

Oil and Gas Pipeline Third Party Damage (TPD) - A New Way to Model External Hazard Failure

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Abstract: Oil and gas pipelines incidents resulting from damage from third parties – collectively referred to as Third Party Damage (TPD) - caused 141 deaths, 440 injuries and incurred \$ 369 million in property losses between 1993 and 2012. Unlike failure causes such as internal and external corrosion, TPD cannot easily be deterministically modelled. Understanding TPD is more a human versus a hardware reliability problem.

Prediction requires some deterministic or mechanistic basis. 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. Most literature involves simple statistical analysis of TPD, identifying basic trends and, but this is not sophisticated or analytic.

This paper outlines a new modelling approach based on a Bayesian Belief Network (BBN) that can incorporate more information sources than those provided empirically by databases. Instead of modelling TPD based on pipeline characteristics, the decision-making process of the third party is examined in more detail than any previous modelling initiative has attempted. This process is informed by expert opinion, and allows things like training, awareness, organization nature and so on to be modelled in a useful way.

Keywords: oil and gas pipeline, pipeline safety, pipeline damage, third party damage

1. INTRODUCTION

According to the United States Department of Transportation's (DOT's) Pipeline and Hazardous Materials Safety Administration (PHMSA): [1]

The biggest threat to the safety of pipelines, particularly in and around cities and towns, arises from people or companies, referred to as third-parties, digging in the vicinity of buried pipelines without realizing the pipeline is there.

Between 1993 and 2012, 1630 onshore Third Party Damage (TPD) incidents were reported to PHMSA. These caused 141 deaths, 440 injuries and \$ 369 million in property damage. [2] The actual costs that include second order effects of energy outages are likely to be orders of magnitude higher.

TPD is the leading cause of oil and gas pipeline failure. With virtually every industry (domestic and commercial) at least partly dependent on fossil fuel energy, TPD failure impacts virtually every facet of society. From 1985 to 1997, 28.1 per cent of all pipeline incidents were caused by TPD. [3] This figure increased to 45.9 per cent for the period 2002 to 2013. [4]

There is a pressing need for us to better understand TPD. Oil and gas pipeline failure research has typically focused on more tangible physical failure mechanisms, particularly corrosion. TPD has received comparatively less focus notwithstanding it is the leading cause of oil and gas pipeline failure. The reasons for this are discussed below, along with what needs to be done to rectify this.

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1.1 TPD is difficult to model

Unlike physical failure mechanisms, TPD cannot be deterministically modelled. External corrosion (for example) is increasingly studied, with incrementally more sophisticated models emerging over time. These models allow a scientific understanding of the underlying failure mechanisms. By understanding both the physics and chemistry involved for these failure mechanisms, effective preventive measures such as the application of coating supplemented by cathodic protection (CP) can be identified. [5].

But we don't have the benefit of science to help us understand TPD. TPD is a 'more human' and 'less hardware' reliability problem. And a useful first step is to examine human reliability analysis (HRA). First generation HRA models use performance shaping factors (PSFs) that drive human error probability calculations. More sophisticated cognitive models are used in second generation HRA models. [6] This means we need to focus on the cognitive processes associated with TPD. That is, we need to examine the decision-making process of third parties.

HRA requires substantial amounts of information – which is not available for pipeline TPD study. This effectively precludes the majority of HRA models, meaning an alternate approach is required. Simple empirical data analysis reveals a correlation between TPD occurrence and pipeline characteristics. For example, TPD occurrence increases when the year of installation of a pipeline is unknown. [4] It can be reasonably inferred that this stems from poor record keeping. And poor record keeping means that there is a higher probability that the exact location of the pipeline has also been lost. Knowing the exact location of the pipeline helps pipeline owners and utilities alike to protect themselves from TPD.

Other, potentially misleading trends are also apparent. TPD is less likely as pipeline wall thickness of increases. This makes intuitive sense. However, wall thickness is proportional (in general) to pipeline diameter. The extent to which a pipeline is underground (depth of cover or DOC) is also generally proportional to diameter. This means that the apparent trend between TPD occurrence and pipeline wall thickness could also be explained (at least in part) by a trend that exists between TPD occurrence and DOC. It is not possible now to understand the true relationship just by focusing on data alone. But we need to know the true relationship if we are to implement adequate mitigation or preventive measures.

1.2 TPD is difficult to predict

Prediction requires a deterministic or mechanistic basis. A basic approach to prediction relies on previous empirical data being representative of the future. This is uninformative and not useful – save for perhaps calculating insurance premiums. The aim of creating a sophisticated model is to understand causality – to find factors that inform engineering decision-making.

Most literature involves simple statistical analysis of TPD, identifying basic trends and relationships. [4] This helps identify potential causal relationships, but is not a sophisticated or analytic basis to identify mitigation (which as discussed above, requires an understanding of causality). Other studies which attempt to characterize TPD causality are overly simple, such as the 12 event fault tree of Chen et al. [7] Of these 12 events, 10 are 'undeveloped' and require further modelling. Those events that are modelled have probabilities 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 satisfactorily produce an accurate predictive TPD model. The two main publicly available data sources are the PHMSA's mandatory reporting database [1] and the Common Ground Alliance's (CGA's) Damage Information Reporting Tool (DIRT.) [8] Both sources involve 'failure events' only. That is, incidents that have the same preceding events and causes but fortuitously do not result in pipeline failure never get reported.

1.3 The way ahead

To be able to do something that reduces the prevalence of TPD, we need to understand what causes it. Which means we need to model the decision-making process of third parties: both ‘good’ and ‘bad.’ And by doing this, we will be able to identify what we need to address to make TPD less likely.

The analysis required is Bayesian. The many reasons for this are expanded below. In short, Bayesian analysis is the only approach that allows all information sources to be used in creating a model. These information sources go well beyond data and involve things like expert judgment and similar cognitive models. And Bayesian analysis can be used to ‘invert’ probabilities. Empirical data can (at best) calculate the probability of a causal event given an outcome. Bayesian analysis can calculate the probability of an outcome given a causal event. This is what we aspire to understand.

This paper outlines a Bayesian approach that utilizes Bayesian belief networks (BBNs) to model third party decision-making that allows us to target effective TPD mitigation activities. The BBN developed below is (by some margin) the most comprehensive approach to modelling TPD more broadly. It uses information obtained from multiple sources within the industry (utility, contractor and regulatory body). Its results have been constrained through the modelling process to align with empirical observations.

The model itself can never be fully validated (for reasons discussed below). But its framework allows all elements of the decision-making process to be included. This model should serve as the catalyst for future work. In so doing, its most important contribution may be the creation of an analysis framework.

2. CONDITIONAL PROBABILITY, CAUSALITY AND PREDICTION

Bayes’ theorem addressed the problem of ‘inverted’ probabilities. That is, if we know the probability of event ‘A’ given event ‘B’ occurred, what is the probability of event ‘B’ given event ‘A’ occurred? These probabilities are ‘conditional’ probabilities in that they are predicated on some other event happening.

The problem of ‘inverted’ probabilities arises when we examine TPD failure data. Databases contain failure events: they don’t contain events where the pipeline was ‘successful.’ But even when the pipeline was ‘successful,’ there would have been many instances of behaviour and precursors for failure. Not all dangerous third party practices will result in TPD. So data analysis can only ever let us estimate the probability of some causal factor given failure.

$$\Pr(C|F) \tag{1}$$

where $\Pr(C|F)$ is the way we write the probability of some causal factor event C given failure event F occurred.

For predictive modelling, we require this probabilistic conditionality to be ‘inverted.’ That is, we are interested in the probability of failure given a causal factor event: $\Pr(F|C)$. This is where Bayes’ theorem applied. Bayes’ theorem (in the context of ‘inverting’ probabilities) is as follows:

$$\Pr(F|C) = \frac{\Pr(C|F)\Pr(F)}{\Pr(C)} = \frac{\Pr(C|F)\Pr(F)}{\Pr(C|F)\Pr(F) + \Pr(C|\bar{F})\Pr(\bar{F})} \tag{2}$$

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

The denominator of the rightmost term in equation (2) highlights the problem with data only analysis. The term is ‘ $\Pr(C|\bar{F})$ ’ is the conditional probability of some causal event given that the pipeline did not fail. The causal event may be the third party not researching pipeline location in an area they are excavating. This may (fortuitously) not cause TPD. There is no database for this conditional probability.

This makes empirical analysis for creating a predictive model impossible, as there is no data that deals with pipeline failure not occurring when causal events occur.

So we must use another very useful information source: expert judgment and opinion. Bayesian analysis naturally allows expert opinion - essentially necessitating the use of a Bayesian modelling framework such as BBNs. And while we have read why data by itself will not satisfactorily allow us to understand TPD the way we want to, there is enough data and experience for us to know how TPD causal chains come together. We are fairly certain that we know the processes and event sequences that lead to TPD related failure. And the rest of this paper describes how this knowledge is used to create our model.

2.1 Understanding TPD

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 first information source is **incident databases**. The PHMSA database mentioned above is legally mandated database (<http://www.phmsa.dot.gov/pipeline/library/data-stats>). United States operators are required to report incidents to PHMSA if they meet any of the following criteria: [9]

- (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. The same cannot be said of all leakage failure modes. A shortcoming of PHMSA data is that can only be broken down by a single attribute, meaning that dependencies are effectively hidden. For example, it is not possible to identify the percentage of pipes that are in a location class and have a particular diameter range – you can only identify groups by one trait or the other.

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 1 compares of apparent 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 rate estimates: in the order of $2.3 - 3.6 \times 10^{-4}$ failures per (km year). Those that have limits in reporting criteria (where only some failures are reported) have lower failure rate estimates: $1.0 - 1.1 \times 10^{-4}$ failures per (km year). It is conceivable that failure rate estimates based on PHMSA data alone could 2 to 3 times lower than actual failure rates.

PHMSA data breaks failure into two cause categories: 'Excavation Damage' and 'Other Outside Force Damage.' From 2002 to 2013, there are four cause sub-categories of **third party damage (TPD)**. [10] From 2002, causes that related to third party damage as per the PHMSA data base were **third party excavation (TPE)** and **other external forces**. [10] However other databases include information for other proximate causes and they are included here.

The CGA is a member-centric organization with a membership of 1700 that typically include utilities and pipeline operators. The CGA maintains multiple databases that feed its DIRT tool. Stakeholders have submitted pipeline damage and near-miss reports which informs an interactive web page. This affords more 'fields,' and by extension parameters, for model development. However, this is a voluntary endeavour which must be understood when attempting to interpret data.

Table 1: Comparison of Gas Pipeline Failure Rates by International Reporting Regime [10]

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)	
United Kingdom	1962-2010	2.3×10^{-4}	United Kingdom's Onshore Pipeline Operators Association (UKOPA) Database	No lower limit
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

The other publicly available database is the NTSB Pipeline Accident Reports (PARs) that are compiled for 'significant' pipeline failure. Consequently, NTSB databases cover a tiny fraction of pipeline failure events. But they do contain extensive analysis about the preceding events which provide significant insight regard pipeline risky third party activities.

The second main information source is **expert opinion**. We know why third parties (necessarily) undertake activities that can be risky from the perspective of the pipeline. We know how they go about doing this. We know what activities they need to undertake to damage the pipeline. We know what steps can mitigate or change their behaviour. And we also know how they will react should they strike barriers such as concrete or cages.

This is information that cannot be captured using data analysis only. And by simply structuring a model that reflects these processes, we can incorporate new realms of information. We can (importantly) incorporate the highly detailed PARs that help us understand what activities were (or were not) undertaken that contributed to the failure event. We can also (in a structured way) incorporate expert judgment that develops the conditional probabilities of each possible sequence of events.

2.2 What did we learn?

The detailed model that was developed (and the way it was developed) is explained below. A preliminary list of key TPD risk factors is summarized here. This is the information we are looking for: areas that we need to target in order improve safety.

The first risk factor is **pipeline robustness** generally. Increasing the diameter, DOC and wall thickness clearly reduces TPD likelihood. There is an obvious relationship between the ability for pipeline strength versus typical stresses associated with TPD. Owners and utilities can (for example) bury pipelines deeper to reduce the probability that third parties will dig deep enough to damage the pipeline.

The second risk factor involves **culture and behaviours**. Public advertising and awareness campaigns are very useful in positively influencing third party behaviour. Historical reductions in TPD are largely attributed to an increased likelihood for third parties to contact utilities before commencing their activity.

Advice and signage is the third risk factor. Clear signage that indicates the presence of pipeline has obvious benefit in terms of making third parties aware of pipeline presence. However, as signage typically does not indicate pipeline presence in advance to the third party, business decisions to continue with excavation regardless are often made in preference to the imposition of delays associated with contacting utilities. The extent to which third parties who are ready to undertake activities on a particular

day have an overwhelming commercial pressure to continue with that activity. This pressure can trump the obvious perils of excavating even when there is signage.

And the final risk factor is **physical barriers**. Many studies 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. [11]

3. MODELLING THIRD PARTY DAMAGE (TPD)

TPD typically results from a sequence of events where each one contributes to the likelihood or enables the next. These events (which include decisions) are generally ‘broadly known:’ sufficient combined expertise exists to be able to (theoretically) list and potentially model these event sequences.

Many modelling techniques do not incorporate sequencing. Fault trees (for example) do not ‘naturally’ consider one event to have occurred before another. Fault trees to be constructed in a way that sequenced events are incorporated, but in a ‘standalone’ way. This is true of many popular reliability modelling techniques.

The modelling approach that best incorporates a sequential approach to scenarios is event sequence diagrams (ESDs). ESDs have been used extensively in accident investigation as they align with the thought process of the investigator and the investigated. The following six step approach was used in the generation of the TPD model.

3.1 Step One – Cluster Failure Event Scenarios

A literature review (which included NTSB PARs) and engagement with our technical network was conducted to identify known scenarios associated with TPD failure. The review examined a wide range of causal factors that include culture related concerns.

3.2 Step Two – Create Specific Failure Event Scenarios

For each historical incident, a generic ESD was developed. This involved recreating the incident in terms of preceding events and decisions made by both the third parties and the pipeline operators.

3.3 Step Three – Develop Generic Failure Event Scenarios

Generic ESDs were extended to include plausible alternatives in the sequence. This allowed ‘branching’ sequences that in some instances avoided pipeline failure. These sequences hypothesized how the third party involved in the historical TPD related failure could have avoided this outcome.

3.4 Step Four – Develop Single Generic ESDs for Initiating Events

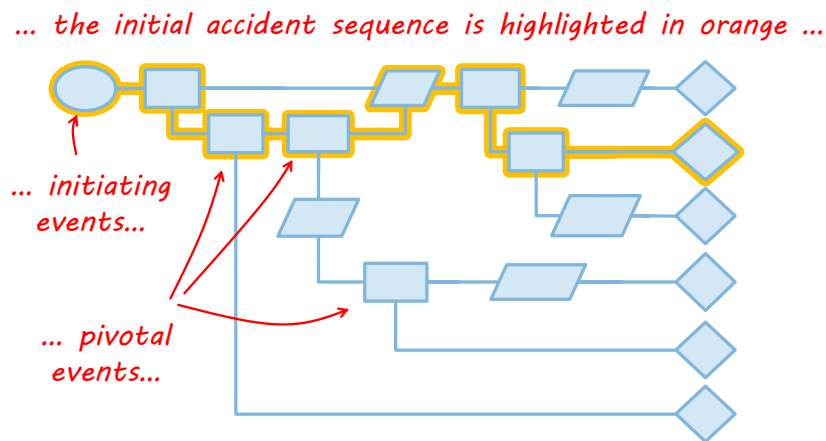
The scenario-specific ESDs were combined to create a single ESD for all TPD scenarios. This was then compared with extant literature regarding TPD to ensure that all possible event scenarios were included. Generally, comparison with literature confirmed the completeness of the ESD, with branches needing to be added in only a few instances. [7]

Resultant ESDs were structured in accordance with an example diagram illustrated in Figure 1. They were reviewed by experts from the NTSB and utility organizations. The orange line in Figure 1 illustrates an actual sequence associated with an historical TPD failure event. All others are those hypothetical event sequences the third party could have pursued to avoid failure.

3.5 Step Five – Develop Bayesian Belief Networks (BBNs)

ESDs are ‘memoryless’ in that the probability that an event will occur is not dependent on how the sequence ‘got’ to that point. This can be overcome by having multiple branches for different scenarios, but this becomes cumbersome even for a moderate number of pivotal events.

Figure 1: Example generalized ESD with an accident sequence highlighted in orange.

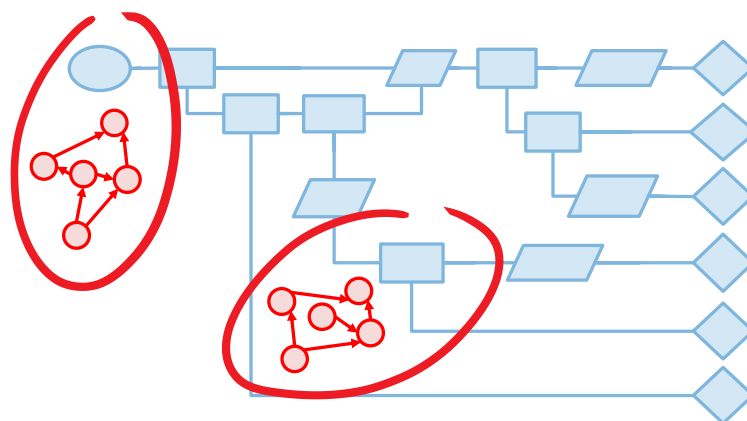


This is why BBNs are important. They involve ‘nodes’ that can exist in different states and can then be used to modify the conditional probability of other nodes existing in other states. These node states can then be used to model the probability of specific branches in the ESD.

This inherently allows multiple node states to affect conditional probabilities of any node, regardless of how far removed from the initiating event it is. Cause and consequence probabilities are linked and quantified using cross probability tables. The use of several models enables us to capture not only data’s uncertainty, but also model’s uncertainty. When hundreds of parameters interact in various ways, a model that would miss only one critical parameter would be useless. Moreover, it is difficult to know which parameter will be important before exercising the model.

The BBN to support and implement the ESD was created with support from industry experts providing judgment with respect to pivotal events in ESDs. The way their uncertainty was characterized is described below in this paper. The process is illustrated in Figure 2.

Figure 2: Event Sequence Diagrams (ESDs) and the development of Influencing Nodes



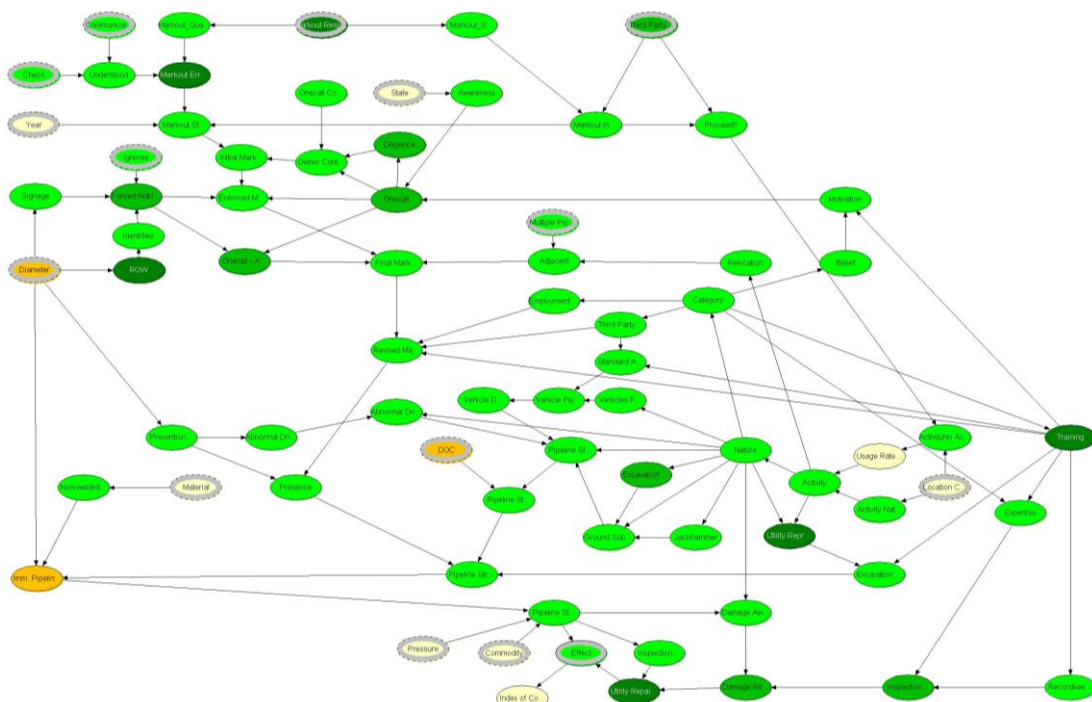
The new TPD BBN is illustrated Figure 3. The details of each node will be described in greater detail in future publications. Figure 3 illustrates the complexity of the model, and how it can be ‘detailed’ enough to accommodate a substantial array of decision making scenarios.

3.6 Step Six – Model Inputs

An observation of pipeline data maintained by owners and utilities across the oil and gas pipeline industry is that there are substantial discrepancies in what is recorded, and data that is recorded is often fiercely protected (and not widely available). For that reason, the model was constructed to limit the required inputs to those legally required for submission to PHMSA. These inputs are:

1. state (location);
2. year of installation;
3. diameter;
4. material;
5. depth of cover (DOC);
6. commodity;
7. location class; and
8. other pipelines in the vicinity (truth variable).

Figure 3: Complete New Bayesian network of TPD



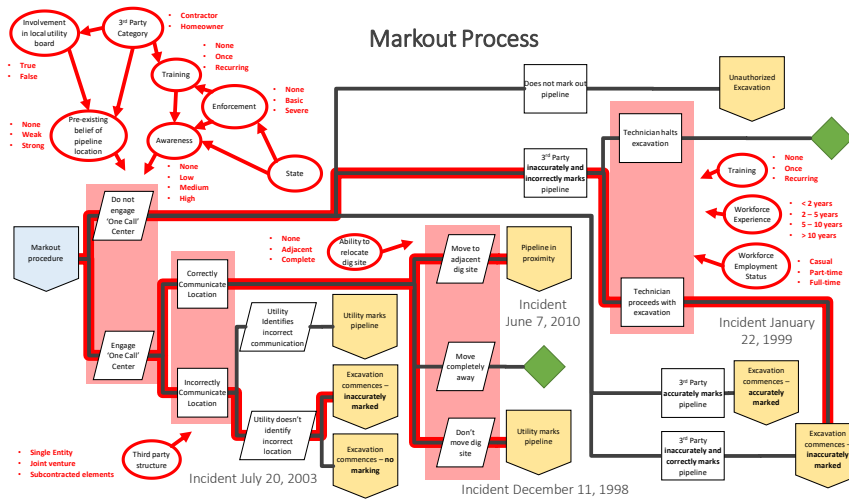
4. MODEL OVERVIEW

While the details of the BBN model are beyond the scope of this paper and will be outlined in forthcoming publications, some key characteristics of the model bear mention here.

For a sequential (human) failure process, BBNs are inherently difficult to visually appreciate and interpret (as shown in Figure 3). The combined ESD-Bayesian network nodes more naturally communicate TPD process. The high-level ESD is particularly complicated, and was created by focusing on specific processes. For example, Figure 4 shows the ESD element that relates to the ‘markout’ process. ‘Markout’ refers to a pipeline owner or utility who, once notified of impending third party activity, sends people to the activity site to accurately indicate on the ground where the pipeline runs.

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. Inaccuracy and delays will introduce risk that the activity commences without the third party being aware of the pipeline presence.

Figure 4: Markout Process ESD Element



4.1 The beta distribution and incorporating expert judgment

The model described in this paper was created using industry experts providing judgment with respect to pivotal events in ESDs. It is important that their identities remain anonymous, as it is imperative that their opinions were provided freely without prejudice. A questionnaire was established in a Microsoft Excel spreadsheet. This spreadsheet allowed experts to independently enter their estimates regarding conditional probabilities. That is, they were asked many questions about the probability of some event occurring given some other event occurred. Their response was naturally bounded by 0 and 1.

The beta distribution was then assumed to model their judgment. The beta distribution is commonly used to model uncertain probabilities, as it is naturally bounded by 0 and 1. Further, the beta distribution is a conjugate prior. That means that a likelihood function which is based on the product of two (or more) other likelihood functions will be a beta distribution if the factors are also beta distributions.

Experts were then asked to quantify their level of certainty on a scale of 1 to 5. When multiple experts were engaged for the same node, 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 had a variance of 1 assumed. For example, one expert provides a point estimate for a conditional probability, \hat{p} , of 0.4. The probability density function of the beta distribution is:

$$f(p) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha, \beta)} \quad (3)$$

where $B(x)$ is the **beta function** which is defined as $\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$, and $\Gamma(x)$ is the **gamma function** which is defined as $\int_0^{\infty} z^{x-1} e^{-z} dz$.

The mean of a beta distribution is:

$$\mu = \frac{\alpha}{\alpha + \beta} \quad (4)$$

Equating the point estimate with the mean yields:

$$\beta = \alpha \left(\frac{1}{\hat{p}} - 1 \right) \quad (5)$$

Using this expression, we can express the variance of the beta distribution as:

$$\sigma^2 = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} = \frac{\alpha^2 \left(\frac{1}{\hat{p}} - 1\right)}{\left(\frac{\alpha}{\hat{p}}\right)^2 \left(\frac{\alpha}{\hat{p}} + 1\right)} = \frac{\hat{p}^2 \left(\frac{1}{\hat{p}} - 1\right)}{\left(\frac{\alpha}{\hat{p}} + 1\right)} = \frac{\hat{p}^2(1 - \hat{p})}{\alpha + \hat{p}} \quad (6)$$

This allows us to express the parameters in terms of the variance:

$$\sigma^2 = \frac{\hat{p}^2(1 - \hat{p})}{\alpha + \hat{p}} \quad \dots \quad \alpha = \frac{\hat{p}^2(1 - \hat{p})}{\sigma^2} - \hat{p} = \frac{\hat{p}^2(1 - \hat{p}) - \sigma^2\hat{p}}{\sigma^2} \quad (7)$$

And similarly for β :

$$\beta = \alpha \left(\frac{1}{\hat{p}} - 1\right) = \frac{(1 - \hat{p})(\hat{p}(1 - \hat{p}) - \sigma^2)}{\sigma^2} \quad (8)$$

For each expert, parameters α and β can be calculated for the beta distribution that describes the confidence in each estimate. We exploit the fact that the beta distribution is a conjugate prior to combine information by multiplying probability density functions. The resultant parameters are defined as:

$$\alpha = 1 + \sum_{i=1}^n (\alpha_i - 1) = 1 - n + \sum_{i=1}^n \alpha_i \quad (9)$$

$$\beta = 1 + \sum_{i=1}^n (\beta_i - 1) = 1 - n + \sum_{i=1}^n \beta_i \quad (10)$$

where α_i and β_i are the parameters associated with the i^{th} expert calculated using equations (7) and (8).

The mean of the resultant probability distribution is used to provide the conditional probability is:

$$p_{model} = \frac{\alpha}{\alpha + \beta} \quad (11)$$

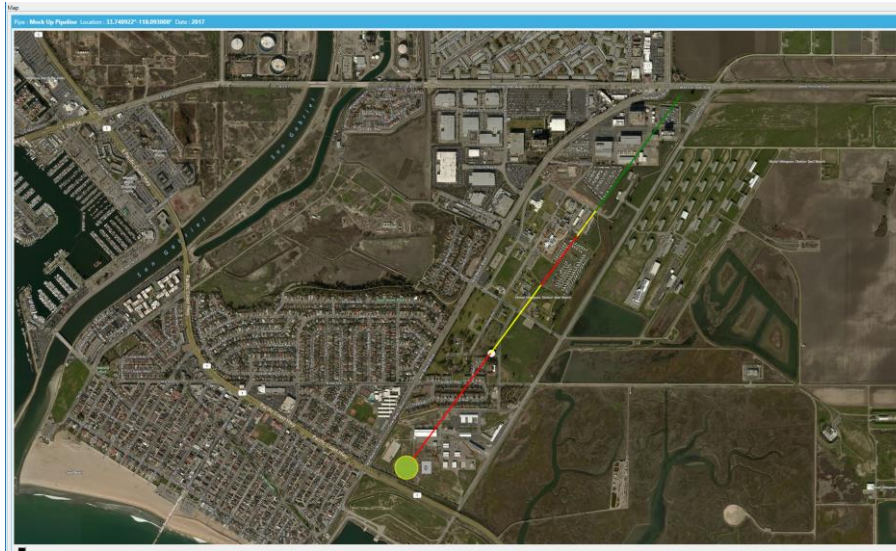
This approach was used for all conditional probabilities where empirical data didn't exist. An example of where empirical data existed for establishing conditional probabilities was 'awareness' associated with third parties knowing that the 'OneCall Center' existed and could be contacted to initiate the markout process described above. The CGA DIRT database reports awareness levels for various geographic areas across continental United States, negating the need for expert opinion.

4.2 Demonstration

The model was demonstrated using Det Norske Veritas - Germanischer Lloyd (DNV GL) proprietary software called MARV™. MARV™ software involves a graphical user interface combining geographical maps, models, and prognostication.

In the example illustrated in Figure 5, a fictitious pipeline was divided into thousands of segments defined by global positioning satellite (GPS) coordinates. Pipeline characteristics were entered as defined in section 3.6. The pipeline diameter, material, year of installation, and commodity class were either identical or 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 DOC and location class. The colours in Figure 5 are relative. That is 'red' represents pipeline segments with the highest risk relative to other pipeline segments.

Figure 5: MARV™ graphical user interface shows pipeline threat model and data (left) and results on a map (right) for TPD



4.3 Application

The TPD model was implemented on an actual pipeline of an industry partner as part of this research. The model outputs corresponded with known instances of TPD and TPD failure. While there was not enough data to validate the model (a problem that will likely stand given the proprietary nature of pipeline characteristics), it was clear that regions of high TPD aligned with observation.

5. CONCLUSION

The TPD model developed above allows a thorough understanding of the causal factors that influence decision makers who are trying to reduce TPD risk. Until now there has been limited scope to understand what affect each will have and whether it represents value for money.

This model can now be used in ‘sensitivity-like’ analyses to identify the key factors affecting TPD for specific pipelines. Because of the way that pipeline characteristics affect TPD prevalence, it is impossible to identify key and cost-effective mitigation factors generally. However, for pipelines of known or likely characteristics in specific locations, this TPD model can be used to identify specific mitigation measures. Beyond the primary risk drivers identified using these techniques, we can also tailor our understanding of what approach is best for different scenarios.

We can understand how television and radio advertising for the OneCall Center would impact TPD in primarily residential scenarios, as this primarily involves homeowners and their contractors striking the relatively small supply lines to houses. We can also understand how owners can benefit from modifying pipeline characteristics such as DOC and diameter et cetera. 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.

The TPD model can also inform urban planning considerations. 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.

In short, the TPD model provides substantially more information than has previously existed for decision makers regarding oil and gas pipeline failure emanating from third party activity.

5.1 Future Work

The ESD upon which the BBN is based should be continually updated as new accident scenarios become apparent. And expert judgment can be continually refined at targeted nodes to improve the conditional probabilities. The BBN itself could be expanded further to incorporate the uncertainty in the combined expert judgment conditional probabilities. As it stands, point estimates are weighted by the relative uncertainty estimates of each expert. The parameters used to describe the combined opinion of these experts could be incorporated in nodes in the BBN to allow this uncertainty to propagate through the results.

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