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Bayesian Network Analysis Of Offshore Decommissioning Waste Management

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Abstract

With the offshore decommissioning industry's estimated expenditure exceeding £17.75 billion over the next decade, this research study focuses on the handling of waste materials generated during this process. A Bayesian network, derived from prior research and publicly available data, was used to analyze the complex interactions influencing waste management decisions. The research study aims to contribute to the understanding of the handling of decommissioning waste materials. The research stresses the importance of informed decision-making to minimize environmental impact and streamline the handling of hazardous waste materials, ultimately contributing to a more sustainable decommissioning approach.

Keywords: offshore decommissioning, bayesian network, waste

1. Introduction

Decommissioning of offshore oil and gas installations is big business. It is estimated that the industry will result in an expenditure of over 17.75 £bn over the next ten years, involving the handling of 913,618 tonnes of topside infrastructure (OEUK, 2022). The number of installations nearing the end of their life is increasing, and it is currently thought that 126 installations within the United Kingdom Continental Shelf will require decommissioning in the next decade (NSTA, 2022).

The decommissioning of offshore oil and gas installations occurs when the installation is no longer economically viable. As it nears this stage, decisions must be made about how to progress – will it be totally removed, partially removed, or repurposed? The decision on its future is primarily governed by the integrity of the installation and the current legislation and regulations laid out by the United Kingdom government. Some countries allow for the installation to be used as part of a rigs-to-reef project, but this is currently not an option within UK waters (OSPAR, 2010).

Once a decision is reached, production is ceased, the wells are sealed and made safe, the installation undergoes decommissioning. This process generates several tonnes of waste materials. Currently, there is an emphasis on reducing the volume of waste that is sent to landfill and encouragement to reuse or recycle materials wherever possible (Perks, 2012; OGA, 2015; Brady, 2022). This is written into decommissioning guidance within the UK and is an industry focus. Newer installations have undergone life cycle analysis as part of their design phase, but previously, this was not considered with older installations (Milios et al., 2019).

The installations currently undertaking or approaching decommissioning may have changed owners, mode of operations, and workforce (Parente et al., 2006; Calder, 2019). These changes may have resulted in the loss of information or lack of knowledge sharing. These installations may contain chemicals that have been reclassified in accordance with changing regulations (Sühring et al., 2019). Hazardous materials may not be brought to light until decommissioning activities are well underway (La Védrine et al., 2015; Anderson et al., 2018).

Aims and objectives

This conference paper aims to further the understanding of the handling of decommissioning waste materials utilising a Bayesian network (BN) to analyse the interactions between the factors that affect the handling of these materials.

The aim will be met through the following objectives:

- The creation of a Bayesian network is based on previous research conducted by the author (Ford et al, 2023).
- Analysis of the Bayesian network through a series of test cases.

2. Background

Decommissioning these installations is challenging due to the different nature of each one. The installation may have changed its owner, mode of operation, and workforce throughout its lifetime. With these changes, information concerning the materials may have been lost or failed to be passed on. This can result in incomplete material and equipment inventories.

Prior to decommissioning commencing, surveys and material testing must take place, but these can often be inadequate and fail to identify the types and quantities of hazardous materials present. Failure to identify and qualify these materials can result in the improper handling of materials, the increased risk of loss of containment and the reduction in recycled materials.

Decommissioning activities begin at least three years before the planned decommissioning of an installation. The first step is to consult with the Department for Energy Security and Net Zero to discuss the decommissioning programme. A decommissioning programme is required as outlined in the Petroleum Act 1998. The decommissioning programme cannot be executed until approval has been granted by the UK Secretary of State. An environmental appraisal must assess the impact of the programme and consider energy usage and emissions. Approval is only granted once these requirements have been satisfied and it has been publicised for stakeholder and public consultation. Following the completion of the decommissioning, a detailed close-out report must be submitted that includes seabed surveys, waste transfer receipts and findings from the activities.

The UK government utilises the waste hierarchy as part of its regulations and guidance. The waste hierarchy is part of the European Union Waste Framework (EU, 2008). It defines waste as "any substance or object which the holder discards or intends or is required to discard". Throughout the decommissioning process, several types of waste are produced and must be disposed of safely. This definition of waste is implemented in England and Wales as part of the Environmental Protection Act 1990. Those handling controlled waste, for example, producers, carriers and disposers, have a duty of care to ensure that the waste is:

- Not unlawfully disposed of.
- Is only transferred to an authorised waste collection agency, registered carrier or licensed waste disposer.
- Not misplaced or escaped from a person's control (Perks, 2012).

The most preferred option is the prevention of the production of any waste materials, but due to the nature of decommissioning, the age of the installations and the hazardous materials involved, this is not always possible. In order to prevent the production of waste, steps should be taken to reuse or extend the life of equipment and materials used. Any materials or equipment that may be prepared for reuse includes any material or equipment that will be reused for the same purpose for which they were conceived. These items are not considered waste but must be prepared through thorough checking, cleaning and repairing so they can be successfully reused without any other pre-processing. Materials that are to be recycled include the reprocessing of the materials or equipment to be used for other purposes. Waste that falls under the other recovery category includes any waste that would be used to replace other materials that are otherwise used for a particular function, for example, construction aggregate. If none of these options can be fulfilled and the waste cannot be recovered, then it must be disposed of.

Previously, discussions with industry experts and the distribution of pairwise comparison questionnaires highlighted that critical factors in the decommissioning process were:

- Reduction in costs,
- Knowledge and best practice sharing,
- Liability throughout the waste stream (Ford et al, 2023).

It was anticipated that there would be an agreement between the respondents from similar backgrounds (Ford et al, 2023); for example, the respondents involved in the education sector would hold similar views, but this was not the case. Each respondent had a different level of expertise, which resulted in their different opinions of the importance of each factor associated with decommissioning. Although a consensus was not reached, this initial research highlights that each of the factors is still an essential factor of decommissioning that needs to be addressed. How this would be addressed still needs to be identified and would involve a higher level of discussion and involvement from industry experts, but due to the almost secretive nature of the industry and the reluctance to cooperate, this is not the case.

It can be seen that for the overall goal – to select the most critical factor affecting the decommissioning process, the understanding of offshore regulations is vital, backing up the findings of previous research. For the remaining criteria, reduction in costs, understanding of liability and knowledge and best practice sharing were identified as critical factors.

Cost reduction was identified as possibly due to the ongoing initiative by the North Sea Transition Authority (NSTA, 2022) to reduce overall costs by 25% and now by a further 10% by the end of 2028. An overall understanding of liability would suggest an understanding of legislation and regulations, which, in turn, would reduce the length and volume of waste. The ongoing issue of a lack of knowledge and best practice sharing has also been highlighted. It makes sense that knowledge sharing would aid the understanding of regulations.

3. Methodology

This research paper forms part of a larger research project being undertaken at Liverpool John Moores University. The initial stage of the research involved a literature review in order to identify the current issues within the decommissioning process and identify if any, gaps in the regulatory framework. The findings of the literature review (Ford et al, 2021) were then used to inform an analytical hierarchy process and the development of a Bayesian Network. On the completion of these stages, a conclusion would be reached, and a decommissioning framework would be developed.

3.1. Probability theory

Probability is the measure of likelihood that an event will occur. It can be expressed as a percentage, decimal form or a fraction. The probability of an event A occurring is defined as:

$$P(A) = \frac{No. of\ outcomes\ favourable\ to\ the\ occurence\ of\ A}{Total\ number\ of\ equally\ likely\ outcomes} = \frac{n(A)}{n(S)} \tag{1}$$

Probability theory is governed by the following axioms:

Axiom 1: The probability of an event is a real number greater than or equal to zero.

$$P(A) \geq 0 \tag{2}$$

Axiom 2: The probability that at least one of all possible outcomes of an event will occur is equal to one.

$$P(A) = 1 \tag{3}$$

Axiom 3: If two events, A and B, are mutually exclusive, then the probability of either occurring is the probability of A occurring plus the probability of B occurring.

$$P(A \cup B) = P(A) + P(B) \tag{4}$$

Events are considered independent if the outcome of one event does not affect the outcome of the other.

$$P(B|A) = P(B) \tag{5}$$

Events are considered dependent if the outcome of one event affects the outcome of the other.

$$P(A\ and\ B) = P(A) \times P(B|A) \tag{6}$$

This basic probability leads onto to Bayes' Theorem which is utilised in Bayesian Networks.

3.2. Bayesian networks

Bayesian networks can be used to explore relationships between key factors and find outcomes for a system in a straightforward, visual manner. Bayesian networks are a type of directed acyclic graph that uses Bayes' Theorem (Neapolitan, 2004).

Bayesian networks are constructed using nodes and links. Nodes represent variables which can either be discrete or continuous. The links between the nodes indicate causality. Each node can be classified as a parent or child node.

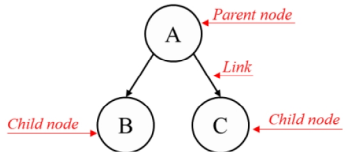
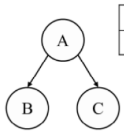


Fig. 1. Example of a Simple Bayesian Network.

A simple BN is shown in Figure 1. In this example, A is a parent of the node of C and a parent node of B. Therefore, nodes B and C are child nodes of A. BN can be developed by the addition of further nodes and links indicating their influences.

BN represents quantitative relationships among modelled variables. The probability distribution for each node is shown in a conditional probability table (CPT). These CPTs can be used to express the relationships between nodes. Figure 2 illustrates the conditional probability tables for a simple BN.

a_1	$P(a_1)$
a_2	$P(a_2)$



	a_1	a_2
b_1	$P(b_1 \mid a_1)$	$P(b_1 \mid a_2)$
b_2	$P(b_2 \mid a_1)$	$P(b_2 \mid a_2)$

	a_1	a_2
c_1	$P(c_1 \mid a_1)$	$P(c_1 \mid a_2)$
c_2	$P(c_2 \mid a_1)$	$P(c_2 \mid a_2)$

Fig. 2. Example of a Bayesian Network with Conditional Probability Tables.

Bayes' Theorem was developed in the 18^{th} century by Thomas Bayes (Weber and Simon, 2016). Previous (unconditional) probability represents the likelihood that an input parameter will be in a particular state. The conditional probability calculates the likelihood of the state of a parameter given the state of the input parameters effected.

Bayes' Theorem is represented using equation 7.

$$P(b|a) = \frac{P(a|b).P(a)}{P(b)} \tag{7}$$

BNs satisfy the local Markov property which states that a node is conditionally independent of its non-decedents, given its parents. The BN uses Bayesian inference probability computation. This inference can come from known probabilities or through calculation through variable elimination. The network is solved when the nodes have been updated using Bayes' Theorem.

3.3. Conditional probability tables

Generating the conditional probability tables for a Bayesian network can often be the most challenging part of the analysis. The aggregated priorities from the AHP analysis will be used to construct the tables for the nodes that correspond to the criteria and alternatives in the hierarchal structure shown in.

When nodes have more than one parent, their probabilities can be determined using the weighted sum algorithm proposed by Das (2008). This approach uses the results from the pairwise comparison and their relative weights.

The example in shows a child node, C, with two parent nodes.

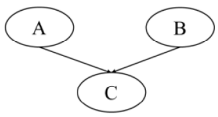


Fig. 3. Simple Bayesian Network

If the parent nodes have the same number states:

$$k_1 = k_2 = \cdots = k_n \\ where\ k_n = the\ number\ of\ states\ of\ the\ nth\ node \tag{8}$$

The compatible states for the parent nodes are represented by:

$$\{comp\ (A_i =\ a_s)\} \equiv \{comp\ (B_i =\ b_s)\} \tag{9}$$

where '≡' indicates the sets are identical.
For Figure 3, the compatible parent combination is:

$$\{comp\ (A\quad = s)\} \equiv \{comp\ (B\quad = s)\} \equiv \{A = s, B = s\} \tag{10}$$

For child node C, the probability distribution will be:

$$P(D|\{comp(A = s)\}) = P(D|\{comp(B = s)\}) \tag{11}$$

This leads to the weighted sum algorithm (Das 2008):

$$P(x^l|y_1^{s1}, y_2^{s2}, \dots \dots \dots . y_n^{sn}) = \sum_{j=1}^{n} w_j . P(x^l|\{Comp(Y_j = y_j^{sj})\} \tag{12}$$

where: $l = 0, 1, \dots, m$ and $Sj = 1, 2, \dots, kj$
This can be applied to the child node C show in Figure 3.

3.4. Data acquisition and analysis

The details for each node are shown in Table 1. The BN consists of 12 nodes, the data for which comes from a variety of sources, shown in Figure 4. If no decommissioning activities are taking place, then no further action is required. If decommissioning is taking place, is there a complete materials and equipment inventory available, and has a full survey of materials and equipment taken place? If the materials have been identified, have the correct

permits for transport been applied for? If not, the consequence would be a liability event. Nodes seven and eight are concerned with whether the decontamination of hazardous waste equipment would take place offshore whilst on the installation or onshore after the equipment has been transported.

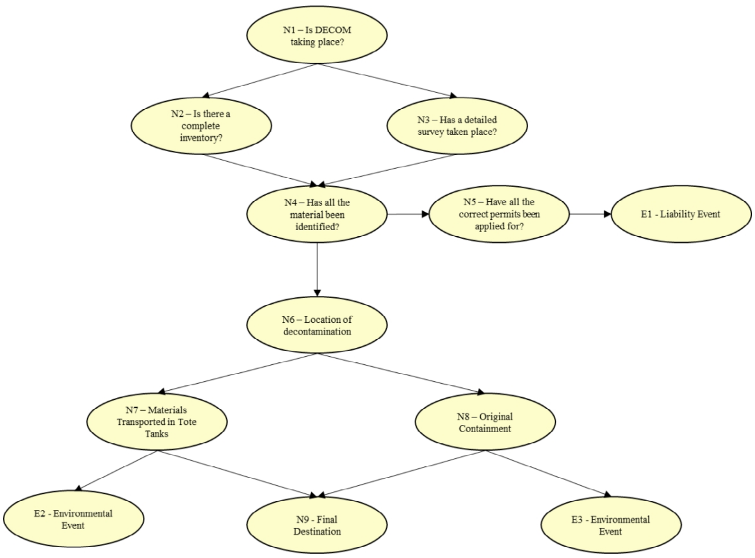


Fig. 4. Bayesian Network.

In the event that decontamination occurs offshore, the hazardous waste would be transported in tote tanks to an onshore site. If decontamination is to take place onshore, it is assumed that the equipment concerned would be isolated for transport. In the event of any failure or leak during transport, the consequence would be an environmental event. The final destination of hazardous waste is either recycling, reusing, or landfilling. The data for this node has been compiled from the publicly available close-out reports for completed decommissioning projects.

Table 1. Node details for bayesian network.

Node Name	Data Source	Number of states	Parents
N1 – Is DECOM taking place?	Yes/No Question	2	0
N2 – Is there a complete inventory?	Previous Research/Expert Opinion	2	1
N3 – Has a detailed survey taken place?	Previous Research/Expert Opinion	2	1
N4 – Has all the material been identified?	Weighted Sum Algorithm	2	2
N5 – Have all the correct permits been applied for?	Previous Research/Expert Opinion	2	1
N6 – Location of decontamination	Data from Close-Out Reports	2	1
N7 – Materials Transported in Tote Tanks	HSE Data	4	1
N8 – Original Containment	PON1 Data	7	1
N9 - Final Destination	Data from Close-Out Reports	3	2
E1 - Liability Event	Expert Opinion	2	1
E2 - Environmental Event	Expert Opinion	2	1
E3 - Environmental Event	Expert Opinion	2	1

3.5. Model validation and sensitivity analysis

A Bayesian network must undergo validation to ensure that it satisfies the axioms (Loughney, 2018). The validation of the model provides confidence in its results. The validation process involves examining several different combinations and scenarios in order to highlight potential problematic areas. A three axiom–based verification procedure was followed, which is used for partial verification of the proposed BN model (Matellini et al, 2013). On completion, a sensitivity analysis is carried out in order to demonstrate how sensitive the network output is to the variations of its inputs.

Axiom 1: A slight increase/decrease in prior probabilities of each parent node should elicit an increase/decrease in the child node. For this axiom, the input of nodes N2-8 were changed by 5%, and the effect on the output node, N9, was noted. It can be seen that this change in the input results in a change in the output node, N9, as hown in Table 2. This shows that the model satisfies axiom one as by altering the values of the parent nodes, the value of the child node has changed.

Table 2. Effect of the change of prior probabilities of parent node on output node.

	5% change in probability					
Probability of N9	N2	N3	N4	N6	N7	N8
Recycle	32.10%	32.58%	32.34%	20.39%	33.05%	55.47%
Reuse	0.52%	0.53%	0.53%	0.37%	0.54%	0.82%
Landfill	67.37%	66.69%	67.13%	79.24%	66.42%	44.61%

Axiom 2: The total influence magnitudes of the combination of the probability variation from (evidence) on the values should always be greater than one from the set of sub-evidence attributes. This is shown by the effect of changing the values of nodes N2-8 on the output node N9.

Axiom 3: The total influence magnitudes of the combination of probability variation from the evidence should be greater than that from the set of x-y attributes. Axiom 3 requires that sub-evidence should have less influence on the values of a child node than evidence received from parent nodes. Parent nodes N7 and N8 are composed of nodes N6, N4, N3 and N2. When evidence is entered 100% into the nodes and the states of each node are 100%, the results are shown in the Fig. 5. It can be seen that the variation satisfies axiom 3.

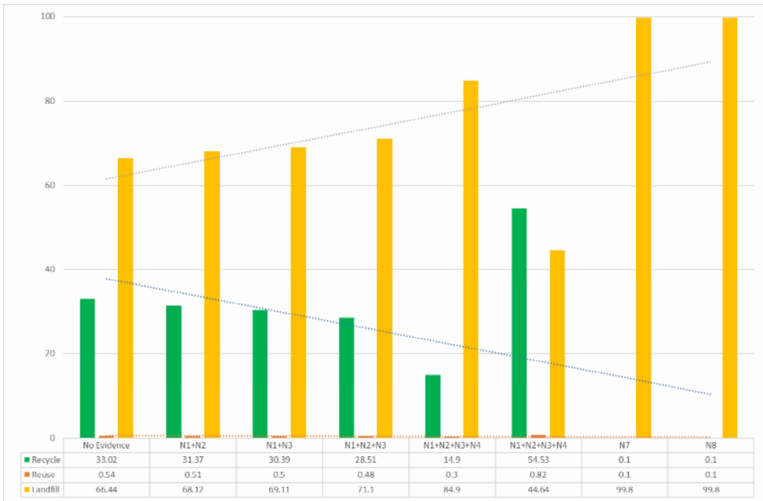


Fig. 5. Effect of variation of child and parent nodes.

A sensitivity analysis was carried out in order to assess the robustness of the model. It demonstrates the response of a given node to the changes in values of other input nodes (Matellini et al, 2013; Loughney, 2018). This demonstrates whether the model is working as intended. For the sensitivity analysis, the node N9 – final destination was examined as this was an output of the model. Knowing which nodes are most influential can assist in experimentation, analysis and further development of the model. Nodes which are not important could subsequently be discarded or replaced. The objective was to test the sensitivity of node N9 to its input nodes. The sensitivity analysis was conducted using the HUGIN sensitivity wizard. Without the use of this tool, the sensitivity analysis would involve increasing and decreasing the states of the chosen input variables by equal percentages to allow for a clear comparison with the chosen output node. The sensitivity wizard in HUGIN requires the user to select the desired focus node and the desired input node. The state for each node is selected so that it would have an impact on the focus node. HUGIN calculates a sensitivity value for the node. This value was, in turn, inputted into an Excel spreadsheet to allow the value to be increased and decreased. The results are presented in Fig. 6. It can be seen that the graph produced is a straight line with a positive gradient. It also indicates that tote tank failure is most influential on the focus node N9 – final destination. When this root node is increased by 5%, the focus node increases by 2%.

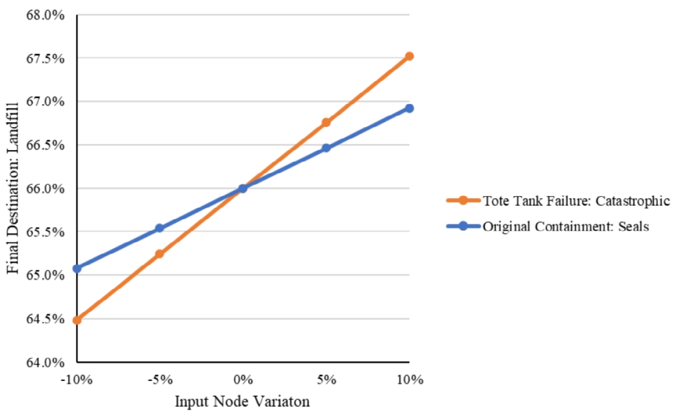


Fig. 6. Sensitivity functions for the input nodes acting on the output node, N9 – final destination.

4. Results and discussion

The focus of the model is to determine the interaction between the critical factors identified through expert discussions and AHP analysis completed as previous research by the author (Ford et al, 2023). The numerical data has been obtained from a combination of these analyses and publicly available data from the HSE and OPRED close-out reports. The marginalised probabilities for each node are shown in Figure 7. Three different test cases were analysed to determine the influence of different parent nodes on a chosen child node.

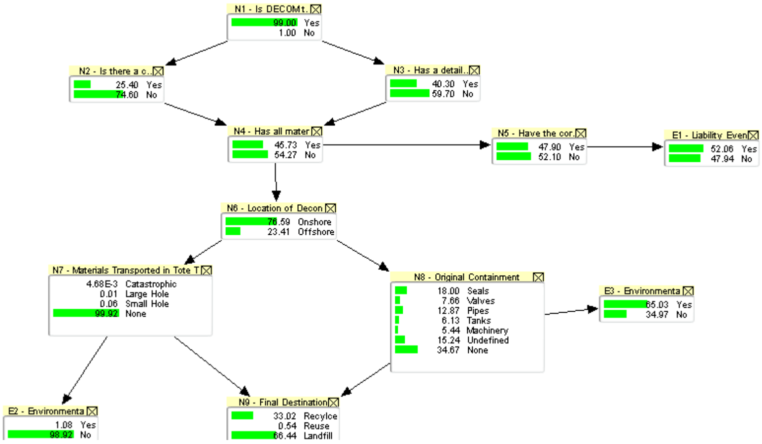


Fig. 7. Marginalised probabilities for each node of the BN model.

4.1. Case 1

This test case involves the scenario where nodes N2, N3 and N4 are in a state of 100% No, as shown in Fig. 8. In this event, the probability of waste reaching landfills increases from 66% to 71%, and the possibility of waste materials being recycled decreases from 33% to 29%. This shows that in the event there is no comprehensive inventory present, and no detailed survey has taken place, the probability of the waste materials being correctly identified decreases, and more waste would be destined for landfill. This would reduce the sustainability of the overall decommissioning project, increase the risk of mishandling, and lead to further consequences.

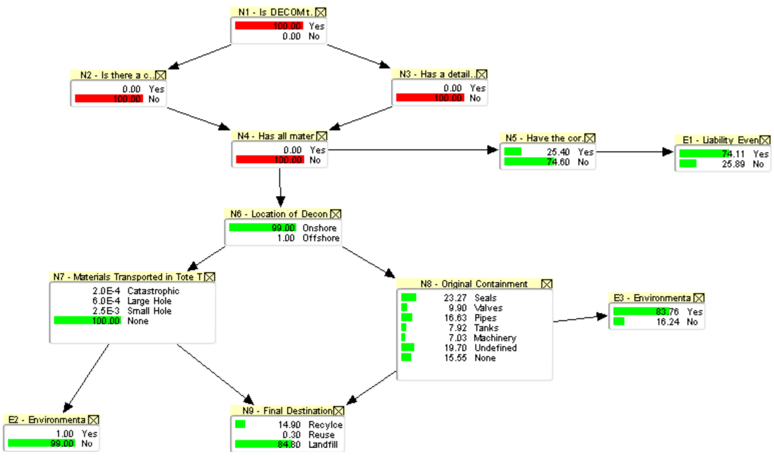


Fig. 8. Test case 1: Nodes 2 to 4 in state100% no.

4.2. Case 2

This test case involves the scenario where nodes N2, N3, and N4 are in a state where 100% Yes. In this scenario, all the historical information concerning equipment and materials is present, the surveys have been completed to a high standard, and the waste materials present have been correctly identified. This results in an increase in the probability of the waste materials being recycled or reused, ultimately increasing the sustainability of the overall project.

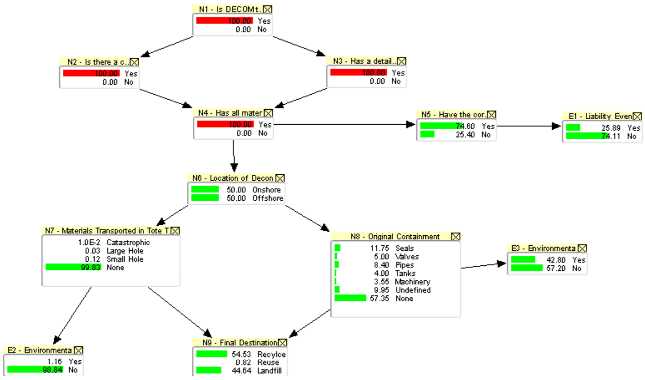


Fig. 9. Test case 2: Nodes 1-4 in state 100% yes.

4.3. Case 3

This test case focuses on the failure of containment during transport. Node 7 is set to 100% catastrophic failure of tote tanks, as shown in Fig. 10. The effect on the final destination node is an increase in probability of the waste materials reaching landfill of 66.4% to 99.8%.

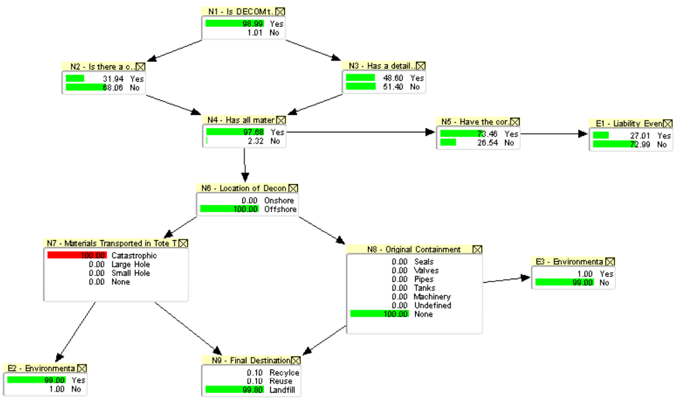


Fig. 10. Test Case 3: Node N7, is set to 100% catastrophic failure.

5. Conclusion

The Bayesian network shows that the final destination of hazardous waste materials is ultimately influenced by their identification. This is dependent on the historical information available and the quality of the survey and testing during the initial decommissioning process. It follows that if hazardous waste materials are incorrectly identified or their presence unknown, they may eventually end up in landfill instead of recycling or reuse. It also increases the risk of environmental or personnel accidents when the material reaches the onshore processing site.

In conjunction with the findings of the previous research, which highlighted the issues surrounding the understanding of legislation, lack of knowledge sharing and the emphasis on reducing costs, this highlights the current issues with decommissioning occurring in the UKCS. Despite stringent legislation and regulations, there is still uncertainty in their understanding.

6. Further research

The results from the Bayesian network, alongside the findings of the previous paper, will be used to develop a holistic decommissioning framework that focuses on the handling of hazardous waste materials. This will be used by stakeholders in the decommissioning process as guidance alongside the current legislation and regulations.

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