A Bayesian Network for Slope Geohazard Management of Buried Energy Pipelines

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ABSTRACT: Geohazards are the ground movement events that impose displacement demands on buried pipelines leading to excessive inelastic strains and possible loss of containment. Lack of data, as well as large uncertainties in the prediction of ground movement and inelastic pipe response are common challenges in geohazard management. A simple Bayesian network is presented in this study to demonstrate the integration of data from multiple sources, as well as prediction of the pipeline condition under a hypothetical ground movement scenario. The methodology used to obtain the network parameters and the challenges associated with the implementation are discussed.

Geotechnical events resulting in ground movement, such as landslides and earthquakes, are termed 'geohazards' as they may lead to loss of containment in buried energy pipelines. Slope creep is the gradual soil movement at a slope due to changes in soil conditions, such as an increase of pore water pressure. Ground movements due to slope creep accumulate over the years and gradually increase the imposed displacements on buried pipelines, leading to excessive inelastic strains that can result in failure.

As steel pipelines can sustain axial and bending strains beyond the elastic limit without immediate loss of containment, monitoring ground movements and pipe deformations at specified intervals provides an opportunity to reduce the probability of pipeline failure by identifying potentially critical strains and implementing slope remediation measures.

Conventional approaches for pipeline structural integrity management are inadequate to address the uncertainties in assessing the probability of pipeline failure. Deterministic assessments are often conservative as uncertainties in the prediction of slope and pipe conditions are not considered explicitly (Yoosef-Ghodsi et al. 2008).

Both qualitative and semi-quantitative approaches focus heavily on the likelihood of slope movement using a combination of expert opinion and historical data of pipeline failures (PRCI 2009, Sen et al. 2018). Several approaches are available offering a framework to quantify failure frequencies as the product of conditional probabilities characterizing the sequence of occurrence of geotechnical events and only pipe size, wherein the required probabilities are often quantified based on expert opinion (Guthrie and Reid 2018, Baumgard et al. 2016, Ferris et al 2016, Porter et al. 2016).

In quantitative assessments, a limit state function is defined as the tensile or compressive strain demand exceeding the strain capacity (also termed 'strain limit'). Soil properties, slope parameters, and pipe parameters are characterized as random variables and used in empirical models to calculate the probability distributions of strain limits and pipe-soil interaction analysis to calculate the probability distributions of strain demand (Zhou 2012, Fraser and Koduru 2016, Koduru and Nessim 2018).

However, strain demand can be difficult to predict, not only due to the large number of environmental factors controlling the amount of ground movement, but also due to the complexity of the pipeline's response to the movement. Moreover, the collection of site-specific data required for model inputs can require significant effort, particularly for slopes in remote locations.

As part of pipeline structural integrity management against geohazards, the following multi-disciplinary data and domain expertise are used: isolated measurements of slope movement from slope inclinometers; estimates of terrain movement from satellite imagery or air photogrammetry, such as LiDAR, InSAR and Digital Elevation Models (Guthrie et al. 2018, Baumgard et al. 2014); pipeline strain gauge data (Dinovitzer et al. 2014); pipe curvature data from inline inspection (ILI); and results from detailed finite element modeling of the pipe-soil interaction (Fredj et al. 2015, Fredj et al. 2016). All of these tools and analysis methods come with varying levels of uncertainty and utilize data with significant temporal and spatial variability.

Bayesian networks (BNs) offer a potential to address this diversity of information sources as this approach is capable of integrating data types from different sources and of different granularity, and has the abty to update the probability estimates based on new inspection data.

1. OBJECTIVE AND SCOPE

The objective of the study described in this paper was to develop a BN for pipeline geohazards. The focus of the development was to demonstrate the integration of multiple data sources to predict the pipeline condition under a hypothetical ground movement scenario. Previous BN studies were limited to the assessment slope safety and did not include pipeline response modeling (Peng et al. 2014).

The scope of the study is limited to ground movements that are primarily parallel to the pipeline axis, as shown in Figure 1. Slope creep along the longitudinal axis occurs most often at the pipeline water crossings (e.g. rivers and streams). As pipeline water crossings occur in all types of terrains – unlike ground movements perpendicular to the pipeline axis that are mostly limited to mountainous regions – this type of ground movement is of greater interest to pipeline integrity management.

The paper provides a detailed discussion of BNs representing pipeline response to slow accumulated ground displacement at a specific slope and presents the results of performing Bayesian inference on the network to estimate probability of pipeline failure, and other pipe response conditions. The BN in the current study is modeled with cumulative ground displacements over a fixed time period instead of the incremental ground displacements.

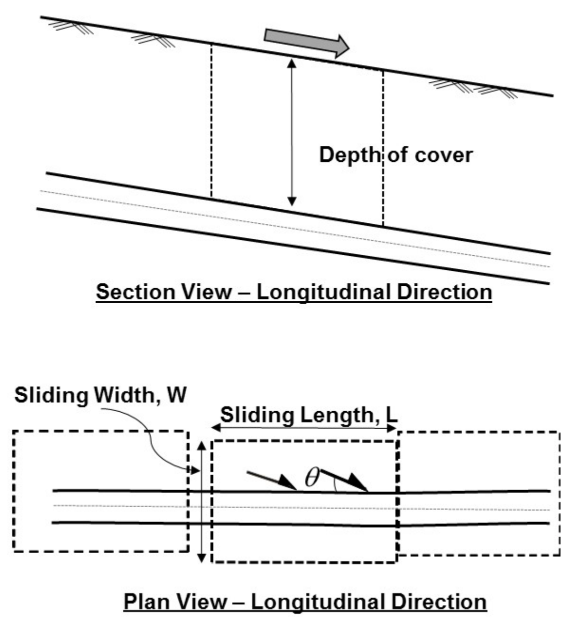

Figure 1: Ground Movement Direction Relative to the Longitudinal Axis of the Buried Pipeline

At first, the development of network structure is explained, followed by the approaches used to develop the conditional probability tables needed to model the network. Next, a numerical example demonstrating the application of the proposed approach to a hypothetical pipeline is presented. The paper concludes with a discussion on the advantages and challenges associated with the development of BNs for slope movement and future work required to develop a comprehensive BN methodology to address geohazards.

2. NETWORK DEVELOPMENT

2.1. Event Nodes

Figure 2 shows the sequence of data collection and analysis steps required to predict pipe condition in a moving slope. Data types used for inference through engineering judgment, structural mechanics and data analysis to estimate site and pipe parameters are listed in Table 1.

In the development of a BN, it is of interest to identify the events related to pipe response, and monitoring information. In the present work, only those parameters related to inspection and monitoring are selected as event nodes. Although there are uncertainties due to inherent randomness in the physical properties and slope geometry, they are not modeled as explicit nodes in this study. Data collection related to these parameters is assumed to be complete with no expectation of updates due to new observations.

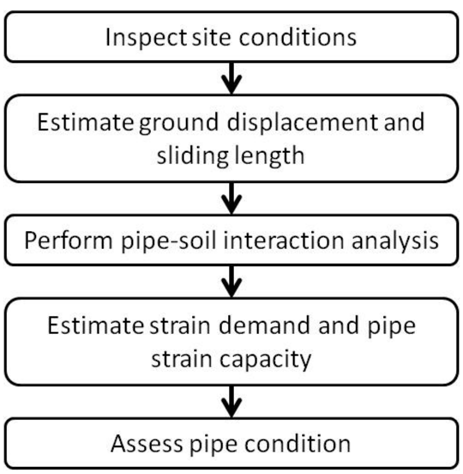

Figure 2: Sequence of Steps to Assess Pipe Condition

2.2. Causal Links

Figure 3 shows the full network diagram with events and links. As shown in the figure, event nodes are modelled to have discrete and finite states that are mutually exclusive and collectively exhaustive. The direction of influence between the event nodes is developed based on the mechanics of pipe-soil interaction under imposed differential ground movements and the sequence of pipe condition assessment events shown in Figure 2. When the slope geometry and buried pipeline elevation profile are known, pipe condition and failure modes depend primarily on cumulative ground displacement and sliding length.

Table 1: Observed and Inferred Parameters.

Parameter	*Direct Measurements*	*Data for Inference*
Slope creep activity	*Field observations instrumentation*	*Field observations, LiDAR, InSAR, ILI*
Slope failure mechanism	*Field observations*	*Slope geometry, Geology, Field observations*
Ground displacement	*Field instrumentation*	*Field instrumentation, LiDAR*
Sliding length	*Field observations*	*LiDAR, Airphoto, InSAR, Slope Geometry*
Location of sliding block	*Field observations*	*Slope inclinometers LiDAR, InSAR*
Soil strength	*Soil tests*	*Surficial geology*
Pipeline alignment	*ILI*	*As-built drawings, Right of way alignment*
Depth of burial	*Depth of cover survey*	*Regulatory requirements*
Pipe material properties (grade, toughness)	*Material tests*	*Pipe vintage, Design value*
Pipe dimensions (Size, wall thickness),	*Direct measurements*	*Design values*
Internal pressure	*Readings at pumping stations*	*Maximum allowable operating pressure*
Pipe strain	*Strain gauges, Pipe curvature from ILI*	*Imposed loads, Pipe curvature from ILI*

Table 2: Event Nodes.

Event	*States*
Slope movement activity	*Active, Dormant*
Ground displacement	*Low (< 500 mm), Moderate (500-1000 mm), High (> 1000 mm)*
Sliding length	*Low (< 40 m), Moderate(40-80 m), High (> 80 m)*
Maximum strain location	*Head of slope, Toe of slope*
Exceedance of tensile strain limit	*True, False*
Exceedance of compressive strain limit	*True, False*
Detectable curvature	*Yes, No*
Limit states	*Local buckling, Girth weld rupture, None*
Failure modes	*Leak, Rupture, None*

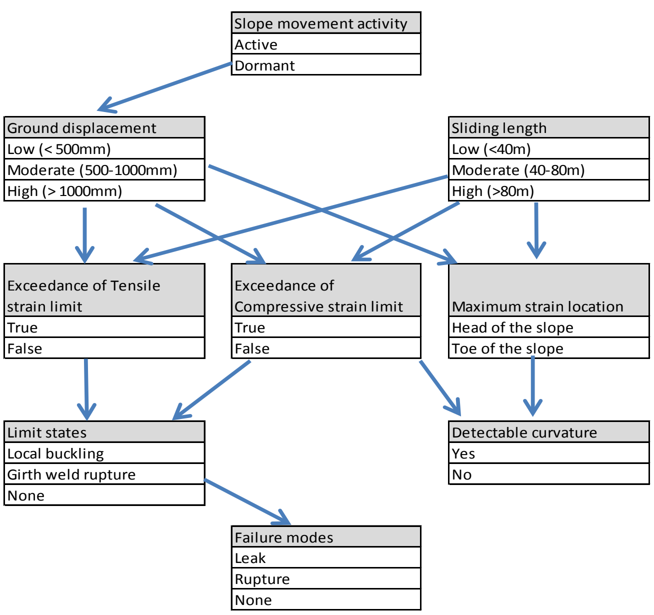

Figure 3: Network Diagram for Proposed Bayesian Network

[1] Event nodes at the arrow head of a link are termed child nodes, while the nodes at the blunt end of a link are termed parent nodes.

3. CONDITIONAL PROBABILITY

Three different approaches are presented to assess the probability of occurrence of child node [1] events conditioned on their parent node states: expert opinion, historical data, and structural reliability methods.

3.1. Expert Opinion

In the literature, probability values associated with qualitatively defined site conditions are available based on expert opinion. For example, the PRCI (2009) guidelines for pipeline construction through geohazard regions provide probabilities for ground movement potential based on qualitative descriptions of the site conditions. While quantifying the probabilities of ground movement occurrence, ground displacement magnitude and the size of moving soil block, experts consider the following site conditions (Baumgard et al. 2016, Guthrie and Reid 2018):

- Historical behaviour of the slope and direct observations regarding the site geology.
- Slope geometry and likelihood of stability of such slopes considering soil types and layers.
- Evidence for movement from slope inclinometers, their location and number.
- Presence of trigger events, such as toe erosion and poor drainage, which affect the rate of ground movement.
- Expected movement zone and movement magnitude based on either terrain observations or numerical analysis with simplified models.

3.2. Historical Data

Slope and pipe conditions associated with historical pipeline failures due to slope creep are often difficult to obtain. Nevertheless, statistical analyses of the available pipeline failure data in conjunction with expert opinion are available in the literature (Baumgard et al. 2016, Ferris et al. 2016).

In this approach, pipeline failure data is divided based on known slope conditions, such as slope length, slope angle, orientation of the ground movement relative to the pipe longitudinal axis and slope crossing angle of pipe profile. The conditional probabilities of pipeline failure are estimated as shown in Eq. (1):

$$P(f\,|\mathbf{s}) = n_s/n \tag{1}$$

where f if the pipeline failure event, $\mathbf{s}$ is the status of site conditions, n_s is the number of failures when site conditions are $\mathbf{s}$, and n is the sample size of the failure data. However, it is challenging to obtain the data regarding the status of site conditions during failure event. Therefore, using historical data in combination with indirect inferences is suggested to estimate the conditional probability tables (e.g., Ferris et al. 2016).

3.3. Structural Reliability

The probability distributions of tensile and compressive strain demands and capacities can be defined using random sampling if the slope conditions can be parameterized with sufficient confidence to be used as inputs in quantitative analysis models for pipeline response. The results of such sampling process can be used to derive the conditional probabilities needed for BNs. The type of analysis models available are empirical models (e.g., Sen et al. 2018), simplified numerical models (e.g., Fraser and Koduru 2016), and detailed numerical models (Fredj et al. 2016). With this approach, parametric data requirements are driven by the selected pipe-soil interaction analysis model, and the estimated probabilities are significantly influenced by the model uncertainties.

4. NUMERICAL EXAMPLE

4.1. Problem Description

Conditional probabilities for the BN shown in Figure 3 were developed to represent a hypothetical pipeline employed in case studies by Yoosef-Ghodsi et al. (2008), Zhou (2012), and Fraser and Koduru (2016). Pipe parameters are shown in Table 3. The pipeline is assumed to be buried in stiff clay and subject to ground movement parallel to the pipe longitudinal axis over a period of 10 years. Table 4 shows the random variables used to model soil strength, sliding length, and angle deviation (θ in Figure 1). Soil properties are treated as spatially correlated within a distance of 30 m. Details of the spatial correlation modeling, finite element model used for pipe-soil interaction analyses and the random sampling approach are described in Fraser and Koduru (2016).

Table 3: Pipe parameters.

Parameter	*Value*
Outer diameter, D (mm)	*508.00*
Wall thickness, t (mm)	*8.74*
Internal pressure (MPa)	*8.27*
Temperature change (°C)	*50.00*
Pipe material grade (API 5L)	*X65*

Table 4: Random variables.

Variable	*Distribution Type*	*Parameters*
Soil undrained shear strength (kPa)	*Normal*	*Mean = 150.00* *Standard deviation = 45.00*
Sliding length (m)	*Uniform*	*Lower bound = 30* *Upper bound = 100*
Angle deviation (degrees)	*Uniform*	*Lower bound = 0* *Upper bound = 10*

4.2. Probabilities

4.2.1. Parent Nodes

The sliding length distribution noted in Table 4 was discretized to obtain the probabilities of discrete event states for sliding length node in the BN. For slope movement activity, both states are assumed to be equally likely as the slope location is unknown, and also the percentage of moving and stable slopes in the geographical region is unknown. Probabilities of slope movement activity may also be assigned based on expert opinion as discussed by Guthrie and Reid (2018), or by extending the BN to include additional slope-specific nodes , such as site geology, indications of historical slope failures, behavior of adjacent slopes and so on..

4.2.2. Conditional Probabilities

Conditional probabilities for ground displacement were derived based on the movement rate provided in Nessim and Koduru (2018). For a mean movement rate of 12.5 mm/yr, the mean cumulative ground displacement over a 10-year period is less than 500 mm. The dormant slopes are assumed to have this mean movement rate of 12.5 mm/yr. In active slopes, mean movement rate is assumed to be closer to 50 mm/yr. Ground displacement probabilities were discretized from the ground displacement distribution at the end of a 10-year period using this movement rate value. Table 5 shows the conditional probability table associated with this node.

Table 5: Conditional Probabilities for Ground Displacement

Ground displacement	*Slope movement activity*	
	Active	*Dormant*
Low	*0.50*	*1.0*
Moderate	*0.48*	*0.0*
High	*0.02*	*0.0*

Conditional probability tables for the exceedance of tensile strain limit, exceedance of compressive strain limit, and maximum strain location nodes were derived using the random sampling data generated by Fraser and Koduru (2016). The probability of exceeding the tensile strain limit is computed using a tensile strain limit of 0.5% strain. As the pipeline steel is typically assumed to reach elastic limit at 0.5% strain, this is a reasonable value to consider for tensile strain capacity at girth welds for a modern pipeline without severe girth weld flaws. The probability of exceeding the compressive strain limit is computed using a compressive strain limit of 1%. This is a conservative estimate in the absence of additional information regarding pipe surface imperfections that initiate local buckling. Table 6 summarizes the probabilities associated for these three nodes for all combinations of the ground displacement and sliding length.

The conditional probabilities for the limit states node depend on the failure mechanisms associated with tensile and compressive strain limits. Girth weld rupture is due to excessive tensile strains, and local buckling is initiated due to excessive compressive strains. For simplicity, the ratio of leaks to ruptures was estimated from the ratio of failure modes due to earth movement in a pipeline industry failure database (Lam 2015), and applied for both local buckling and girth weld rupture due to lack of historical data to identify the limit state initiating the failure. Tables 7 and 8 show the conditional probabilities for these two nodes. Probability of detecting a change in pipe curvature due to buckling depends on the ILI tool performance specifications. Table 9 provides the required conditional probabilities for this node.

Table 6: Conditional Probabilities for Strain Limits and Maximum Strain Location

Ground displacement	*Sliding length*	*Exceed strain*		*Location (Head)*
		T	*C*	
Low	*Low*	*0.00*	*0.00*	*0.5*
Low	*Moderate*	*0.00*	*0.00*	*0.5*
Low	*High*	*0.47*	*0.09*	*0.8*
Moderate	*Low*	*0.00*	*0.00*	*0.5*
Moderate	*Moderate*	*0.00*	*0.00*	*0.5*
Moderate	*High*	*0.41*	*0.15*	*0.7*
High	*Low*	*0.00*	*0.00*	*0.5*
High	*Moderate*	*0.02*	*0.00*	*0.5*
High	*High*	*0.53*	*0.31*	*0.6*

Table 7: Conditional Probabilities for Limit States

Exceedance of Compressive strain limit	*True*		*False*	
Exceedance of Tensile strain limit	*True*	*False*	*True*	*False*
Local buckling	*0.5*	*1.0*	*0.0*	*0.0*
Girth weld rupture	*0.5*	*0.0*	*1.0*	*0.0*
None	*0.0*	*0.0*	*0.0*	*1.0*

Table 8: Conditional Probabilities for Failure Modes

Failure mode	*Limit states*		
	Local buckling	*Girth weld rupture*	*None*
Leak	*0.6*	*0.6*	*0.0*
Rupture	*0.4*	*0.4*	*0.0*
None	*0.0*	*0.0*	*1.0*

Table 9: Conditional Probabilities for Curvature Detection

Exceed compressive strain limit	*Strain location*	*Detectable curvature*	
		Yes	*No*
Yes	*Head*	*0.5*	*0.5*
Yes	*Toe*	*1.0*	*0.0*
No	*Head*	*0.0*	*1.0*
No	*Toe*	*0.0*	*1.0*

4.3. Inference and Bayesian Update

Figure 4 shows the inference of failure probabilities. The total probability of pipe failure is 15%.

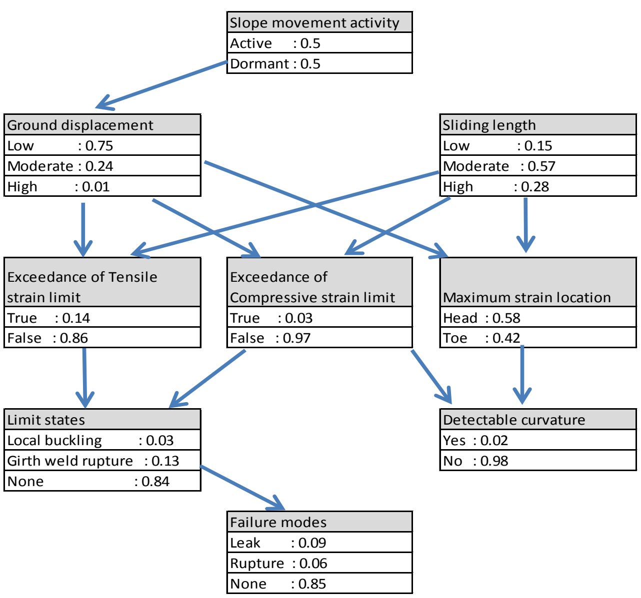

Figure 4: BN Inference to Assess Failure Mode Probabilities

Figure 5 shows the updated probabilities at all nodes if curvature was detected by an ILI tool. Detection of curvature in the pipe surface by the tool confirms the compressive strains exceeding strain limit by updating the event node probability of exceedance of compressive strain limit to 1.0, and increases the probability of leak from 9% to 60%. This implies the estimated probability of failure of the pipeline is entirely based on local buckling limit state defined in Table 8.

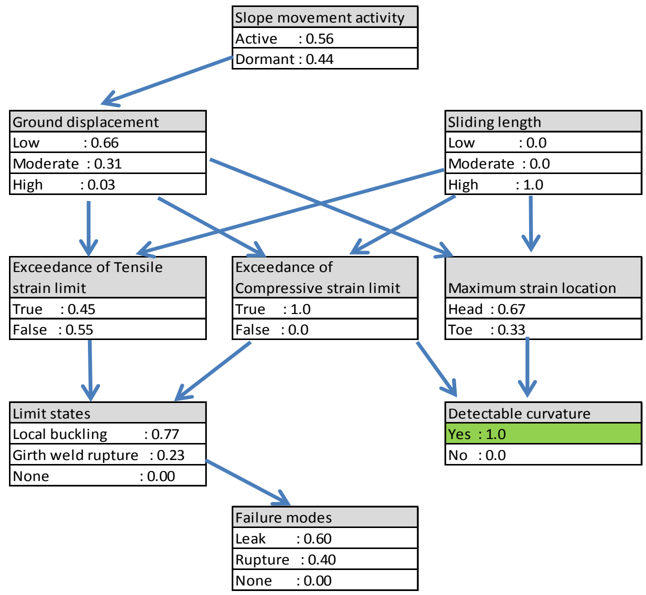

Figure 5: BN Update Following a New Observation

4.4. Discussion

The BN shown in Figure 3 demonstrates the use of data from multiple sources to quantify the probability of failure in each failure mode. Expert opinion was included to assess slope movement activity, historical data to assess the conditional probabilities in Table 5 and Table 8, and structural reliability model results to assess the probabilities shown in Table 6. Advantages of this approach are:

- Integration of expertise from multiple domains, e.g., geotechnical engineering for ground displacement assessment, and structural engineering for pipe-soil interaction modeling.
- Update of failure probabilities without multiple steps involving domain experts and different types of analyses.

- Transparent use of available evidence as the outcome of an ILI tool's results is visibly represented in Figure 5.
- Flexibility to scale the BN to include additional nodes to represent historical site conditions, geotechnical observations, and strain capacities for a more detailed consideration of site-specific factors.
- Ease of extending the BN to develop a generic model to assess pipe conditions across multiple sites.

BNs handle uncertainty either in parametric data or in probabilistic relationships but cannot update both simultaneously. For example, the update shown in Figure 5 addresses the update to parametric data. It is limited to updates to the predicted probabilities of node status. It is not possible to update the conditional probabilities derived in Tables 5 to 8 with the same BN. The probabilistic relationships can be updated only by regenerating the BN with the same network structure and updated conditional probability tables, or by re-structuring the BN through expert judgement.

The update to the probabilistic relationships (e.g., structure of a BN) without manual intervention is possible with additional data, but those data sets are expected to have a large sample size and be comprehensive in representing all possible data relationships. However, as there is considerable expert knowledge, and understanding of the pipe-soil interaction mechanics, BNs remain the best approach to address the challenges in geohazard management.

The important issues to address when using BNs for geohazard management are:

- The conditional probabilities are subject to uncertainties due to dependence on expert opinion and use of simplified models to represent geotechnical phenomena.
- Modeling the time dependent nature of geohazard events leads to a significant increase in network size as well as the need to define additional conditional probabilities.
- Approximate nature of conditional probability tables to represent the relationships between nodes introduces additional uncertainty in probability predictions. However, reduction of this uncertainty with the use of structural reliability methods is not possible without using complex models for pipeline response.

These issues are not unique to BNs but exist in one form or another in all the available approaches to estimate failure probabilities due to geohazards. BNs provide the best opportunity to leverage all the available data and infer the status of events that cannot be directly observed with the use of observations from the related events.

5. CONCLUSION

A simple BN was developed in this study to demonstrate the integration of data from multiple sources to predict the probability of pipeline failure due to slope creep. This BN was limited to a site-specific application and focused on the assessment of pipe response due to ground movement, and the updated inference of pipeline failure probability through observation of pipe response (i.e., change in curvature). Possible future enhancements include expanding the two top nodes without parent nodes to have their own network. In that case, the top event node status will be an output from a different BN, which has a network structure representative of the geological and geotechnical aspects with greater granularity. Furthermore, BNs representative of pipeline at multiple slopes that are inspected by the same ILI tool can have a common event node representing the inspection result. This will enable inference of the node status for slopes at remote sites through the use of additional data from the slopes that are more accessible.

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