on Bayesian network risk management method, would enable effective, systematic, and verifiable decision-making using all knowledge and data available to the pipeline company. The MARV™ tool would help increase safety, integrity and reliability of pipelines in California by enabling operators to anticipate potential pipeline failures. The tool would also improve the ability of different stakeholders to communicate risk.

The sections below describe the specific benefits that may result from this project.

Safety Benefits

Under the United States Department of transportation, the Pipeline Hazardous Materials Safety Administration (PHMSA) collected pipeline incident reports since 1970. In California, on average, there are 5 incidents annually for the past 20 years, and 9 annually for the past 3 years[6]. Total costs associated with these incidents have been $605 million in the past 20 years and $18 million in the past 3 years. Based on 20-year data, there have been 0.12 fatalities and 0.67 injuries per incident, with average monetary damage per incident of about $6 million.

The MARV™ tool improves risk assessment by integrating scattered expert knowledge and uncertain data to capture new failure processes. This could help pipeline operators better detect potential pipeline failures, and enable more effective decision-making regarding the failure risks. Better decision-making would reduce failures and associated injuries and fatalities for maintenance workers and people who live near pipelines.

Based on historical trends, if the MARV™ tool can reduce two pipeline incidents each year, it would decrease fatality and injury, and reduce monetary damage an average of $12 million per year.

Reliability

The MARV™ tool can help decision-making based on the best knowledge and data available to the pipeline company. This would allow companies to anticipate threats and perform timely corrective actions, thereby reducing failures and pipeline network downtime.

Reduced Costs

Pipeline companies can use the tool to make cost-effective decisions on pipeline maintenance and operations. The project demonstrated how sensitivity analysis on the threat models can drive decision-making on whether to gather more data or to mitigate risk. When the model predicts a high probability of failure with low uncertainty, the model recommends mitigation actions. On the other hand, if the probability of failure is high with high uncertainty, it is possible that gathering more data will reduce risk and therefore expensive mitigation actions might not be required.

From an operational perspective, MARV™ can prioritize data-gathering resources that contribute most to risk reduction. Pipeline companies can use this tool to make cost-effective decisions on pipeline maintenance and operations, and therefore reduce pipeline failure risks while managing costs. In addition, the increased safety will reduce costs related to injuries, fatalities, property damage and environmental cleanup.

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[6] Pipeline incident 20 year Trends. PHMSA. https://phmsa.dot.gov/pipeline/library/data-stats/pipelineincidenttrends, Accessed on October 9, 2017.

Retain Knowledge within Pipeline Organization

The current risk assessment practices used by pipeline companies are not sufficiently predictive because they do not quantitatively link the leading indicators to risks. Mechanistic understanding of failure processes is necessary to anticipate failures that have not yet occurred. Furthermore, system data is sparse and the knowledge is scattered among different experts. MARV™ can integrate diverse sources of knowledge, including the mechanistic understanding of failure processes, the ability to update from real-time sensors and monitoring data, and can function with sparse data. This enables the pipeline company's knowledge to be retained despite the experts' departures or retirements. In addition, the tool integrates the augmented knowledge with sensor and monitoring data. It can then analyze all the available information to provide actionable decision-making assistance to pipeline operators in a data-driven and systematic manner.

Enhance Communication of Risks

The MARV™ tool could enable effective, systematic, and verifiable decision-making using all the knowledge and data available to the pipeline company. The tool presents its results in a user-friendly graphical interface, which enhances pipeline operators' ability to communicate risks and mitigation actions of a complicated system to internal and external stakeholders. For example, it could help regulators to understand threats and the maintenance needs of the pipelines when approving pipeline costs.

Increase Consumer Confidence

Although the project is not directly focused on consumers, the visual representations of the threats in MARV™ increase the ability to communicate risk mitigation actions by pipelines which could lead to greater consumer confidence. MARV™ can improve a utility's safety and reliability records which would improve its reputation.

Enable Economy

Most businesses require reliable supplies of electricity and natural gas. For certain businesses and industries with critical natural gas loads, the lack of a reliable gas supply could be economically devastating. MARV™ could improve reliability of natural gas supply, and therefore attract economic development, or prevent businesses and industries from leaving the state.

Health Benefits

The release of hydrocarbons from natural gas leaks can contaminate the soil and ground water. In addition, inhaling natural gas can aggravate asthma and other respiratory conditions. The MARV™ tool can reduce the likelihood of leaks, which will lead to improved public health.

Reduce Greenhouse Gas Emissions

The primary component of natural gas is methane which is a potent greenhouse gas. According to the Environmental Protection Agency, methane is more efficient at trapping radiation than carbon dioxide. Pound for pound, the comparative impact of methane is more than 25 times greater than carbon dioxide over 100 years (EPA, n.d.). By increasing the safety and reliability of natural gas pipelines, the MARV™ tool can help reduce the likelihood of leaks and other incidents in which methane is released from pipelines into the atmosphere.

Project Level Benefits

The MARV™ tool has been customized, demonstrated and validated for California pipelines. The successful demonstration of the tool with Southern California Gas Company (SoCal Gas) could assist other utilities in California applying to their systems. The project benefits California natural gas ratepayers by increasing pipeline safety and reliability as detailed above. In addition, the project itself is expected to provide benefits to the California economy as DNV GL expands it pipeline risk management services and commercializes MARV™. In addition, knowledge gained from this project will benefit SoCalGas and the pipeline industry in general.

Economic Benefits Through Tool Commercialization

Since DNV GL's project team is based in California, any expansion of the company's MARV™-related risk management services will create additional revenue and jobs in California. Initially, the tool's path to market will be through technical service by DNV GL consultants using the tool. However, it is DNV GL's goal to eventually license the software tool directly to users in the pipeline companies. If successful, DNV GL would start expanding risk management services to the pipeline companies in California and beyond, and the tool would create technical consulting and software-related jobs for the MARV™ team which is primarily based in California.

In addition, the knowledge of the two UCLA research scientists who worked on this project will be retained in the university and passed on in the academic setting.

Knowledge Transfer to Southern California Gas Company

Since knowledge transfer to SoCal Gas is not limited by confidential agreements, all data, threat models, and results from the project have been presented to SoCal Gas using the MARV™ interface, as well as in two meetings at SoCal Gas headquarters in Los Angeles.

Knowledge Transfer through Industry Conferences

Two conferences have been selected to openly present work done in this project:

- **International Pipeline Conference (IPC) 2018, Calgary, AB, Canada:** This conference was selected because this conference draws members of the pipeline industry from around the world including California operators. The IPC is internationally renowned as the world's premier pipeline conference. This is a not-for-profit conference and proceeds continue to support educational initiatives and research in the pipeline industry.
- **Probabilistic Safety Assessment and Management 2018: UCLA, Los Angeles, CA:** The Probabilistic Safety Assessment & Management (PSAM) conference focuses on risk, risk management, reliability, safety, and associated topics. It meets internationally every two years, and will next be held at UCLA in September 2018. The PSAM conference brings together experts from various industries, research organizations, regulatory authorities and universities in the fields of nuclear, process and chemical industries, off-shore and marine, transportation, space and aviation, IT and telecommunications, bio and medical technology, civil engineering, financial management and other fields. The

multi-disciplinary conference is aimed to cross-fertilize methods, technologies and ideas for the benefit of all.

LIST OF ACRONYMS

Term	Definition
ANSI	American National Standards Institute
BNT	Bayes Net Toolbox
Bayes theorem	Describes the probability of an event, based on prior knowledge of conditions that might be related to the event.
BN	Bayesian Network. A type of Probabilistic Graphical Model that can be used to build models from data and/or expert opinion. They can be used for a wide range of tasks including prediction, anomaly detection, diagnostics, automated insight, reasoning, time series prediction and decision making under uncertainty.
Bow-tie method	A risk evaluation method that can be used to analyze and demonstrate causal relationships in high risk scenarios. Once the control measures are identified, the Bowtie method also identifies the ways in which control measures fail.
Cathodic disbondment	The loss of adhesion between a cathodic coating and its metal substrate due to the products of a corrosion reaction that takes place in the interface of coatings.
CFR	Code of Federal Regulations
Confidence interval	A range of values so defined that there is a specified probability that the value of a parameter lies within it.
Coupon	Pre-weighed and measured metal strips used to estimate the rate of metal corrosion in a system by comparing the initial weight with the weight following a period of time of exposure to corrosive elements in the system.
CP	Cathodic protection. Prevents corrosion by converting all of the anodic (active) sites on the metal surface to cathodic (passive) sites by supplying electrical current (or free electrons) from an alternate source.
DOC	Pipeline Depth of Cover
DOT	Department of Transportation
EC	External corrosion
ECDA	External Corrosion Direct Assessment
ESD	Event Sequence Diagram
HCA	High Consequence Area

Term	Definition
Holidays	Defects or holes in pipeline coatings that expose the bare pipeline steel to the underground environment.
ICDA	Internal Corrosion Direct Assessment
ILI	In-line inspection
IPC	International Pipeline Conference
Markov process	A random process whose future behavior cannot be accurately predicted from its past behavior and which involves random chance or probability.
MARV™	Multi-Analytic Risk Visualization
MATLAB™	MATLAB (matrix laboratory) is a numerical computing environment and proprietary programming language developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other computer languages.
mm/year	Millimeters per year
mV	Millivolts
Monte Carlo technique	A mathematical technique that generates random variables for modelling the risk or uncertainty of a certain system, with the random variables or inputs modelled on the basis of probability distributions.
NACE	Established in 1943 as the National Association of Corrosion Engineers, NACE International provides globally recognized standards that cover major industries including oil and gas, infrastructure, transportation, and maritime.
NIST	National Institute of Standards and Technology
NTSB	National Transportation Safety Board
O_2	Oxygen
pH	A measure of acidity or alkalinity of water soluble substances.
PHMSA	Pipeline and Hazardous Materials Safety Administration
POF	Probability of failure. The likelihood that a piece of equipment will fail at a given time and an important part of effective risk analyses. POF is half of the equation when determining risk as part of Risk Based Inspection method.
Poisson process	In probability and statistics, a type of random mathematical object that consists of points randomly located on a mathematical space

Term	Definition
	that is used as a mathematical model for seemingly random processes.
PSAM	Probabilistic Safety Assessment & Management Conference
psi	Pounds per square inch
SCC	Stress corrosion cracking
SCCDA	Stress Corrosion Cracking Direct Assessment
SMYS	Specified Minimum Yield Strength
SoCal Gas	Southern California Gas Company (utility company)
Stochastic model	A form of modeling that includes one or more random variables to estimate probability distributions of potential outcomes in systems and phenomena that appear to vary in a random manner.
Stray current	Currents flowing through paths other than the intended circuit; metallic structures like buried pipelines represent a low-resistant current path and can be vulnerable to the effect of stray currents, such as corrosion.
TPD	Third party damage. Damage caused by third-party excavation or other activities near and around pipelines.
UCLA	University of California, Los Angeles

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APPENDIX A:
User Instruction of "RiskLI" MATLAB Package

The RiskLI package is intended for identifying the risk leading indicators of the risk and reliability models that are constructed using Discrete Bayesian Belief Network. The package is coded in MATLAB, and it makes use of the Bayesian Network Toolbox (BNT). BNT is a powerful MATLAB toolbox for studying and making inference in all types of Bayesian Belief Networks.

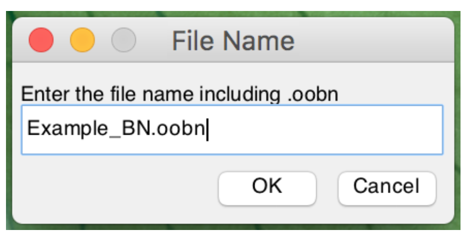
The RiskLI takes a Bayesian Network as an input and sorts the nodes and states based on their influence on uncertainty and risk of the model. The top-ranked nodes and states are candidates of risk leading indicators. The package only accepts ".oobn" files for input, and the output format is".xlxs".

Prior to running the RiskLI package, take the following steps:

1. Add the "xlwrite" package and the BNT package to the current MATLAB path.
2. Make sure that the ".oobn" file of the BN under study is saved in the same directory as the RiskLI.

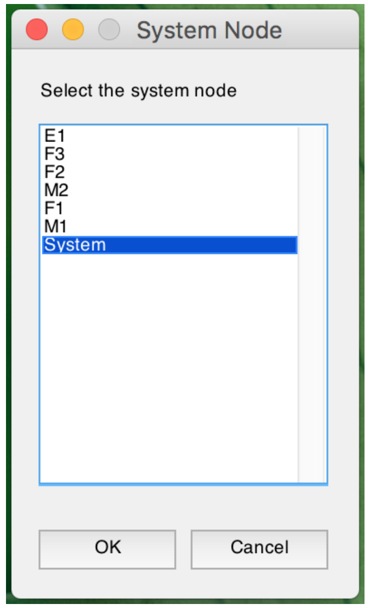
While running the algorithm, you will see the following prompts that request your answer.

1. **File name**:



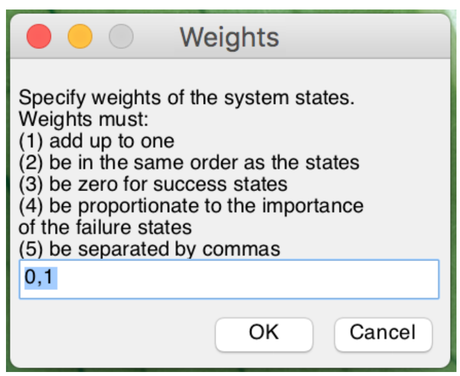
Type the BN file name including ".oobn", in the box. The preset file name is "Example_BN.oobn" that is the Bayesian Network of the illustrative example presented in this report. Press the return key or ok button to input the file name.

2. System Node:



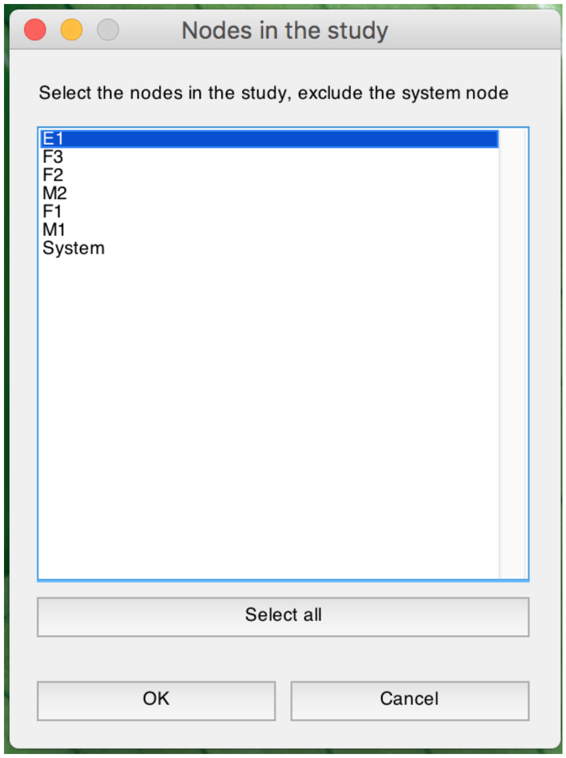
Select the system node from the list. Press the return key or ok button to input the system node.

3. Weights of the system node's states:



Insert the state's weights in the box. Make sure that the weight assignment follows these rules: (1) weights must add up to one, (2) they must be in the same order as the states, (3) the more critical failure states must have larger weights, (4) the weights of the success states must be assigned zero, and (5) they must be separated by commas. For example, for a system node that has three states [success 1, success 2, failure 1], you should input "0, 0, 1."

4. Nodes in the study:



Select the nodes you want them to be considered in the analysis. To include multiple nodes, press and keep the shift key and select the nodes at the same time. Make sure not to include the system node. Press the return key or ok button to input the nodes names.

The results of the nodes and states ranking are printed in a file named "Results.xlsx". This excel file has two sheets. The first sheet contains the sorted list of the nodes, and the second sheet includes the node-state pairs ranking. The file is saved in the same directory as the current MATLAB path.