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BaNTERA: A Bayesian Network for Third-Party Excavation Risk Assessment

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ABSTRACT

Third-party damage constitutes a major threat to underground natural gas pipeline safety; in the U.S., between 2016 and 2020, it caused eleven fatalities, twenty-nine injuries, and $124M USD in property damage losses. Several research studies have been carried out to identify the causes and contextual factors leading to third-party damage. However, there is a lack of models that are not only causally-based, but also comprehensive and suitable for modeling the probabilities of a pipe hit and subsequent damage. This paper presents the development process and results of building BaNTERA, a probabilistic Bayesian network model for third-party excavation risk assessment in the U.S. BaNTERA's capabilities for risk-informed decision support are presented in three ways: verification of the model's performance, validation of its damage rate predictions with historical industry data, and application in multiple case study scenarios. Preliminary results indicate that BaNTERA offers valuable insight including and beyond a probability estimation of third-party damage. Using the best available industry data and previous models derived from multiple sources, different inference methods can assist in pipeline damage prevention and risk mitigation. As such, BaNTERA represents a promising holistic and rigorous tool for addressing third-party excavation damage in natural gas pipelines.

1. Introduction

A leading cause of pipeline failure is third-party damage [1,2]; in the U.S., between 2016 and 2020, it was the cause of an average of 20.75% of the total number of incidents on transmission and distribution lines as reported by the Pipeline and Hazardous Materials Safety Administration (PHMSA) [1]. Collectively, these incidents resulted in eleven fatalities, twenty-nine injuries, and a total monetary loss of $124 USD in property damage. Fig. 1 illustrates that despite fluctuations in annual costs, the proportion of third-party damage incidents is fairly constant in time [1]. Due to the significant amount of property damage and safety risks posed by failures in excavations near pipelines, there have been a number of research projects and studies carried out that identify the root causes and context factors that may lead to third-party damage [3–7]. However, there is a noticeable lack of models that are not only comprehensive, but also causally-based, and updated in terms of technology, practices, and regulation for modeling the probabilities of a pipe hit and subsequent damage.

This paper presents the process and results of building Bayesian Network for Third-Party Excavation Risk Assessment (BaNTERA), a comprehensive probabilistic model for the assessment of natural gas pipeline hit and subsequent damage probabilities in excavation activities in the U.S. Using different forms of causal inference, BaNTERA expands upon insights gained from observable evidence, which can then be used to mitigate potential excavation-specific risks or drive more appropriate risk management actions. BaNTERA combines a wide variety of data and causal information. The Bayesian network approach used in building BaNTERA allows the model to incorporate multiple data sources and model multivariate joint probability distributions while providing a causal structure representing an analyst's knowledge of an excavation scenario.

The paper is structured as follows. Section 2 presents the necessary background information on third-party excavations, Bayesian networks, and current state of the art in modeling third-party damage scenarios. This is followed by a description of the methodology used to develop BaNTERA in Section 3. Then, in Sections 4–6, further information is provided about building BaNTERA, including the formulation of a third-party damage-specific taxonomy and high-level model architecture, the construction of BaNTERA's structure, and the strategies behind data selection and model parameterization. After presenting BaNTERA's parameterization results in Section 7, its probabilistic inference capabilities are applied to a number of different case study excavation scenarios in Section 8. A discussion of the model, its implications, and limitations are then included in Section 9, followed by concluding remarks in Section 10.

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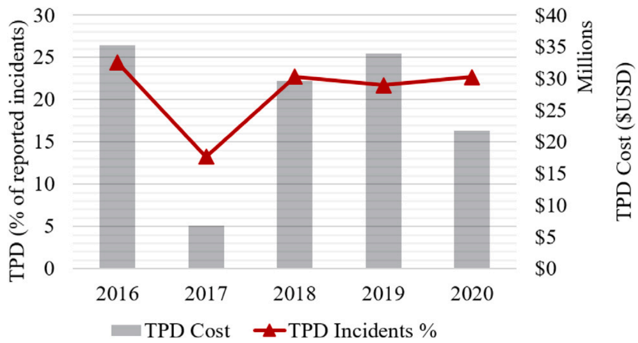

Fig. 1. Third-party damage (TPD) constitutes a large portion of excavation incidents involving gas pipelines, leading to significant monetary losses in property damage. *Source:* [1].

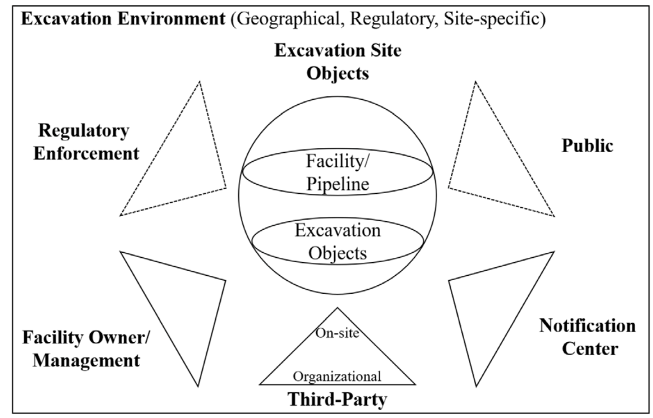

Fig. 2. Conceptual diagram of an excavation site. The context of an excavation site consists of actors (triangles) interacting with site objects (ovals) within a larger excavation context.

2. Background

This section provides general background information relevant to the development of BaNTERA.

2.1. Third-party excavation process and site description

The general excavation process considered for BaNTERA is structured on the best dig-in practices provided by the Common Ground Alliance (CGA; an organization that promotes damage prevention across underground utilities in the U.S.) around the use of the 811 One Call system [4,5]. These practices were considered so as to use the most generic damage prevention data-collection process in the U.S. In particular, the CGA's Damage Information Report Tool (DIRT) [4] incorporates data from multiple stakeholders from the natural gas industry, making it a comprehensive summary of data-collection and reporting practices on excavation damage to U.S. underground pipelines.

According to the CGA, prior to the excavation, the third-party excavator marks the anticipated digging area. He or she then calls the local 811 One Call center or submits an online form providing dig and site information at least two working days before digging. If the location contains underground facilities, the responsible utilities are notified and a utility service representative locates and marks the utility's facilities. Following this, the One Call center notifies the excavator to begin the excavation. The excavator proceeds to dig safely by exposing underground utilities using hand tools to avoid accidental damage. Failure to appropriately execute any of these steps may result in a gas pipeline getting hit. If the hit occurs with a strong enough force to overcome the pipe's inherent resistance, third-party damage in the form of a puncture failure can occur.

Fig. 2 shows a conceptual diagram of the primary entities, both actors and objects, at an excavation site; this defines the scope of the excavation context within which BaNTERA could be applied. The three main actors are the third-party excavators, the owner or manager of the pipeline, and the One Call notification center. Each has characteristics that pertain to on-site actions as well as broader organizational practices. Although the public and regulatory enforcement could be considered key stakeholders, they do not directly interact with the excavation site. As such, when building BaNTERA, they were considered part of the environment where the excavation occurs.

In addition to the actors mentioned above, the excavation site also consists of the facility and other objects pertaining to the excavation including the excavator, facility maps and records, and the notification ticket. The environment in which the interactions between the actors and the objects occur relates to the specific circumstances that are present at the excavation site. Example environments include geographical, regulatory, and site-specific contexts.

2.2. Bayesian networks

An excavation process is comprised of multiple factors that may impact the likelihood of third-party damage. Moreover, these factors are usually causally dependent on each other. These features must be considered when choosing a modeling approach.

Bayesian networks are probabilistic graphical models that encode a detailed knowledge base on a system. As such, they can be used to address the difficulty of modeling third-party damage by representing how risk influencing and other causal factors interact at an excavation site and lead towards damage.

In risk and safety applications, Bayesian networks are widely used as causal models to express the joint probability distribution of a system's variables; in this instance, the system considered is the third-party excavation process. These variables and their causal conditional dependencies are represented, respectively, by the nodes $V = \{V_1, V_2, \dots, V_n\}$ and arcs of a directed acyclic graph (DAG), also referred as a Bayesian network's structure. The dependency strength between two variables is quantified through a conditional probability table (CPT) or function (CPF) depending on whether the variables involved are discrete or continuous. The Bayesian network model corresponds to the prior joint probability distribution $Pr_0(V_1, V_2, \dots, V_n)$. Mathematically, this distribution can by computed using the factorization formula in Eq. (1):

$$Pr_0(V_1, \dots, V_n) = \prod_{i=1}^{n} Pr(V_i \mid pa(V_i)), \tag{1}$$

where $pa(V_i)$ corresponds to the parent nodes of V_i; that is, the set of nodes in the Bayesian network that have an outgoing edge directed at the node V_i.

As Bayesian Network structures are based on the conditional relationships between their nodes, the joint probability distribution of the system's variables can be updated with new knowledge about the system via evidence on the nodes. The assignment of observed evidence to a set of nodes $\{V_k = v_k\}$ leads to a Bayesian update from which the posterior distribution $Pr_1(V_1, \dots, V_k = v_k, \dots, V_n)$ is obtained. In doing so, analysts can use Bayesian networks to perform three types of probabilistic inferences.

- *Forward inference:* primarily predictive, this inference type propagates evidence from causes to effects. Fig. 3a shows how evidence $V_1 = v_1$ can affect $Pr(V_3 \mid V_1 = v_1, V_2)$.
- *Backward inference:* primarily diagnostic, this inference type propagates evidence from effects to causes. Fig. 3b shows how evidence $V_3 = v_3$ can diagnose $Pr(V_1 \mid V_3 = v_3)$.

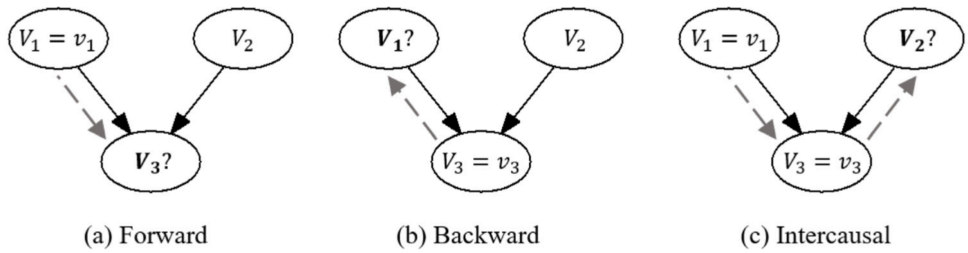

Fig. 3. Visual representation of Bayesian network probabilistic inference reasoning methods. Dashed lines indicate the flow of knowledge towards the specific node of interest, marked with a question mark.

- *Intercausal inference:* primarily explanatory, this inference type propagates evidence between causes with a common effect. Fig. 3c shows how evidence $\{V_1 = v_1, V_3 = v_3\}$ can explain away $Pr(V_2 \mid V_1 = v_1, V_3 = v_3)$.

2.3. Previous third-party damage models

A variety of modeling approaches have been used to identify third-party damage root causes and their context factors [8–13]. Across the relevant pipeline damage literature, faults trees are the most common technique for modeling different failure modes of a pipeline [14–17]. In the context of third-party damage, these fault trees model pipeline damage as a result of the failure of a set of safety barriers present in a pipeline system. For example, in an excavation scenario, pipeline damage is more likely to occur if a pipe was marked incorrectly by a utility service representative and the depth of excavation exceeds the cover depth of the pipeline. Chen and Nassim's [18] fault tree model for third-party damage is widely used within the industry to predict the probability of hitting a pipeline in an excavation activity. This model served as the basis for future fault tree research on third-party damage that expanded the scope of the model with larger sets of safety barriers and damage causes [10,19–21]. Although fault trees are still a popular industry tool for addressing and evaluating the risks of third-party damage, they face parameterization and structural limitations. Third-party damage data are often incomplete, which poses a significant problem for parameterizing and updating fault trees. Furthermore, fault trees rely on Boolean logic to describe a system's failure, which is not an adequate approach to account for the complex dependency relationships present in an excavation process [19].

The logic structure within a fault tree can be easily mapped to a corresponding Bayesian network; as such, fault tree-based Bayesian networks have been used to expand the dependency structure within fault tree modeling. For example, in their attempt to capture multiple pipeline failure types in a single fault tree-based network, Wang et al. [22] included a simplified representation of third-party damage. Fault tree-based Bayesian networks have also been used to model common causes between the basic events of a fault tree. For instance, Xiang and Zhou [19] expanded Chen and Nessim's fault-tree model into a Bayesian network in order to include common causes between basic events such as the public awareness level of one-call centers. Li et al. [23] proposed a fault tree-based Bayesian network for third-party damage on subsea pipelines in order to relax the modeling limitations of conventional fault trees. Although fault tree-based Bayesian network models address some of the limitations of fault tree modeling, they still rely on Boolean logic, limiting their ability to realistically represent complex dependency relationships in pipeline risk assessments.

On their own, Bayesian networks offer both modeling and probabilistic inference capabilities for risk assessment beyond those of fault tree-based methods. By providing a more complete representation of the modeled system's causal dependencies and associated uncertainties, decision-makers are capable of diagnosing pipeline damage root causes, predicting damage probabilities, and investigating intercausal dependencies for a variety of damage scenarios. Outside the third-party damage context, this approach has gained wide popularity for modeling and characterizing pipeline risks as the context surrounding a damage scenario can vary widely. This trend is prevalent in modeling corrosion damage, one of the leading causes of pipeline damage. Smith et al. [24] used in-line inspection data as inputs to a physics-based Bayesian network to predict the corrosion growth rate for gas pipelines. Following this, Smith et al. [25] used Bayesian networks for data-driven inspection planning for oil and gas pipelines based on key pipeline parameters such as age, location, and the current state of the pipeline coating. Similarly, Zhang et al. [8] used a series of Bayesian networks to relate pipeline parameters to leakage orifice size and failure probability due to corrosion or external interference.

This trend has permeated into recent third-party damage research to address the complexity inherent in understanding excavation pipeline damage. Jackson and Mosleh [6] developed a Bayesian network risk model based on the decision making process that a third-party faces during excavation activities. They model the excavation process using event-sequence diagrams and integrated both physical (e.g., pipeline diameter, material, and depth of cover) and human-related (e.g., excavator awareness of one-call systems and training) variables. However, this model is still in an initial phase of development, has not been validated, and does not have details on either structure or parameterization. Guo et al. [7] model the evolution of pipeline damage risk, leading up to and following third-party damage and pipeline failures. Their study, however, emphasizes the consequences of pipeline damage more than the causal relationships that led to third-party damage. In their research to model unintentional third-party damage, Cui et al. [3] developed a "3rd Party Disturbance Index" based on a number of damage indicators informed by both background and fundamental factors. The disturbance index was framed as a Bayesian network; however, all damage indicators were considered as independent, which does not accurately captures the complexity of an excavation activity. Although the above-mentioned models overcome the limitations of fault tree-based Bayesian networks, they do not capture a sufficiently comprehensive set of up-to-date root cause factors, or their dependencies, necessary for modeling third-party damage.

Initial efforts by GTI Energy to provide a more comprehensive model for third-party damage has led to preliminary Bayesian networks for assessing the risk of natural gas pipeline third-party excavation damage. These models evaluate factors that center around different aspects of pipeline damage, including those that contribute to the puncture resistance of a pipeline [26] and the probability of a locating and marking issue [27]. These models, however, have yet to be incorporated into a comprehensive model for the risk assessment of third-party damage.

Collectively, these studies mentioned in this section represent a solid foundation on which to build a comprehensive third-party damage model and decision support tool through the use of a Bayesian network approach. However, there is still a need to effectively capture third-party damage risk. The model presented in this paper is designed to be used for real-world applications and addresses these limitations by incorporating greater node granularity and dependency relationships by leveraging modern guidelines and up-to-date datasets. As such, the model can serve as a meaningful decision support tool for different natural gas pipeline stakeholders.

3. Methodology for developing BaNTERA

A multi-step process was used to build BaNTERA as a comprehensive decision support tool for third-party excavation. This section presents the methodology used to create the model, including building a taxonomy for the excavation context, developing the model's structure, and parameterizing the model nodes. These features were obtained by performing the following 3 steps:

1. *Define a taxonomy and high-level model architecture.* Prior to model development, a high-level description of the current processes, actors, and objects involved in a third-party excavation scenario was outlined to bound the scope of BaNTERA and to determine the dependencies among the variable's considered for its construction. This was done by first developing a structured hierarchical taxonomy and then identifying the model's architecture and dependencies of the risk-influencing factors (RIFs) involved in such a scenario.
2. *Define BaNTERA's structure.* The model's structure was subsequently defined by placing the different elements from the taxonomy into the model's high-level dependency architecture.
3. *Process the data and parameterize BaNTERA.* Formulating the conditional probability dependencies between BaNTERA's nodes requires the integration of different and distinct data sources. A multi-step parameterization methodology was used to parameterize BaNTERA. This methodology's input are a set of data sources and a Bayesian network structure. Then, through a data processing and node parameterization steps, a parameterized Bayesian network model is obtained.

Each portion of the abovementioned methodology is described in Sections 4–6.

4. Taxonomy and high-level model architecture

4.1. Third-party damage excavation taxonomy

Based on the processes and conceptual excavation site described in Section 2.1, a detailed hierarchical taxonomy of the third-party excavation scenario was built. This taxonomy is separated into the three large categories identified in the conceptual excavation site ("Actor", "Objects", and "Environment") and provides both broad and specific terms. The full taxonomy is provided in Appendix A, and a summary overview is provided below.

The "Actor" section in the taxonomy provides terms and concepts associated with the third-party excavator, the facility owner and manager, and the One Call notification center. The subsections within the third-party and facility owner terms focus around on-site actors and practices, while the terms associated with the notification center are related to its performance quality.

There are two main groupings within the taxonomy's "Objects" category, which captures the equipment and physical items found at the excavation site. The first group is associated with the characteristics and nature of the pipeline, while the second group comprise the excavator machinery and other physical objects associated with the excavation site. The pipeline is described in more detail than other objects at the site, as understanding the pipeline's physical features can lead to a better understanding of the pipe's resistance to potential damages, such as puncture.

The final category, "Environment", provides further details about the context and background in which the excavation occurs. This is further split into three smaller context groups. The "physical environment" describes the geography and other natural hazards present at the site, while the "legal environment" covers regional and regulatory oversight. Last, "excavation environment" describes the excavation site with respect to the current and previous excavations.

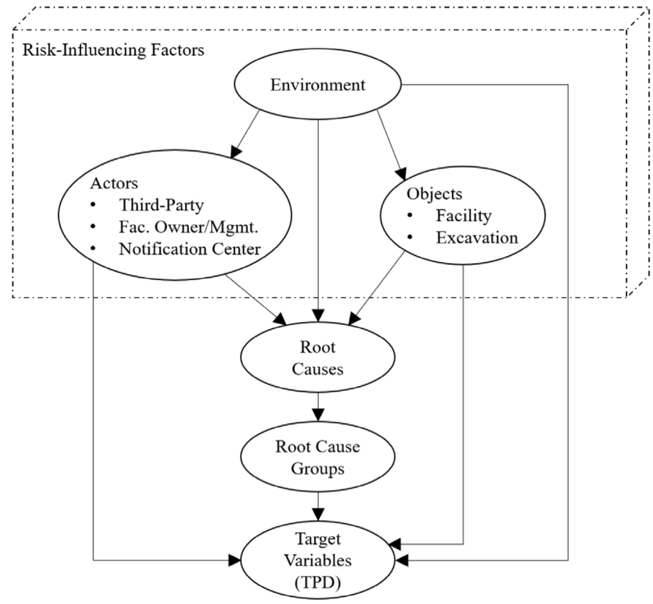

Fig. 4. Conceptual diagram of third-party damage model outlining the causal flow from excavation context nodes and risk-influencing factors context nodes to root causes and target variables.

4.2. Relevant factors, hierarchical structure, and associated dependencies

The third-party excavation taxonomy illustrates a wide range of context factors that were considered when creating BaNTERA. The likelihood of pipeline damage at these sites is impacted by these different factors, and should be captured in a meaningful structure within the model. Fig. 4 presents the conceptual diagram of the relevant factors, hierarchical structure, and associated dependencies used to model third-party damage within BaNTERA. This diagram is based on expert knowledge, PHMSA incident reports causal factors, and CGA incident reports causal factors. As shown in Fig. 4, at the bottom of BaNTERA are *target variables*, which represent scenario summary information, such as the sufficiency of pipe hit preventive measures, the pipe hit itself, and subsequent damage. Target variables depend on the other node types existing in the excavation process space; one such type consists of the groups of root causes that contribute to third-party damage. These groups capture accumulated relationships of similar pipeline damage root causes. These groups are similar to those expressed by the CGA's DIRT [4], which are based on distinct steps of the excavation process (that is, notifying, locating, and excavating). The CGA DIRT Data Committee identified six different root cause groups to provide a high-level perspective of what can go wrong when following CGA-proposed best excavation practices. These groups are "excavation practices", "invalid use of request", "locating practices", "miscellaneous", and "no locate request".

The next level of model nodes in BaNTERA to consider are the root causes and the context variables that affect them. This part of BaNTERA has the greatest number of variables that can vary during the excavation process, making this part of the model the most interactive. Root causes defined by the CGA DIRT are considered for its construction. This decision was taken due to the wide use of CGA DIRT root causes by utility companies. Moreover, the number and definitions of root causes considered by the CGA DIRT are more comprehensive (i.e., granular) than other sources such as PHMSA's. However, CGA DIRT's root causes are mainly focused on the excavation process itself and not on its context. To expand the range of acknowledged factors that can contribute to third-party damage target variables and, in particular, its root causes, a set of risk-influencing factors (RIFs) were defined based on the context of an excavation. According to the taxonomy presented in

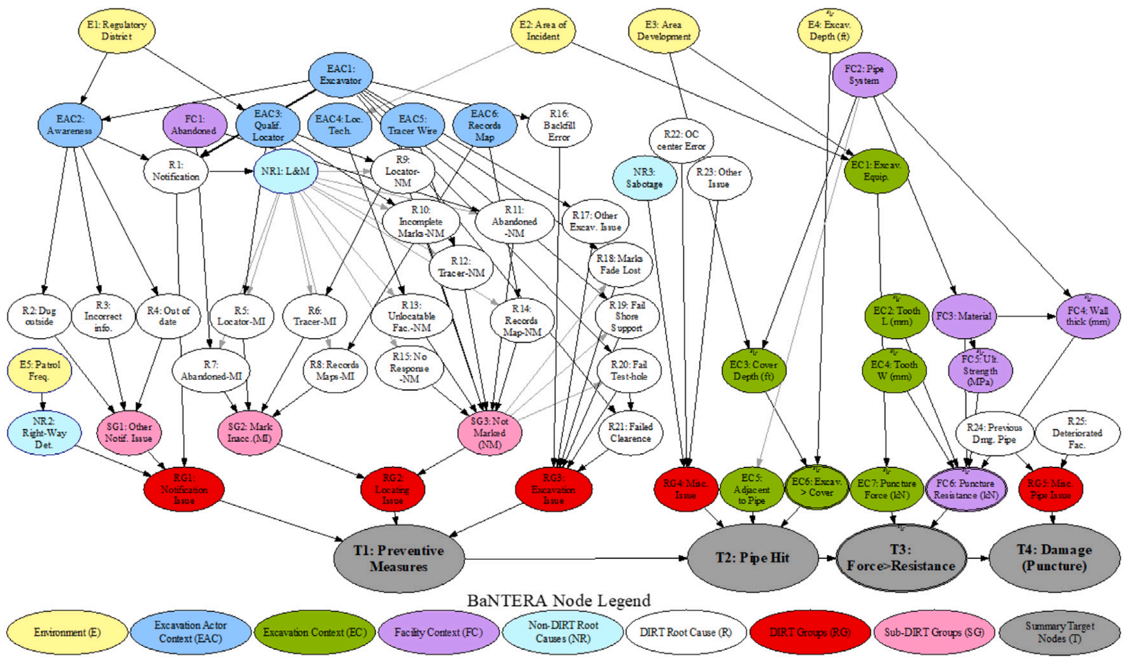

Fig. 5. BaNTERA's structure. A detailed list of the nodes and node characteristics is presented in Appendix B. Visualization made in GeNIe. Color legend: gray — target summary nodes; red — DIRT root cause group; pink — DIRT root cause subgroup; white — DIRT root cause; light blue — non-DIRT root cause; blue — third-party excavation actor context; yellow — environment context; purple — facility context; green — excavation context.

Section 4.1, RIFs were distinguished in two categories by what kind of measures could be adopted to mitigate them: actor-based RIFs (e.g., encouraging excavation best practices, increasing awareness on One Call centers, among others) and object-based RIFs (e.g., improving pipeline materials, maintenance of locating technologies, among others). These factors are themselves affected by a third RIF, the environment in which the excavation takes place. According to the taxonomy defined in Section 4.1, this environment can be physical (e.g., geographical features), legal (e.g., regulatory oversight), or related to the excavation activities themselves (e.g., excavation depth).

5. BaNTERA structure

BaNTERA was structured using the defined nodes and arcs reflecting node relationships and dependencies identified in Fig. 4. The result is a comprehensive model that captures not only the root causes of third-party damage, but also provides a method of expressing failure through context described within the taxonomy and the overarching RIFs. Fig. 5 shows BaNTERA's structure.

Similar to the high level generalized conceptual model shown in Fig. 4, BaNTERA's structure consists of nodes that provide different functions within the model and different types of information. At the bottom of the structure are the summary target nodes that combine root cause information and excavation-related context. These provide information into potential occurrences of pipe contact, puncture, and damage during a third-party excavation. The parents of the target nodes are the large root cause sub-group and group nodes, which capture accumulated relationships of similar root causes. These groups are similar to those expressed in the DIRT report, which are based on distinct steps of the excavation process (i.e., notifying, locating, excavating). The next step up in the structure are specific root causes and the risk-influencing nodes that affect them. This part of the structure has the greatest number of nodes that can vary during the excavation process, making it highly interactive. Lastly, the top of the structure consists of overarching context nodes. These nodes represent the environment in which the excavation is taking place.

The sixty-four nodes captured in BaNTERA's structure represent different causal contexts and root causes for third-party damage. The color of the nodes reflects what kind of information they provide. As shown in Fig. 5's legend, white, light blue, red, pink, and gray nodes describe specific root and general causes for third-party damage during an excavation. There are forty of these root cause nodes within BaNTERA. White and light blue nodes are individually described root causes of damage, while red nodes indicate the formation of a root group based on a number of similar root causes. Pink nodes are used to provide an initial amalgamation of root causes into smaller root cause groups, which are then joined to form a root cause group. Gray nodes describe the summary target nodes that BaNTERA is trying to represent. The other twenty-four nodes represented in BaNTERA's structure describe the context in which the third-party damage occurs. Yellow nodes describe the overall excavation environment nodes that are specific to the context of the excavation site, while the blue, green, and purple nodes relate to context factors associated with the specific excavation site scenario. Blue nodes describe the context associated with the third-party excavation actors, which includes both the excavator itself and the utility locator. Green nodes describe the context of the excavation site, while purple nodes are used to represent pipeline characteristics. These causal context factors can also be placed within the overarching RIFs described in Section 4.2.

According to PHMSA [28], there are four pipeline damage types due to excavation activities: dents, gouges, coating damage, and puncture. In this current version BaNTERA, puncture damage is the only damage type considered for modeling third-party damage. This decision stemmed from the fact that, to the best of the authors' knowledge, Brooker's puncture damage model [29–31] was the only one that provided a level of granularity sufficient enough to be included in BaNTERA's complex dependency structure. The implications of this decision are discussed in Section 9.

6. Data processing and BaNTERA parameterization

Formulating the conditional probability relationships between BaNTERA's nodes requires the integration of different and distinct data sources. A conceptual structure to the multi-step methodology used to parameterize BaNTERA, consisting of data processing and node parameterization, is represented in the diagram in Fig. 6. Each portion of the parameterization methodology is described in the following sections.

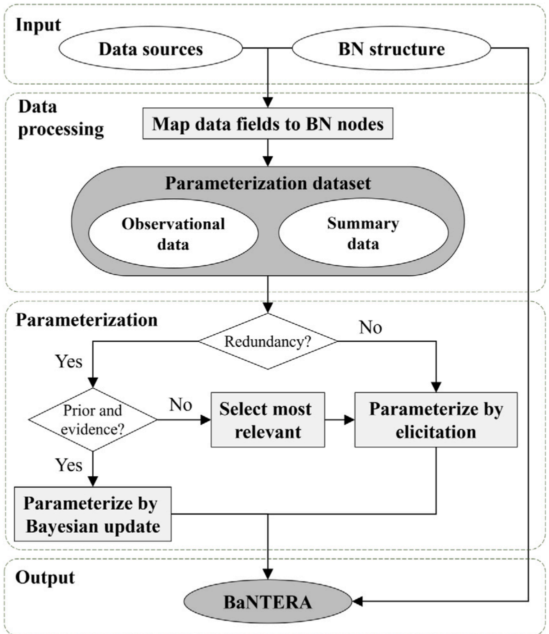

Fig. 6. Graphical representation of BaNTERA's parameterization methodology.

6.1. Data sources used to parameterize BaNTERA

After defining BaNTERA's structure in Section 5, different data sources were selected to parameterize its CPTs and CPFs. These data sources have varying amounts of data granularity, redundancy, and quality. Data was limited to those that contained conditional dependency information between BaNTERA's nodes. In order to reflect the present conditions of pipeline damage risk, only data from 2016–present was used during the parameterization process.

The following four data sources were used to parameterize BaNTERA:

- *Partner utility company damage reports (Source A).* This data source contains more than 7,000 third-party damage reports from a U.S. partner utility company between 2016–2020. These reports provide more than forty different context and damage cause related fields, including "root cause", "excavation tools", and "excavator type", among others. Source A's high granularity, low data redundancy, and limited missing data makes it an ideal data source to inform BaNTERA.
- *PHMSA's gas distribution and transmission incident data. (Source B).* Since 1970, PHMSA has maintained records of incident data [32]. Due to Source B's high quality, granularity, and public availability, numerous third-party damage models include it in its parameterization process [3,7,26]. However, the amount of useful entries in this data is relatively small, in the order of 200. In addition, this source has low granularity on specific root causes. Given this issues, this data source is only used on nodes that are not present on more comprehensive sources.
- *CGA's 2018 and 2019 DIRT database (Source C).* CGA's annual DIRT database [4,33] provides an extensive set of summary statistics on the different aspects of an excavation and its risks based on voluntarily provided damage reports between 2018–2019. Each year, approximately 35,000 reports are used to estimate these summary statistics. As the damage reports themselves are not available for public use, this data source is useful for node validation and as a starting point for parameterizing node relationships not present in more comprehensive sources.
- *GTI Energy previous models (Source D).* In the development of BaNTERA, GTI Energy provided three Bayesian network models developed in 2019 designed to address third-party damage and locating and marking risks during excavation activities [26, 27]. These Bayesian networks were parameterized by aggregating damage reports data from 2016–2018 provided by multiple utility companies throughout the U.S. Consequently, these models are useful sources of validation and prior information for nodes that can be updated with more recent data. These Bayesian networks also provide information on complex variable constructions, such as "sufficiency of preventive measures", that must be defined by experts in the field. Collectively, these models provide information on 74 different variables relevant to an excavation process.

6.2. Data processing

Data from the selected data sources described above were processed into a format that is consistent with BaNTERA's structure. In order to do this, each data source field was first mapped to a node in the network structure. Most nodes in BaNTERA could be linked to relevant fields across the different data sources, making the mapping process a straightforward one. Field redundancy between data sources was reduced by standardizing names using CGA's DIRT reporting field names; for example, the root cause field in Source A called "Excavated outside delineated area" was renamed "Excavator dug outside area described on ticket" to align with CGA DIRT's reporting scheme.

The end result is a comprehensive parameterization dataset for BaNTERA consisting of observational data as well as a summary data. The observational portion consists of a collection of features from third-party damage incidents on natural gas pipelines. This dataset includes the collections of damage reports found in Sources A and B, as well as data concerning the relative counts of any instances of interest, such as the CPTs and CPFs of the Bayesian networks provided by Source D. In contrast, the summary portion of the parameterization dataset include data that represents a summary statistic relevant to a specific node in BaNTERA's structure, such as the percentages of third-party damages across U.S. regulatory districts provided in Source C. Both the observational and summary portions of the dataset were used to parameterize different parts of BaNTERA based on the nature of the node of interest. For instance, nodes representing specific root causes and their conditional dependencies were parameterized as a CPT using the observational dataset, while nodes representing broad generalizations of factors were parameterized using the summary dataset.

6.3. Node parameterization strategies

Two different types of parameterization strategies were used based on whether there was information redundancy or previously defined causal relationships available: elicitation and Bayesian update.

6.3.1. Parameterization by elicitation

Since four different independent data sources were used to parameterize the nodes within BaNTERA, information redundancy exists across the summary and observational data in the parameterization dataset. As shown in Fig. 6, parameterization by elicitation was used if only one piece of redundant data is selected as relevant or if only one piece of information is found on the parameterization dataset. The elicitation methods used vary whether a node represents a discrete or continuous variable. Discrete nodes were parameterized by the following methods:

- *Relative count of events.* CPT parameters derived from this approach were based on the frequency of occurrence for each particular node state in a dataset. For example, node "E2: Area of Incident" CPT was parameterized by counting the amount of excavations in the dataset that where performed on exposed ground, soil, pavement, or other, between 2016–present.

- *Conditional assignment.* Discrete nodes representing a Boolean relationship between its parents were parameterized by conditional assignment. For example, node "EC6: Excav. > Cover" was parameterized by counting the instances in which the node's parent "E4: Excav. Depth (ft)" values were greater than its other parent "EC3: Cover Depth (ft)".

For continuous nodes, the following elicitation methods were used:

- *Distribution fitting.* Nodes presenting continuous data were modeled by fitting a probability distribution over the data. For example, node "EC3: Cover Depth (ft)" was parameterized by fitting a truncated Normal distribution to the depth of cover of pipelines involved on excavations performed between 2016–present.
- *Histogram.* In some instances, a clearly defined probability distribution does not match the values observed in the data. In those cases, like node "E4: Excav. Depth (ft)", a histogram was defined by experts over ranges of observed excavation's depth values.
- *Functional equation.* Nodes that represent physical models were parameterized through functional equations. For example, BaNTERA's "FC6: Puncture Resistance (kN)" node was parameterized using Brooker's puncture model [29–31].

6.3.2. Parameterization by Bayesian update

As shown in Fig. 6, this parameterization strategy was used for nodes in which redundant information on them not only existed across the parameterization dataset, but also where one piece of information could be considered as prior information. Any remaining information was then treated as new evidence. This parameterization is used, for example, when some of Source D's previous Bayesian networks node's CPTs are updated with more recent data from Sources A and B.

As this condition only held for discrete nodes, they were parameterized through a Beta-Binomial Bayesian update procedure. By assuming that a node's CPT entries are independent and represent the expected success probability p of independent binomial trials of hypothetical excavation scenarios, the node's uncertainty can be modeled as $p \sim Beta(\alpha, \beta)$. If the trust on the prior data is high, the method of moments [34] was used to define a Beta distribution prior for $p \sim Beta(\alpha_0, \beta_0)$ as:

$$\alpha_0 = \frac{\mu^2 - \mu^3}{\sigma^2} - \mu^2$$
$$\beta_0 = \frac{\alpha_0(1-\mu)}{\mu}, \tag{2}$$

where μ and σ are the mean and standard deviation of the prior data. On the other hand, if the trust on the prior data was low, the following weak prior for α_0 and β_0 was used [35]:

$$\alpha_0 = 0.5$$
$$\beta_0 = \frac{1-\mu}{2\mu} \tag{3}$$

The probability p was then updated using the data considered "new evidence" as:

$$p = \frac{\alpha_0 + k}{\alpha_0 + \beta_0 + n}, \tag{4}$$

where k is the number of occurrences of a node's CPT entry and n the total number of observations.

7. BaNTERA's parameterization results

The result of Section 6 is a fully parameterized version of BaNTERA's structure presented in Section 5. The obtained prior probabilities of BaNTERA's target nodes are calculated by simulating 1000 excavations and can be found in Table 1. Additionally, continuous nodes in BaNTERA (see Appendix B) were sampled 10,000 times and discretized in order to compute BaNTERA's joint probability distribution for each simulated excavation. An example excavation simulation can be found in Appendix C. These simulations were run using the GeNIe software through a Python-based PySMILE wrapper [36]. For the rest of this paper, this same simulation process will be used to report the probability results on a node in BaNTERA as an expected value. To capture the variability introduced by the continuous nodes in BaNTERA, 95% equal-tailed credible intervals are reported for each expected probability (i.e., the interval which contains 95% of the simulated expected probabilities).

Table 1
Prior expected probabilities and 95% equal-tailed credible intervals for BaNTERA's target nodes based on 1000 simulated excavations. Five significant digits are used to present these results. This is done to show summation to one for probability values; however, this feature should not be considered as the precision of the BaNTERA.

Target nodes	States	Expected probability	95% CI [Lower, Upper]
T1: Preventive Measures	Sufficient Insufficient	0.88832 0.11168	[0.88340, 0.89725] [0.10275, 0.11660]
T2: Pipe Hit	No Yes	0.99689 0.00311	[0.99590, 0.99830] [0.00170, 0.00410]
T3: Punc. Force > Resistance	No Yes	0.99747 0.00253	[0.99670, 0.99870] [0.00130, 0.00330]
T4: Damage (Puncture)	No Yes	0.99746 0.00254	[0.99660, 0.99880] [0.00120, 0.00340]

Table 2
Model verification comparing BaNTERA's third-party puncture damage rates per 1000 notified excavations to the average damage rates of Sources A and D. BaNTERA's results are shown in terms of: expected value (E), 95% equal-tailed credible intervals, and local sensitivity analysis results over a 10% parameter spread.

	Third-party damages per 1000 notified excavations
Source A average (2017–2020)	1.410
Source D average (2016–2018)	1.620
BaNTERA (third-party puncture damage)	**E = 1.531** **95% CIs = [1.490, 1.567]** **10% spread: [0.74, 2.36]**

In order to verify that BaNTERA reflects the damage rates present in the data sources used for its parameterization, we compare its output to Sources A and D average third-party damage rates per 1000 notified excavations. In addition, a 10% spread local sensitivity analysis was performed to account for model uncertainty.[1] These comparisons are shown in Table 2. It is important to highlight that Sources A and D damage rates are for all types of excavation damages, not just puncture (as BaNTERA's output). In addition, although Sources A and D damage rates can be seen as valuable sources of information for BaNTERA's validation, they do not necessarily correspond to nationwide statistics (e.g., source A only considers data from one state). Given this, only Source A and D are used for verification purposes.

BaNTERA was validated by checking its consistency with historical industry data. The natural gas industry generally maintains records on excavation damage rates per 1000 notified excavations. PHMSA, in particular, maintain public historical records on these rates for all U.S. states distribution lines [39]. Even though these nationwide statistics

[1] Model uncertainty can be addressed through sensitivity analyses to assess the impact of alternate but credible assumptions [37]. In this work, BaNTERA's sensitivity was analyzed by assuming a local X% spread on each parameter of the model; that is, each CPT entry was increased and decreased on X% and the overall reachable range of the outcome of interest, recorded. Both 10% and 20% spreads were considered in this work to account for possible parameter variability not present in the data used to parameterize BaNTERA. For information on the sensitivity analysis algorithm, refer to [38].

Table 3
Model validation comparing BaNTERA's third-party puncture damage rates of distribution lines per 1000 notified excavations to PHMSA's 2020 excavation damage rate. PHMSA's rates are shown in terms of an overall nationwide average (E) and its region-level minimum and maximum values. BaNTERA's results are shown in terms of: Expected value (E), 95% equal-tailed credible intervals, and local sensitivity analysis results over a 10% and 20% parameter spread.

	Damage rate of Distribution lines per 1000 notified excavations
PHMSA's nationwide 2020 data (general excav. damage)	E = 2.712 min, max = [1.980, 3.556]
BaNTERA **third-party puncture damage**	**E = 1.540** **95% CIs = [1.508, 1.570]** **10% spread: [0.744, 2.366]** **20% spread: [9.825e−3, 3.178]**
BaNTERA **third-party pipe hit**	**E = 2.518** **95% CIs = [2.461, 2.563]** **10% spread: [1.207, 3.876]** **20% spread: [0.000, 5.210]**

are not limited to third-party damage or puncture damage as BaNTERA is, they provide a relevant source of information for model validation. Therefore, BaNTERA's third-party puncture damage rate is compared to PHMSA's 2020 nationwide average, and region-level minimum, and maximum, excavation damage rates per 1000 notified excavations in distribution lines. This comparison can be found in Table 3. BaNTERA predicts an expected puncture damage rate of 1.540; however, since puncture is less likely to occur than other excavation damages (such as dents and gouges), this prediction should be considered as a lower bound for overall excavation damage rate statistics. On the other hand, since a pipe hit rates involve both damaged and undamaged pipelines, BaNTERA's expected pipe hit probabilities are used as an upper bound of comparison with PHMSA's benchmark overall damage rate. Furthermore, in order to take into account the statistical discrepancies between BaNTERA and PHMSA damage rate formulation (i.e., BaNTERA will consider third-party puncture and pipe hit probability as damages, whereas PHMSA considers overall excavation damages), local sensitivity analysis were performed. Table 3 shows this analysis's results as minimum and maximum bounds on BaNTERA's outputs considering a 10% and 20% parameter spread.

8. Case studies

Two case studies are provided in this paper to illustrate BaNTERA's capabilities as a holistic decision support tool for addressing the third-party excavation damage problem. The studies illustrate different types of inference that can be used to answer excavation process-related queries of interest to various stakeholders. The first case study shows how a natural gas utility operator could estimate the risk of an 811 One Call ticket by using BaNTERA's predictive capabilities, while the second study shows how regulatory agencies could utilize BaNTERA's diagnostic and explanatory capabilities for policy risk-informed decision support.

8.1. Predictive capabilities of BaNTERA: Estimating the risk of an 811 One Call ticket

One of the safety barriers against third-party damage in an excavation is the notification process. Excavators notify an intent to excavate through the 811 One Call system and provide information on different aspects of the excavation activity. This information is processed in the form of a notification ticket, which is provided to utility operators. A notification ticket provides valuable information about an expected excavation activity, including location, and excavator type, which can be used as predictors of potential locating and marking errors and improper excavation practices. As such, this type of information is highly relevant to utility operators, as they would like to predict the risk of pipe damage and identify whether further safety actions should be performed in potentially high-risk excavations.

Table 4
Shared and distinct evidence used in both scenarios for estimating the risk of an 811 One Call ticket.

Scenario	Node name	Evidence
1,2	EAC1: Excavator	General_public
	EAC2: Awareness	Aware
	R1: Notification	Yes
	E1: Regulatory District	South_atlantic
	E2: Area of Incident	Under_soil
	E3: Area Development	Class_3_location
	FC2: Pipe System	Distribution
	EC5: Adjacent to Pipe	Yes
1	EC1: Excav. Equip.	Hand_tools
2	EC1: Excav. Equip.	Excavator_backhoe_trackhoe

Table 5
BaNTERA's results for estimated pipe hit and puncture damage probability for both types of 811 One Call ticket scenarios. The values reported are the expected values based on 1000 simulated excavations.

Scenario	Target nodes	Node state	Expected probability	95% CI [Lower, Upper]
1	T2: Pipe Hit	Yes	0.00673	[0.00647, 0.00691]
	T4: Damage (Puncture)	Yes	0.00275	[0.00264, 0.00282]
2	T2: Pipe Hit	Yes	0.00672	[0.00650, 0.00693]
	T4: Damage (Puncture)	Yes	0.00423	[0.00409, 0.00436]

In this case study, information from a hypothetical 811 One Call ticket for a fencing job is used to predict the probability of the work resulting in third-party pipe damage. The ticket indicates that home-owners are notifying their intent to excavate in a suburban house lot located in College Park, Maryland. The ticket also highlights the presence of a gas pipeline permanent mark on the site and provides information on the specific excavation equipment that will be used.

This case study consists of two similar scenarios related to the hypothetical excavation scene described above. As shown in Table 4, the ticket information for both scenarios is assigned as evidence for different node states within the model. These scenarios were each simulated 1000 times through BaNTERA using the GeNIe software to determine the expected likelihood of pipe damage due to puncture failure; the resulting estimated pipeline hit and damage probabilities for the simulated excavations are shown in Table 5.

- *Scenario 1.* The 811 One Call ticket information on the fence work specifies the use of a low impact hand tool like a shovel. In this scenario, BaNTERA estimates that the expected probability of a pipe hit is 0.673%, 2.16 times more likely than in a general excavation (0.311% according to Table 1). Despite this large increase, the expected probability of damage is estimated to be just 0.275%, only 1.08 times more likely than is expected in a general excavation (0.254% according to Table 1).
- *Scenario 2.* The 811 One Call ticket information on the fence work specifies the use of a high impact mechanized equipment, such as a track hoe. In this scenario, BaNTERA estimates that the expected probability of a pipe hit is similar to the one obtained in Scenario 1 (0.672% for the former and 0.673% for the latter, according to Table 1); however, the use of high impact excavation equipment results in a 0.423% expected probability of damage; 1.67 times more likely than the prior of 0.275% in a general excavation.

These two scenarios illustrate how BaNTERA's values for pipe hit and pipe damage probabilities can vary given differing evidence for other nodes in the model.

8.2. Diagnostic and explanatory capabilities of BaNTERA: Informing policy decisions

The previous case study considered how BaNTERA could evaluate the risk of an excavation based on its notification ticket; however, a common issue is the lack of notification prior to an excavation activity [32,40]. According to the 2018–2019 CGA DIRT databases [4, 33], at least a third of reported third party damages had a lack of notification as a root cause of the incident. Both PHMSA and the CGA have identified that further policy actions must be made regarding the notification problem.

This case study shows how BaNTERA can be used to help inform policy decisions, such as the notification problem mentioned above. By identifying the main factors and causal dependencies that lead to third party damage given a notification issue, the model can provide insight into potential actions that can reduce potential third-party damage. In order to do this, the following two scenarios were each simulated 1000 times based on an observed instance of pipeline damage:

- *Scenario 3.* A policy maker is interested in evaluating the probability of observing a lack of notification given a damage on a pipeline. Using the related scenario evidence specified in Table 6, BaNTERA indicates that 66.13% of damaged pipelines incidents are expected to have occurred on an excavation that did not have a notification.
- *Scenario 4.* A policy maker is interested in calculating the probability of observing an excavator that is unaware of the required notification practices damaging a pipeline. Using the results from Scenario 3, a further analysis is made into the sources of these excavation incidents. The scenario evidence and simulation results from BaNTERA presented in Table 6 show that pipelines damaged in excavations that were not disclosed are expected to be caused 81.32% of the time by unaware excavators.

The results from Scenario 4 highlight a major issue for addressing the third-party damage notification problem: there are some excavations that were not reported by excavators who were aware of the region's notification practices. The following two scenarios were studied to gain further insight into this issue:

- *Scenario 5.* A policy maker is interested in determining the probability of observing an excavation that was not reported given the presence of a damaged pipeline and an excavator that was aware of required notification practices. The scenario evidence and simulation results from BaNTERA presented in Table 6 show that this instance of failing to observe notification procedures is expected to be observed with a 26.73% probability.
- *Scenario 6.* To further narrow down potential risk-informed policy actions, a policy maker is interested in identifying which specific type of excavator (i.e., professional or non-professional) is most likely to be involved in the type of event described in scenario 5. The scenario evidence and BaNTERA's simulation results presented in Table 6 indicate that in 68.72% of excavations that resulted in pipeline damage and where the excavator did not follow notification procedures even though he or she was aware of notification practices, the excavator is expected to be a professional excavator.

BaNTERA's results from Scenario 6 corroborate a major issue in pipeline safety identified in both the 2018 and 2019 CGA DIRT reports [4,33], namely, that some professional excavators, who are aware of the necessary notification procedures, are choosing not submit a notification for intent of excavation to a One Call center.

Table 6
Scenario setup, node evidence, and results of applying BaNTERA towards risk-informed decision making. The target node's expected probability and 95% equal-tailed credible interval (bold) is based on 1000 simulated excavations.

Scenario	Scenario set up: Evidence and Target node (bold)	Node state	Expected probability	95% CI [Lower, Upper]
3	T4: Damage (Puncture)	Yes	–	–
	R1: Notification	**No**	**0.66133**	**[0.66131, 0.66135]**
4	T4: Damage (Puncture)	Yes	–	–
	R1: Notification	No	–	–
	EAC2: Awareness	**Non_aware**	**0.81315**	**[0.81315, 0.81315]**
5	T4: Damage (Puncture)	Yes	–	–
	EAC2: Awareness	Aware	–	–
	R1: Notification	**No**	**0.26733**	**[0.26731, 0.26735]**
6	T4: Damage (Puncture)	Yes	–	–
	EAC2: Awareness	Aware	–	–
	R1: Notification	No	–	–
	EAC1: Excavator	**Professional**	**0.68719**	**[0.68719, 0.68720]**

9. Discussion

As a holistic decision support tool, BaNTERA provides a number of benefits for addressing third-party excavation damage in U.S. natural gas pipelines. The first advantage of utilizing BaNTERA is its comprehensiveness with respect to the variety of variables and dependency relationships normally considered to model third-party damage. This was achieved by integrating the best available data from multiple well-recognized industry and government sources with previous models on different causes of third-party damage within a Bayesian network. Although the CGA DIRT data-collection process was used as the baseline for BaNTERA's construction and data integration, its datasets, which are standardized across the industry, are suitable for incorporating damage prevention data as they are continually updated in terms of definitions, technology, and regulation. In fact, CGA continuously adapts its data-collection practices in order to provide relevant and up-to-date damage prevention insight and recommendations to stakeholders throughout the U.S. Also, it is worth noting that prevention practices are fairly similar across continents [7], making BaNTERA easily adaptable for applications outside the U.S.

Another advantage of BaNTERA is that it is constructed for use over a wide range of third-party excavation contexts and locations; this greatly expands its applicability to excavation sites across the U.S. To the best of the authors' knowledge, this is the first third-party damage model built with this objective in mind.

As expected in a complex system such as a third-party excavation, the data sources used to parameterize BaNTERA (see Section 6.1) do not consist of the same data fields nor have the same levels of granularity. For example, Source C considers twenty-six distinct root causes for third-party damage, whereas Source B considers only twenty. Additionally, Sources B and C capture nationwide statistics, while Sources A and D provide region-level information. Differences among data sources pose a challenge when they are integrated into a single model and require further assumptions to be made about variable dependencies. Ultimately, this can lead to a model output that may not accurately reflect the third-party damage rates present in the data used for its parameterization. To verify BaNTERA's performance, a comparison was made between the model's predicted damage rates with those from Sources A and D. BaNTERA's expected third-party puncture damage rate (1.531 damages per 1000 notified excavations) successfully falls between the values captured in Sources A and D (1.410 and 1.620, respectively); however, the variability introduced by the model's continuous nodes, shown in the 95% credible intervals ($[1.490, 1.567]$), is not enough to account for the differences in damage rates. Performing a local sensitivity analysis by applying a 10% parameter spread accounts for possible parameter variability in BaNTERA. As the resulting damage rate spread from this sensitivity analysis ($[0.74, 2.36]$) includes the

Table A.7
Comprehensive taxonomy of actors, objects and environments within a third-party excavation context.

1. Actors	2. Objects	3. Environment
1.1. Third-Party	2.1. Facility	3.1 Physical
1.1.1. On-Site	2.1.1. Type of Facility	3.1.1. Geography
1.1.1.1. Excavator Operator	2.1.1.1. Transmission/Distribution	3.1.2. Hazards
1.1.1.1.1. Training/Experience	2.1.2. State of Facility	3.2. Legal
1.1.1.1.2. Attitude Towards Pipeline	2.1.2.1. Previous Damage	3.2.1. Location
1.1.2. Organizational	2.1.2.2. Deteriorated Facility	3.2.2. Oversight
1.1.2.1. Excavation Policy	2.1.2.3. Abandoned Facility	3.2.2.1. Enforcement Policy
1.1.2.2. Training Practices	2.1.3. Pipe Characteristics	3.2.3. Public
1.2. Facility Owner/Management	2.1.3.1. Pipe Wall Thickness	3.2.3.1. Awareness of Pipeline
1.2.1. On-Site	2.1.3.2. Pipe Material	3.2.3.2. Attitude Towards Pipeline
1.2.1.1. Locator Training/Experience	2.1.3.2.1. Ultimate Strength of Pipe Material	3.3. Excavation
1.2.1.2. Marker Training/Experience	2.1.4. Depth of Cover	3.3.1. Depth of Excavation
1.2.2. Organizational	2.1.5. Additional Facility Protection	3.3.2. Excavation Dynamic
1.2.2.1. Maintenance Policy	2.2. Excavation/Construction	3.3.2.1. Interactions
1.2.2.2. Training Practices	2.2.1. Excavator	3.3.3. Previous Excavation History at Site
1.2.2.3. Popularity	2.2.1.1. Excavator Tooth Length	
1.3. Notification Center	2.2.1.2. Excavator Tooth Width	
1.3.1. Quality of Responses	2.2.2. Notification Ticket	
1.3.2. Quality of Records	2.2.2.1. Dig Time	
	2.2.2.2. Dig Location	
	2.2.3. Locator Equipment	
	2.2.4. Facility Maps/Records	
	2.2.5. Excavation Monitoring Tools	

average damage rates from Sources A and D, BaNTERA is shown to have the potential of integrating data from disparate sources to provide a comprehensive assessment on third-party excavation damage.

To validate BaNTERA as a trustworthy decision support tool for nationwide use, model outcomes were compared to industry data for outcome consistency; that is, whether if BaNTERA is able to predict the 2020 PHMSA excavation damage rate statistics for natural gas distribution lines. The results from this analysis indicate that BaNTERA's predicted puncture damage rate (1.540 damages per 1000 notified excavations) is approximately half of what PHMSA had reported (2.712). A lower value in damage rates is expected from BaNTERA as puncture damage is the least likely damage type to result from an excavation work; other damage types such as dents, gouges, and coating damage require less force to be inflicted to a pipe [26,28]. As such, a more appropriate comparison would be between BaNTERA's outcome and PHMSA's minimum distribution line damage rate (1.980), as puncture damage can serve as a lower bound for damage rates.

Although those two values are more comparable, it is not possible to objectively determine whether the difference between BaNTERA's outcome and PHMSA's minimum distribution line damage rate is statistically significant; as such, local sensitivity analyses were conducted by applying both a 10% and 20% parameter spread to account for possible parameter variability in BaNTERA. The results from these analyses indicate that BaNTERA's damage rate range from a 10% parameter spread ($[0.744, 2.366]$) includes PHMSA's minimum value, while a 20% parameter spread ($[9.825\text{E}-3, 3.178]$) is needed to generate a large enough damage rate range to include PHMSA's 2020 average.

The result presented above shows that, under the current assumptions of the model, BaNTERA is unable generate a spread of damage rate values that includes the maximum distribution line damage rate value reported by PHMSA (3.556 damages per 1000 notified excavations). This is because puncture damage is at most a lower bound for damage rates; there are other potential sources of damage. A similar validation analysis exercise can be performed, however, using the probability of a pipe hit as an upper bound. By assuming that every hit results in pipe damage, more likely damage types, such as dents and gouges, are then included in BaNTERA's output damage rates. Using this assumption, BaNTERA predicts a third-party damage rate (2.518) that is much closer to PHMSA's general excavator's average damage rate. However, it still does not capture PHMSA's maximum damage rate value. A local sensitivity analysis was performed by applying a 10% parameter spread to account for possible parameter variability. BaNTERA's resulting spread of damage rate predictions ($[1.207, 3.876]$) includes all of PHMSA's 2020 industry damage rate values, showing that the model has a high potential for becoming a trustworthy decision support tool for addressing damage to natural gas pipelines in third-party excavations.

The final advantage of using BaNTERA lies in its predictive, diagnostic, and explanatory capabilities for risk-informed decision support. The different case study results presented in Section 8 demonstrate how BaNTERA can be used by different stakeholders to answer specific third-party damage-related queries of interest over a number of distinct scenarios. Utility managers interested in maintaining facility operations and asset safety, can use BaNTERA to predict the risk of damage to their pipelines within specific excavations or pipe segments. Regulatory organizations and mutual benefit associations, such as PHMSA and the CGA, respectively, can take advantage of BaNTERA's probabilistic inference capabilities to support policy decisions and recommendations by diagnosing the most likely causes of third-party damage and by explaining under which excavation conditions they are more likely to occur. By addressing the interests of multiple parties, BaNTERA provides a single decision support platform that is not only usable for quantifying third-party damage risk and identifying how to reduce it, but also enhances information and knowledge transfer between natural gas pipeline stakeholders.

9.1. Improvement opportunities

BaNTERA is built as a proof-of-concept model for a comprehensive probabilistic third-party excavation decision support tool; as such, there are a number of opportunities to improve model structure, parameters, and functionality.

The first area of improvement is addressing is the necessary complexity of the model. Excavation scenarios are significantly complex to model, and can vary between different regions and companies. As BaNTERA was designed for a broad range of potential third-party excavation scenarios, some nodes are relatively broad in scope. Nevertheless, BaNTERA still serves as a base for more specific excavation problems and applications, as Bayesian networks nodes can be tuned for specific data, and its structure expanded or condensed as needed.

Table B.8
List of the nodes in BaNTERA, node characteristics, and the techniques and data sources used to parameterize each node.

Node ID	Node name	Node definition	Node type	Discrete/ continuous	Parameterization method used	Data sources used[a]
E1	Regulatory District	Regulatory District	Environment	Discrete	Elicitation - Relative count of events	C
E2	Area of Incident	Area of Incident	Environment	Discrete	Elicitation - Relative count of events	B
E3	Area Development	Area Development	Environment	Discrete	Elicitation - Relative count of events	B
E4	Excav. Depth (ft)	Depth of Excavation (ft)	Excavation Context	Continuous	Elicitation - Histogram	D
E5	Patrol Freq.	Patrol Frequency	Environment	Discrete	Elicitation - Relative count of events	D
EAC1	Excavator	Excavator Type	Third-Party Context	Discrete	Elicitation - Relative count of events	A
EAC2	Awareness	Notification Awareness	Third-Party Context	Discrete	Elicitation - Relative count of events	C
EAC3	Qualif. Locator	Qualified Locator	Third-Party Context	Discrete	Elicitation - Relative count of events	D
EAC4	Loc. Tech.	Locating Technology	Third-Party Context	Discrete	Elicitation - Relative count of events	D
EAC5	Tracer Wire	Tracer Wire Functionality	Third-Party Context	Discrete	Elicitation - Relative count of events	D
EAC6	Records Map	Facility Records/Map	Third-Party Context	Discrete	Bayesian update	Prior - D; Evidence - A
EC1	Excav. Equip.	Excavation Equipment	Excavation Context	Discrete	Elicitation - Relative count of events	B
EC2	Tooth L (mm)	Excavator tooth length (mm)	Excavation Context	Continuous	Elicitation - Distribution fitting	D
EC3	Cover Depth (ft)	Depth of Cover (ft)	Excavation Context	Continuous	Elicitation - Distribution fitting	D
EC4	Tooth W (mm)	Excavator tooth width (mm)	Excavation Context	Continuous	Elicitation - Distribution fitting	D
EC5	Adjacent to Pipe	Excavation adjacent to pipeline	Excavation Context	Discrete	Elicitation - Relative count of events	D
EC6	Excav. >Cover	Excavation Deeper than Cover	Excavation Context	Discrete	Elicitation - Conditional Assignment	N/A
EC7	Puncture Force (kN)	Puncture force (kN)	Excavation Context	Continuous	Elicitation - Histogram	D
FC1	Abandoned	Abandoned Facility	Facility Context	Discrete	Bayesian update	Prior - D; Evidence - A
FC2	Pipe System	Pipeline System	Environment	Discrete	Elicitation - Relative count of events	A
FC3	Material	Material	Facility Context	Discrete	Elicitation - Relative count of events	D
FC4	Wall thick (mm)	Pipe wall thickness (mm)	Facility Context	Continuous	Elicitation - Histogram	D
FC5	Ult. Strength (MPa)	Ultimate strength of material (MPa)	Facility Context	Continuous	Elicitation - Distribution fitting	D
FC6	Puncture Resistance (kN)	Puncture resistance (kN)	Facility Context	Continuous	Elicitation - Functional equation	N/A
NR1	L&M	Action of locating and marking	Non-DIRT Root Cause	Discrete	Elicitation - Conditional assignment	N/A
NR2	Right-Way Detected	Right way of excavation detected	Non-DIRT Root Cause	Discrete	Elicitation - Relative count of events	D
NR3	Sabotage	Sabotage	Non-DIRT Root Cause	Discrete	Elicitation - Relative count of events	B
R1	Notification	Notification made to One Call Center/ 811	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R2	Dug outside	Excavator dug outside area described on ticket	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R3	Incorrect info.	Excavator provided incorrect notification information	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R4	Out of date	Correct dig time relative to valid ticket start date/time	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R5	Locator-MI	Locator error (marked inaccurately)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R6	Tracer-MI	Tracer wire issue (marked inaccurately)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R7	Abandoned-MI	Abandoned facility (marked inaccurately)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R8	Records Maps-MI	Incorrect facility records/maps (marked inaccurately)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R9	Locator-NM	Locator error (not marked)	DIRT Root Cause	Discrete	Elicitation - Relative count of events	D
R10	Incomplete Marks-NM	Incomplete marks at damage location (not marked)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R11	Abandoned-NM	Abandoned facility (not marked)	DIRT Root Cause	Discrete	Elicitation - Relative count of events	D
R12	Tracer-NM	Tracer wire issue (not marked)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R13	Unlocatable Fac.-NM	Unlocatable facility (not marked)	DIRT Root Cause	Discrete	Elicitation - Relative count of events	D
R14	Records Map-NM	Incorrect facility records/maps (not marked)	DIRT Root Cause	Discrete	Bayesian update	Prior - D; Evidence - A
R15	No Response-NM	No response from operator/contract locator (not marked)	DIRT Root Cause	Discrete	Elicitation - Relative count of events	D
R16	Backfill Error	Improper backfilling practices	DIRT Root Cause	Discrete	Elicitation - Relative count of events	C
R17	Other Excav. Issue	Improper excavation practice not listed elsewhere	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R18	Marks Fade Lost	Marks faded or not maintained	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R19	Fail Shore Support	Excavator failed to protect/shore/ support facilities	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R20	Fail Test-hole	Excavator dug prior to verifying marks by test-hole (pothole)	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R21	Failed Clearance	Excavator failed to maintain clearance after verifying marks	DIRT Root Cause	Discrete	Elicitation - Relative count of events	C
R22	OC center Error	One Call Center error	DIRT Root Cause	Discrete	Elicitation - Relative count of events	C
R23	Other Issue	Root cause not listed elsewhere	DIRT Root Cause	Discrete	Elicitation - Relative count of events	A
R24	Previous Dmg. Pipe	Previous damage	DIRT Root Cause	Discrete	Elicitation - Relative count of events	C
R25	Deteriorated Fac.	Deteriorated facility	DIRT Root Cause	Discrete	Elicitation - Relative count of events	C
RG1	Notification Issue	Notification Issue	DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
RG2	Locating issue	Locating issue	DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
RG3	Excavation Issue	Excavation Issue	DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
RG4	Misc. Issue	Non-actionable (miscellaneous) factors	DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
RG5	Misc. Pipe Issue	Miscellaneous - pipe-based	DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
SG1	Other Notif. Issue	Other Notification Issue	Sub-DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
SG2	Mark Inacc.(MI)	Facility marked inaccurately	Sub-DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
SG3	Not Marked (NM)	Facility not marked	Sub-DIRT Group	Discrete	Elicitation - Conditional assignment	N/A
T1	Preventive Measures	Sufficient Actionable Preventive Measures	Summary Target Nodes	Discrete	Bayesian update	Prior - D; Evidence - A
T2	Pipe Hit	Pipe Hit	Summary Target Nodes	Discrete	Elicitation - Conditional assignment	N/A
T3	Force>Resistance	Puncture Force>Puncture Resistance	Summary Target Nodes	Discrete	Elicitation - Conditional assignment	N/A
T4	Damage (Puncture)	Damage (Puncture Failure)	Summary Target Nodes	Discrete	Elicitation - Conditional assignment	N/A

[a] A - Partner utility company damage reports; B - PHMSA gas distribution and transmission incident data; C - CGA's 2018 and 2019 DIRT Database; D - Previous GTI Energy models

A current limitation of BaNTERA is that the only pipeline damage type represented in the model is puncture damage. Although BaNTERA's damage rate predictions based on puncture are a good approximation of damage rates based on all types of pipeline damage, it should realistically serve as a lower bound value for damage rate. If a pipe is hit in an excavation, it is likely that coating damage, dents, and gouges would occur rather than puncture. Pipe hit rates predicted by BaNTERA where shown to serve as a good upper bound approximation for damage rates; however, to thoroughly represent third-party damage, further damage type models should be incorporated into the model.

Lastly, a recurring challenge throughout any third-party damage model, including BaNTERA, is the limited availability of success space data [6]; that is, information about excavations that did not result in damage. This appears in a number of forms; ticket datasets typically do not specify the party responsible in the ticket, and utilities are not collecting granular information on excavations without incidents. On top of this, a large amount of excavation activities and damages are not reported [4,41]. Collectively, these data limitations are a detriment to accurately modeling third-party damage. While the research and industry communities are addressing this issue by combining damage data with expert judgment [6,8], limited data sources and data availability can nevertheless restrict the usefulness of third-party damage models. This can be seen in BaNTERA's node "T1: Preventive Measures". Although the node represents both sufficient and insufficient damage prevention practices in an excavation activity, its parent nodes are parameterized primarily with historical damage data. Additional expert judgment was needed to construct this node's CPT outside of a "failed excavation" space in which damage has occurred to one that also includes excavations without third-party damage. The limited availability of success space data makes third-party damage models highly sensitive to the expert judgment used in parameterizing the variables that represent both damage and success spaces. Further efforts should be made by both the industry and regulatory agencies to obtain third-party specific information on successful excavation activities. By doing so, third-party damage models such as BaNTERA can incorporate this data and become more robust for real-world applications.

10. Conclusion

This paper presented BaNTERA, a comprehensive probabilistic model for third-party excavation risk assessment of natural gas pipeline hits

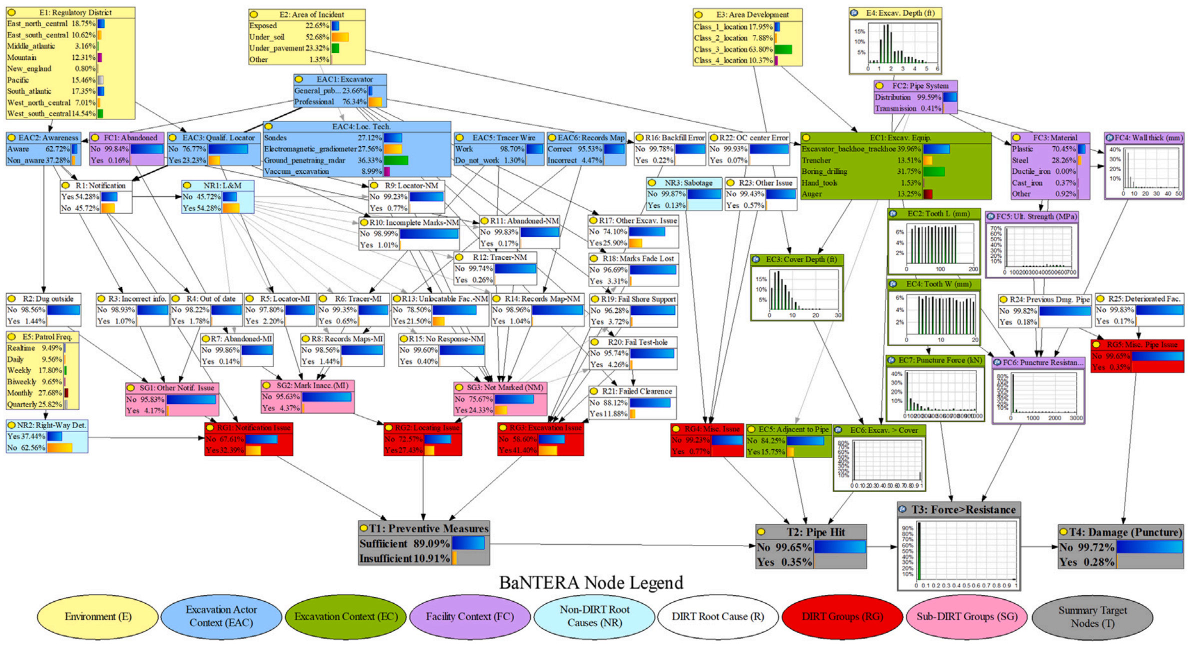

Fig. C.7. Sample parameterization of BaNTERA's nodes. These values represent possible prior probabilities for a generic third-party excavation site. Parameterization and visualization made with GeNIe [36].

and subsequent damage. The causal Bayesian network structure inherent in the model provides opportunities for decision-makers to gain insight into third-party excavation practices and outcomes at varying levels of granularity using different methods of inference reasoning. The results from BaNTERA's parameterization and application to a range of case study scenarios indicate a successful and validated integration of historic data from multiple data sources, modern guidelines and root causes, expert judgment-derived causal relationships, and previous third-party damage models. This distinguishes BaNTERA from previous models which lack a comprehensive set of up-to-date risk-influencing factors, or their dependencies, needed for assessing thirds-party damage risk. Although it is the first step in providing a more comprehensive model for third-party damage risk assessments, the research and methodology behind developing BaNTERA, as well as its preliminary results, are promising for expanding the capabilities of third-party excavation management and providing more effective policies aimed at improving pipeline safety.

Future opportunities for improving BaNTERA's functionality, parameterization, and structure, include: collecting more data, particularly on excavations without pipeline incidents, to improve parameterization accuracy; adding additional pipeline damage type models to more thoroughly represent third-party damage; and performing further validation prior to model use in live scenarios. These will strengthen BaNTERA as a viable predictive screening tool for future excavations based on ticket submissions, as well as a diagnostic aid for root cause identification in third-party excavation incidents. Ultimately, further data and model validation will enable BaNTERA to become a widely used tool that offers the robust support currently needed for risk-informed regulatory and policy decisions within the third-party damage prevention space.

CRediT authorship contribution statement

Andres Ruiz-Tagle: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Austin D. Lewis:** Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Colin A. Schell:** Data curation, Visualization, Writing – original draft. **Ernest Lever:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition, Resources. **Katrina M. Groth:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Hierarchical Taxonomy at the Third-Party Damage Site

See Table A.7.

Appendix B. BaNTERA Nodes

See Table B.8.

Appendix C. Parameterized third-party damage Bayesian network model

See Fig. C.7.

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