Application of Bayesian Model for Third Party Damage Assessment of Cross-Country Oil Pipeline under Uncertainty

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Abstract: As a result of incessant pipeline damages and resultant consequences of fires, explosion and environmental pollution due to third-party events to cross-country pipelines in Nigeria, stakeholders are looking at solutions in dealing with third-party threats to reduce the human and the financial losses. To address this challenge, a Bayesian Network (BN) threat model has been developed. The model addresses multiple interactions between several parameters for risk reduction and mitigation, such as the technological (*e.g.*, leak detection, aerial survey), the human (*e.g.*, intelligence, community partnership) and the operational (*e.g.*, staffing, training, patrol) measures. Moreover, the complexity of the interaction increases when considering that some of the measures are further compromised by internal failings and collusions within some stakeholder organizations. The Bayesian network model is created to better describe the third-party events by identifying and quantifying the relationship between the influential factors aimed at reducing the threat. The main focus of this paper is the construction of a model that shows the threat reduction of those multiple parameters' interactions resulting from third-party interference. The model will enable the pipeline stakeholders and operators to determine those parameters or interventions that have the most impact on threat reduction and hence the overall reduction in pipeline loss of containment. In addition, this Bayesian network model allows for the causal relationship to be modelled through an intuitive graphical representation that can be updated when new field data becomes available. The model has the potential to analyze a system-wide pipeline failure risks under uncertainty and can also focus on a sub-threat arising from the third-party activities, for example, political sabotages, in order to gain a wider understanding and to identify an effective combination of risk reduction and intervention factors.

Keywords: Bayesian Network, Third Party Damage, Pipeline Risk Assessment, Sabotage, Theft.

1 Introduction

This paper assesses the threats to loss of containment of the cross-country refined products pipelines due to third party activities in Nigeria using Bayesian Network model. The incessant pipeline damages and resultant consequences of fires, explosion and environmental pollution due to third-party events in Nigeria have been widely investigated (Anifowose *et al.*, 2012; Omodanisi *et al.*, 2014; Ambituuni *et al.*, 2015). The European pipeline database also shows an astronomical increase in the pipeline third-party damage due to intentional purposes, from two incidences in 2012 to 87 in 2015 (Cech *et al.*, 2018). Stakeholders have been looking for solutions in dealing with third-party threat to reduce the human and financial losses and environmental damage.

A Bayesian Network threat model which considers the multiple interactions of parameters for risk reduction and mitigation has been developed. The model is designed to better describe the third-party damage events by identifying and quantifying the relationship between those influential factors aimed at reducing the threat. The main focus of the paper is the construction of a model that shows the threat reduction of those multiple parameters' interactions resulting from third-party activities. The model will enable pipeline operators and stakeholders to determine the parameters or Risk Control Options (RCOs) that have the most impact on the threat reduction and hence on the overall reduction in pipeline loss of containment. This Bayesian Network model allows for the causal relationship to be modelled through an intuitive graphical representation that can be updated when new field data becomes available.

The model presented here has the potential to analyze system-wide pipeline failure risks under uncertainty and can also be used to focus on a sub-threat arising from the third-party activities, such as political sabotages, in order to gain a wider understanding and to identify an effective combination of risk reduction and intervention factors.

2 Background

Pipelines have been a cost effective way of products transportation in large volumes, including oil and gas in Nigeria and across the world. The potential safety and environmental hazards resulting from pipeline operations need to be identified and assessed, with appropriate measures put in place to reduce, mitigate or manage the hazards.

Third party damage, especially due to deliberate acts, is amongst the top pipeline loss of containment threats in developing countries, caused mainly by social, economic or political factors. Identifying and adequately managing these threats using a combination of technology, human psychology, government intervention, and the company

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management systems have been a top priority for stakeholders across the industry. However, the lack of specific data on third party related events, their interventions and effectiveness make a reliable cause and effect assessment difficult. Additionally, such lack of data prevents a direct determination of the different factors or combination of factors that will provide an optimum package of measures to reduce or eliminate the threat.

The use of a Bayesian Network model and expert elicitation has shown to be a good way to identify the most effective measures and their contribution to the risk reduction of the third party damage threat.

3 Methodology

3.1 Bayesian Theorem

Bayes' Theorem relates the conditional and marginal probabilities of events *H* and *E*, for instance, and describes the probability of an event based on the prior knowledge of related events or conditions. The Theorem interprets probability as a measure of a degree of belief. This degree of belief is then used to account for evidence given a certain proposition.

The Theorem is derived from the conditional probability product rule. Assuming the *H* event is the hypothesis and *E* is the evidence and we want to assess the relative belief degree of *H* given *E*, the Bayes Theorem probability (*P*) is invoked as *P(H/E).* This is the probability of *H* given *E* and can be represented as (Eleve-Datubo, 2005):

$$P(H/E)P(E) = P(E/H)P(H) \qquad |(1)$$

which can be rearranged as Equation (2)

$$P(H/E) = \frac{P(E/H)P(H)}{P(E)} \qquad |(2)$$

P(H) is called the *prior or marginal* probability of *H* and represents the state of knowledge of *H* at the initial stage before the evidence is considered whilst *P(H/E)* is called the *posterior* or *likelihood* function and represents the updated knowledge given the evidence *E*. *P(H/E)* is also referred to as the *conditional* probability of *H* given *E*. *P(E)* is the marginal probability of E and the evidence to enable *P(H)* to be updated. The inverse of the derivation is taken as the normalizing constant. Linguistically, the Bayes' Theorem can be represented as

$$Posterior = \frac{Likelihood \text{ x } Prior}{Evidence} \qquad |(3)$$

For a set of evidence variables (*E*), a joint probability distribution of a hypothesis (*H*), given variables E = {e_1, e_2 ...e_n}, is computed using the conditional probability rule as:

$$P(H/e_1,e_2,......e_n) = \frac{P(e_1,e_2,......e_n/H)P(H)}{P(e_1,e_2,......e_n)} \qquad |(4)$$

The Bayes' rule models a probability that updates beliefs about uncertain parameters given new data. Once new evidence is observed, the prior probability is updated by carrying out posterior probability analysis. It is noted that not all Bayesian studies apply the above rule. For instance, Vose (2008) has shown that some analysts re-evaluate the *prior* whenever new data become available. This effectively defers the application of the Bayes' rule to an indefinite future. However, as a general rule, Bayes rule entails a loop process of continuous updating the hypothesis (*H*) as new evidence (*E*) emerges. As more evidence is observed, the influence of the prior beliefs reduces in significance; given adequate evidence, the results of the Bayesian rule approach that of the frequentist approach.

3.2 BN Modelling Process

To analyze the third party pipeline failure characteristics and the effectiveness of the intervention or risk reduction factors using the BN model, a generic model has been adapted. The steps ensure robust analysis and forms part of the quality control procedure that ensures that the model performs consistently as expected irrespective of the domain of application. It also ensures that the process and results are comparable across domains.

The contained number of steps and the details vary from application to application and also depend on the level of modeling detail envisaged. However, the basic procedure shares a similarity with the generic BN model and has been adapted here as described below.

3.2.1 Identification of a Set of Variables Appropriate to the Problem

This step entails identifying the number of variables that are required in the model. In identifying the variables, care should be taken to ensure that the number is kept to the minimum that is necessary to provide expected results. In this research, the determination of factors that affect pipeline integrity and loss prevention mechanism due to third party damage is the main driver of the variables' development. To reduce complications and difficulties that will arise from unwieldy variables (and hence the Conditional Probability Table - CPT), the number of parent nodes for each child is limited to a maximum of four. This ensures that all the identified major factors affecting risk reduction mechanism for third party pipeline failure are included, whilst ensuring that the number of variables is manageable for a less complicated assessment. The granularity of the analysis is balanced with the practicality of the available information and the modelling effort.

3.2.2 Creation of Node Corresponding to all Variables Identified

Having identified all variables, this step involves creating nodes that describe the problem to be addressed. The nodes represent the relevant variables identified in the previous step and their development involves a determination as to whether it will be a discrete, continuous or it will have several states.

3.2.3 Identification of a Set of States for each Variable

The states of each variable are to be determined based on the available data, the modeler's perspective and the complexity envisaged. The states of the nodes can be discrete, continuous or involving several ones.

3.2.4 Specification of the State of each Node

For this assessment, Boolean states "yes / true" and "no / false", have been adopted for all the nodes.

3.2.5 Identification of Node's Dependency

The identified nodes are connected to the influencing/influenced nodes via arc connections. This creates the directed acyclic graph (DAG) that the BN relies on for information parsing and probability propagation. The nodes which represent the cause and effect are linked to one another via directed edges or arcs.

The model ensures that the established assessment nodes are appropriately connected to the variables identified and the levels of information propagation via arc direction are correct.

3.2.6 Construction of Conditional Probability Table

A CPT for each node is set at this step either based on available data or expert elicitation. The number of probabilities required depends on the structure of the model.

In this assessment, the information that makes up the CPT is obtained from a combination of publicly available data from the Nigerian National Petroleum Corporation (NNPC, 2016) and unpublished proprietary data. Where direct data is not available, expert elicitation and symmetric models in line with Riahi *et al.* (2014) are used to complete the CPT.

3.3 Construction and Data for BN Modelling

The variables including a threat to loss of containment and the various RCOs in the sequence of intervention are translated to corresponding parent and child nodes in the Bayesian Network. The nodes can be expressed as having a degree of effectiveness as an RCO, represented by the likelihood ratio. The causality between the events is translated to the corresponding CPTs. The CPTs are then constructed as shown in Section 3.2.6. Both the nodes and their corresponding CPTs are then inputted into a BN program and variables are connected to nodes that may influence them or be influenced by them. This process involves a reference to the sequence of events from the top node to determine the most effective way of connecting the nodes together. The network is reviewed to ensure that there are no missing factors.

3.4 Results and Analysis

The required data are checked and then all the values entered in the CPT are normalized, so that each set of the nodes has a total sum of 1.

The software package Hugin Researcher 8.4 is used to build the model and perform the runs (Hugin, 2018). The analysis of the results includes extracting marginal probabilities and interrogating the data to extract the beliefs for certain assumptions and input. The baseline model provides the marginal probabilities of the end event given the various input conditions of the contributing variables. The baseline results can be further analyzed; adding additional evidence we observe the impact on the final results. Such analysis of the "what if" scenarios can be used to better understand the impact of each input variable or sub-variable.

Predictive, diagnostic and sensitivity analysis can also be carried out as part of the decision making process and model validation (see Section 3.5) so as to provide useful insights and support managers in assessing the predicted impact of a certain risk control measures. It can also help post-incident analysis, where the risk control options can be diagnosed to find the likely optimum measure or package of measures that could have prevented that incident or reduce its magnitude.

3.5 Sensitivity Analysis and Validation

To ensure that the BN model behaves as expected, a sensitivity analysis is then carried out. The aim is to test how sensitive the model is to the incremental or decremental changes to the inputs on each node.
Also, validation is carried out as part of the procedure. The process entails checking for the accuracy of the model's representation of the real system. A correctly validated model offers confidence to the users that the results are a good representation of the real life scenario for the given assumptions.

There are several approaches for model validation, ranging from subjective to objective statistical assessment. For this model, the validation process was in the form of sensitivity studies employing the three axioms as outlined by Jones *et al.* (2010). A sound model with a logical inference should be able to pass the following three axioms:

Axiom 1: A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of the child node.
Axiom 2: Given the variation of subjective probability distributions of each parent node, its influence magnitude to the child node values should keep consistency.
Axiom 3: The total influence magnitudes of the combination of the probability variations from X attributes (evidence) on the values should be always greater than the one from the set of $X-Y$ ($Y \in X$) attributes (sub-evidence).

4 Case Study

4.1 Description of the Pipeline System

The BN model is applied to an onshore cross-country pipeline *Section 2B* system located in South-west Nigeria. Figure 1 shows the pipeline location, the relevant pipeline colored in light green, connects Lagos, in South-west Nigeria, to Mosimi and terminating at Ilorin in North-central Nigeria.
The case study is a continuation of a previous study (Hassan, 2018) where a modified Failure Mode and Effects Analysis (FMEA) has been utilized to identify and rank all potential failure modes for the pipeline system. The failure mode with the highest likelihood is the pipeline loss of containment due to third party damage. This case study has taken the failure mode and its contributing risk reduction option variables for analysis and decision making.

4.2 Modelling Domain and Variables

To identify the initial variables that will inform the modelling, assessment of the main primary risk reduction variables appropriate for onshore oil and gas pipelines both in Nigeria and globally has been carried out. As a result of incomplete or lack of information on the Nigerian (and similar geographies) for pipeline third party damage and the effective risk control measures, a literature survey has been carried out so that the experience of other countries and operators can be learnt and utilized in addition to the existing data from operators and regulatory agencies in Nigeria. These together formed the primary sources for identifying and grouping the RCOs that have been used in the model.

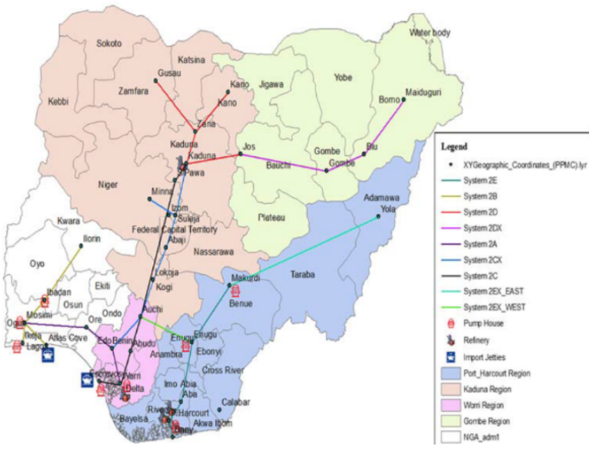

Figure 1: Onshore Pipeline Map - Gas Study System is "2B" (Anifowose *et al.*, 2012)

Threats to pipeline loss of containment can be minimized or avoided by a measure that follows into the following: (i) detection measures, (ii) prevention measures (iii) mitigation measures and (iv) other measures. Our RCOs fall therefore under these four parent nodes. Directly beneath each of the parent nodes there are the tier 2 factors, or mid events. The root event (tier 3) in this case is the reduction or elimination of third party damage loses. These are illustrated in Figure 2.

4.3 Data Input and BN Construction

This section details all the variables and their grouping that form the BN model including assumptions made and the variables' states.

4.3.1 Events:

The top, mid and root events that have been developed and used in the BN modeling are shown in Table 1.

Table 1: Events Hierarchy

Root Event	Mid Events	Top Events
Third party damage loss reduction	Detection measures	• Leak detection • Surveillance • Patrol • Supervisory Control and Data Acquisition (SCADA)/staffing measure
	Prevention measures	• Burial depth • Pipeline Cover • Barrier • Public Education
	Mitigation Measures	• Right of way control • Spill response • Industry cooperation
	Other measures	• Intelligence • Security forces • Punishment • Community partnering

4.3.2 Assumptions

The model is developed with a specific focus on:

- Countries or geographies where adequate or reliable data is not available to determine the most optimum package of risk reduction measures for third party damage threat, especially intentional damages.
- Geographies where there are an above-average number of incidents of pipeline third-party interference, especially relating to hot tapping and criminal destruction.
- The scope of the top events is limited only to two qualitative options: whether the intervention is effective or not. The degree of effectiveness is not assessed.

The model is developed with the aim to highlight the applicability of the model in pipeline risk reduction decision making with the abovementioned focus, irrespective of the data entered or the data source. Therefore, the accuracy of the input data does not affect the model's validity; the inaccurate data will only affect the end results.

The model is limited to finding out the beliefs of the likely effectiveness of the risk reduction measure(s) for the pipeline loss of containment due to third party activities. It does not assess the costs or benefits of the measures or the ease and speed of implementation.

Several data sources relevant to the problem have been used, including NNPC (2016), PPMC (2014), USDT (2012), Rui (2011) and OGUK (2012). The choice of the data depends on the relevance; the predominant data sources for the primary variables are those provided by NNPC and PPMC. Extensive expert elicitation has been used for where data is either not available or where subjective beliefs are necessary.

4.3.3 Model Structure

The BN model has been developed based on the details outlined in Section 4.3.1, which shows the relationships between the main risk reduction factors and their conditional dependencies. The BN model simulates the cause and effect of those various RCOs such as intelligence sharing and punishment. The Hugin Bayesian model is shown in Figure 2 with each risk reduction option and their respective marginal probabilities.

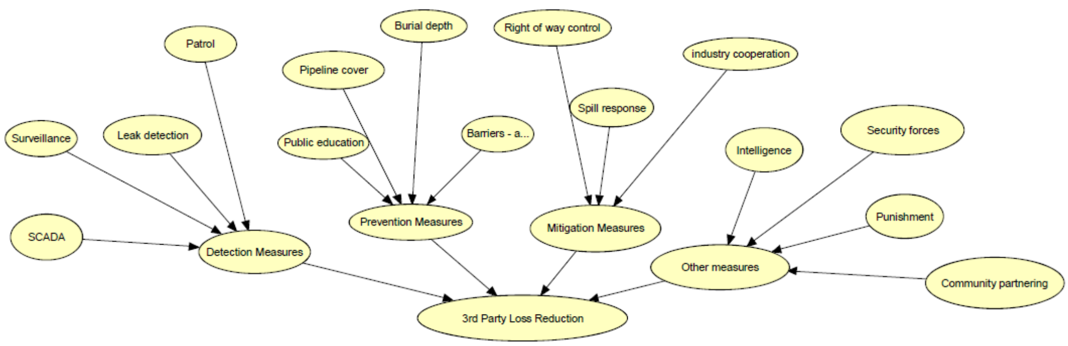

Figure 2: Hugin Graphical Output of the BN Model

4.4 Results and Analysis

The analysis of the BN model is carried out with respect to a selected RCO in order to assess its effectiveness compared to the baseline results. The RCOs can be broadly divided into two categories, those options that require hard or technical provisions (*e.g.*, leak detection, SCADA) and the other ones that require soft or non-technical provisions (*e.g.*, partnerships, public education, intelligence gathering). The selected RCOs that have been quantitatively analyzed in this section are those non-technical provisions that generally tends to change the behavioral pattern of the potential stakeholders whose action may lead to the loss of containment. These include community partnering, public education, industry cooperation, intelligence gathering & sharing, surveillance, patrol, and punishment.

The baseline results, with the main CPTs inserted, indicate that the "as built and operate" system's effectiveness in terms of loss of containment prevention or reduction has only about 23% likelihood of being effective. This indicates a significantly low likelihood of success and may explain the spate of pipeline damages being recorded. Figure 4 shows the marginal probability of the 3rd party loss reduction effectiveness.

The quantitative analysis involves inserting evidence for certain RCOs to observe how such evidence will influence the top node, which is the factor of interest. Such analysis assesses the contribution that RCOs will have on the threat that is being analysed. For example, if the operator wants to know which area to focus, they can assess what impact the improvement in community partnership will have on the overall reduction in the threat. Table 2 shows that if improvements were made to the community partnership, for example, it will improve the effectiveness of the loss reduction potential from 23% to 25.1%. However, a separate assessment carried out indicates that a further deterioration of the effort on community partnership, *i.e.*, with an evidence that it is not being carried out, will only reduce the loss reduction effectiveness from 23% to 22.7%, a decrease of 0.3%. This indicates there is very little that is being done in that aspect.

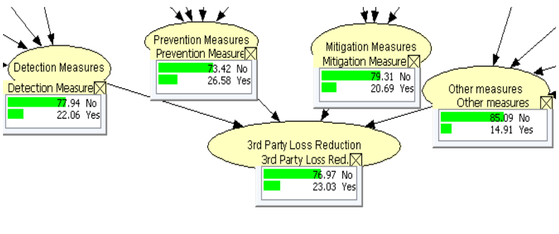

Figure 3: Baseline BN Results with Marginal Probability

The results in Table 2, based on the data and experts' elicitation, indicate that investment in public education on the benefit of the pipelines to them and to the economy of the country has the most positive contribution to reducing the threat of third party damage, increasing the marginal probability from 23% to 33.3%. The high contribution from that RCO may be because of the belief by the experts that the pipeline operators and the government are not doing enough to educate the public about the benefits of that infrastructure. Conversely, punishment is the least effective measure, with an increase of just 3.5%, which is interpreted as the failure of the current approach of punishment, which in Nigeria has not been successful.

Table 2: Marginal Probabilities for Individual Evidence

Selected RCOs	Marginal probability	% improvement
Baseline	23	
Surveillance	30.9	34.3
Patrol	24.5	6.5
Public education	33.3	44.8
Industry cooperation	26.2	13.9
Intelligence	27.1	17.8
Punishment	23.8	3.5
Community partnership	25.1	9.1

The operator may decide that they want to assess a combination of RCOs to observe the combined effectiveness of some or all of the selected factors. Table 3 shows some of the combinations and their contributions to the loss reduction potential. For example, a combination of surveillance and patrol increases the top event effectiveness from 23% to 32.4%. From Table 3, the most effective combination of measures is that of community partnership with public education, which has a combined marginal probability of 35.2%, up from 23%.

Table 3: Marginal Probabilities for Combined Evidence

Combination RCOs	Marginal probability	% improvement
Baseline	23	
Surveillance + Patrol	32.4	40.9
Community partnership + Public education	35.2	53.0
Intelligence + Industry cooperation	29.6	28.7
Punishment + Surveillance + Patrol	33.2	44.3
Community partnership +	38.7	68.3

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Intelligence + Public education	

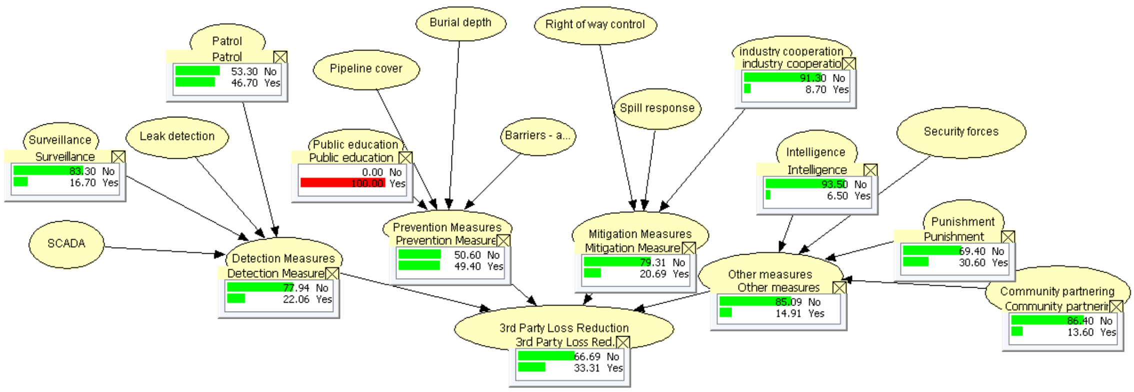

Figure 4: BN Model with Public Education Evidence is inserted

If all selected RCOs were to be implemented, the combined increase of the marginal probability of the top event would be 130%, increasing from 0.23 to 0.57. This implies a significant improvement that might be possible with non-technical and, perhaps, less expensive interventions, yet very effective in reducing the threat of third party damage. One of the barriers to effective risk reduction is the non-availability of financial resources to implement such measures. With limited resources, it is important for managers to allocate such resources to RCOs that are the most cost effective, preferably the ones that require less expenditure and provide better outcomes. The selected measures, with the exception of surveillance, are all relatively cheap to implement and together can reduce the likelihood of third party damage happening, or if it happens its consequences can be reduced by more than half the current level.

The pipeline 2B system is estimated to be losing more than $51 million dollars annually (Ekwo, 2011) attributed to just product loss. This figure will be of a higher order of magnitude, if the cost of environmental clean-up and compensation for any consequence, that may occur, is included in the assessment. A reduction of 50% in the pipeline loses will offer a great financial boost to the operator, reduce the environmental damage and boost economic development.

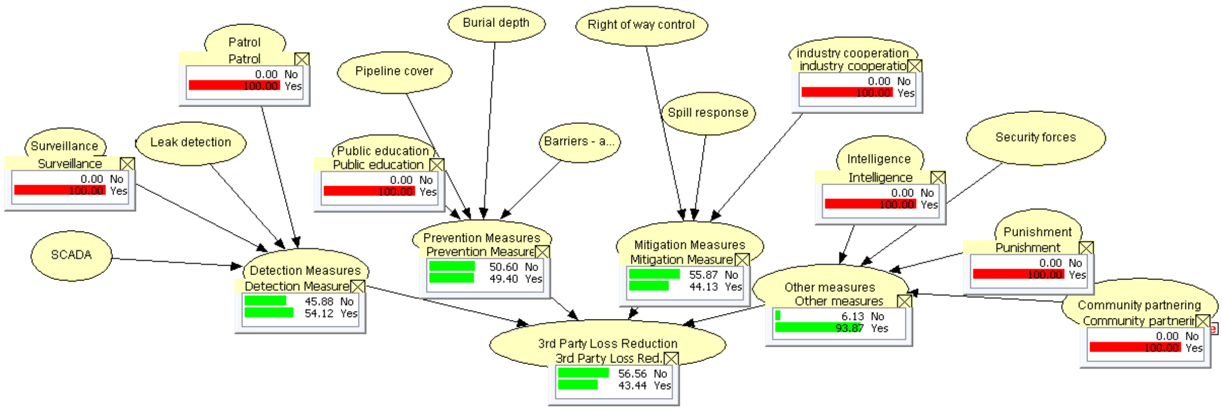

Figure 5 : BN Model with all the Selected Factors' Evidence is inserted

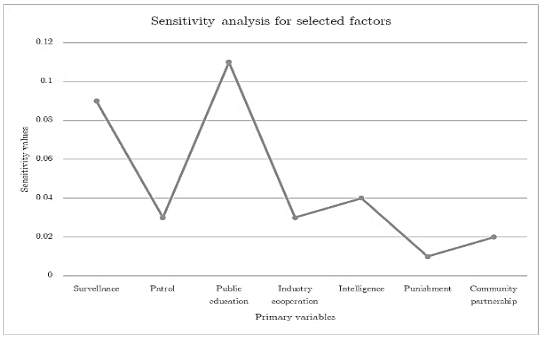

Figure 5: Sensitivity of inputs on third party threat

4.5 Sensitivity Analysis and Validation

Sensitivity analysis and validation have been carried out to validate the results of the assessment and ensure that the model works when presented with a wide range of inputs. The input sensitivity analysis is limited to the selected factors that have been analyzed in Section 4.4. We believe that the results apply to the whole model.

Figure 5 shows the graphical representation of the sensitivity of the third party loss prevention on various RCOs. It can be seen that changes in the likelihood function of the public education node influence the parent's node the most, whilst punishment produces the least influential effect on the parent node. This is consistent with the results presented in Section 4.4.

A unit increase or decrease in the patrol RCO produces about 3% change to the top node; on the other hand, a unit change of surveillance produces 8% of change to the top node.

For the validation, the three axioms outlined in Section 3.5 have been tested against the assessment. For example, providing "yes" evidence to the patrol RCO increases the marginal probability slightly from 23% to 24.5%. Additionally, when "yes" evidence is provided to the surveillance and patrol factors, the top node marginal probability increases from 23% to 32.4% which is greater than when only a single child node, the patrol is evidenced. Conversely, when "no" evidence is provided to the patrol RCO, the marginal probability decreases slightly 23% to 21.7%. When both patrol and surveillance are evidenced as "no", the top node marginal probability reduces from 23% to 20.2%.

Conclusions

This work analyzed the refined petroleum products pipeline risk reduction options and examined how they affect the effectiveness of reducing the threat of third party damage. A case study of a pipeline system in Nigeria has been used to show how the model can be applied. This assessment focused on mostly non-technical RCOs including public education, community partnership, intelligence, etc.

The model provides the operator with tools to assess the effectiveness of each RCO or a combination of them. It also allows the operator to assess the cause and effect of inserting evidence, either to assess a potential benefit of certain intervention or during post-accident analysis in order to identify a likely lapse in the RCO that may contribute in the loss of containment. The operator could use the analysis for "what if" scenarios to understand better the positive and negative impacts of each input variable or sub-variable.

The model accommodates subjective judgements from experts and allows for beliefs updates for given information, making it ideal for operators to keep updating their uncertain parameters as more data becomes available.

It is hoped that the model will assist decision makers in selecting the most suitable RCOs for a given budget and ease of implementation, taking into account the local conditions.

The key advantage of the model is its ability to incorporate both objective and subjective data; this is important for developing countries, where historical data is often unavailable or not reliable. The use of subjective data obtained using experts' elicitation ensures that the results reflect the local industry best practices and experience. However, it has a drawback in that, for example, the implementation of some RCOs, such as community partnership and punishment in Nigeria is widely acknowledged as defective and may, therefore, have influenced the opinion of the expert so as to imply the RCOs are ineffective, when in reality it is their implementation in a particular local condition that may be ineffective.

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