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Risk Analysis of Equipment Loss During Marine Survey Operation by Integrating Fault Tree to Bayesian Network

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ABSTRACT

The process of deploying and towing the survey equipment for several marine survey activities is essential since it visualises the seabed and improves data accuracy. Since the equipment is deployed to an underwater level, the risk arises with the deployment. These risks include potential contact with submerged objects and the seabed, which can result in the loss of equipment and have detrimental environmental consequences. This study aims to analyse the risk-associated factors related to the loss of survey equipment using Fault Tree Analysis (FTA) and Bayesian Network (BN). The constructed FTA was converted into BN to find the relationship between Basic events and simulate the probability of updating Basic events. The sensitivity analysis results of the BN model indicate that "Procedure Failure" is the Basic contributor to the loss of survey equipment. The findings from this study will have practical implications for stakeholders, enabling them to enhance the safety of marine survey activities, particularly by mitigating the occurrence of equipment loss during operational procedures.

Keywords: *bayesian network, FTA, marine survey, research vessel*

1. INTRODUCTION

Marine survey activities are one of the crucial prerequisites for several ocean-related activities, such as cable routing, cable maintenance, dredging, and environmental baseline assessment. The emerging demand for marine survey and research activities underwater requires equipment to be deployed under the water level to a certain depth to obtain better quality and accuracy of the data. The deployment risk occurs since the equipment has been put at an underwater level. These risks could involve encountering underwater items or the seabed, leading to equipment loss and adverse environmental effects. Therefore, the appropriate risk assessment for marine survey operations should have been conducted. To date, two studies related to safety assessment have been found in marine survey operations. Several authors used FTA (Fault Tree Analysis) to investigate and analyse the most critical risks of seismic survey operations [1] and utilise FTA to improve the Safety of Marine Cable Survey Operations [2].

Despite its advantage in mapping various system failure scenarios, FTA also has drawbacks, such as the inability to express a connection between Basic events. Various studies have successfully integrated the FTA with more advanced methods, such as the Bayesian Network (BN), to improve the quality of the FTA. FTA is a static instrument due to its inability to update probability states. Moreover, BN is weak in determining how failure causes unwanted events [3]. For more accurate results, FTA has been integrated into the BN to overcome the limitations of each model [4]. Historical data and expert knowledge are essential tools of FTA that can be integrated into BN to improve its performance and simplify the modelling process [5]. Therefore, mapping FTA into a BN is a practical approach that minimises the complexity of the failure probability model and overcomes each weakness [6].

The study that combines FTA and BN is widely used for maritime risk analysis. For example, the study by[7] focused on FTA and BN methodology on collision in open sea accidents based on organisational and regulatory conditions. BN is also used to help incorporate multi-status variables often encountered in safety analysis that FTA cannot consider [4]. Another example of integrating FTA to BN in the maritime sector is a risk analysis of ship accidents by integrating BN with FTA methodology [8]. Moreover, [9] combines FTA and BN, where FTA is used for a comprehensive accident risk identification analysis. BN is used for predictive analysis from cause to consequence and the risk of tripping accidents on power transmission lines.

Since the quantity of studies that focus on risk analysis in marine survey operations is considered infrequent, this study aims to analyze the risk-associated factors related to the loss of survey equipment using FTA and BN to find risk mitigation strategies, which help to reduce the probability of equipment loss on marine survey activities.

2. METHODOLOGY

2.1 Fault Tree Analysis

The fault tree analysis methodology is based on identifying failures or top events to be assessed. The Fault tree diagram is constructed top-down, from the top event to each cause until Basic events are obtained [10],[11]. The step for constructing the fault tree can be started by assuming that the failure or top event has already happened and then determining the possible factors or causes which could contribute to top event occurrence [12].

In the Fault Tree Diagram, some gates represent how the failure of Basic events is related within the system or how the failure of Basic events mixes to make the system fail [13]. Fault Tree Analysis diagram is designed using 'AND' or 'OR' gates. The 'AND' gate is used to relate the simultaneous failure causes of an event, while the 'OR' gate is used if the failure causes of an event occur directly. Figure 1 shows the example of the Fault Tree Diagram and its information.

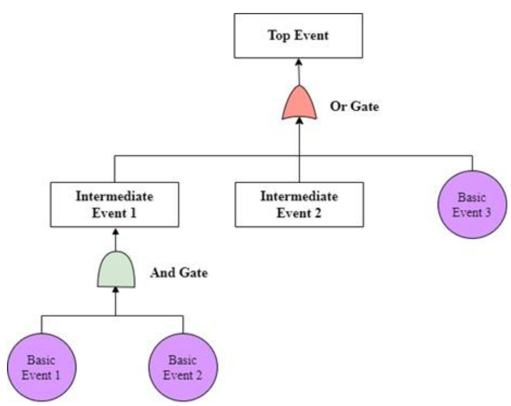

Figure 1. Example of Fault Tree Diagram

In maritime industries, FTA plays a vital role in understanding accident factors. Other research, such as risk analysis of maritime accidents in an estuary: a case study of Shenzhen Waters, has also used FTA in its methodology [8]. The analysis used FTA to estimate the probability based on accident statistics and ship traffic flow. In other ship accident research, fault tree analysis (FTA) was applied to create a risk hierarchy that defines the level of relationship among factors [14]. In collision analysis, fault tree analysis (FTA) was utilised to determine critical events and their logical structure [13]. In gas process facilities, the FTA was used to assess the failure [4]. FTA has also been used in marine survey operations to analyse the cause of survey equipment failure [2].

2.2 Bayesian Network

The Bayesian Network is a powerful method to analyse causal factors of maritime accidents. Several authors [15]–[18] have used BN to analyse several accident types' causal factors by data-driven influenced BN. Moreover, BN also used for studying maritime collision [19]–[21], piracy [22], and sinking accidents [23],[24].

A Bayesian network, also known as a causal model, is a graphical model that depicts the conditional independence of a set of random variables [25]. To connect the relationship between variables (nodes), the Bayesian network approach uses a Directed Acyclic Graph (DAG) model. For example, if an arrow connects nodes A and B, this might be understood as A causing B to occur [26]. The nodes are made up of states that express the nodes' current state. Furthermore, Bayesian networks take a qualitative and quantitative approach to problems. The Bayesian Network represents the qualitative method, a causal relationship between nodes. On the other hand, the quantitative approach is expressed in the numerical values of conditional probability tables at each node [27]–[29].

The input of conditional probability is pivotal in BN's analysis. For example, parent node A has child node B connected by the DAG. Since event A has been known, the probability of event B with the knowledge of event A can be calculated by: P(B|A) = x. On the other hand, when event B is known, the likelihood of event A can be determined by:

$$P(B) = \frac{P(A_i)P(B|A_i)}{P(B)}, i = 1,2,3, \dots, k \quad (1)$$

$$P(B) = P(A_1)P(A_1) + \cdots + P(A_k)P(A_k) \quad (2)$$

Where $P(B|A_i)$ is the conditional probability of B when A_i is already known, $P(A_i)$ is the prior probability of the hypothesis, $P(A_i|B)$ is the posterior probability, and P(B) is the probability of B without dependency from A or the marginal probability.

2.3 Mapping FT into Bayesian Network

Some techniques should be used to convert Fault Tree (FT) into BN. This analysis will convert the FT Diagram to BN using techniques from [4],[10]. The graphical mapping from the Fault Tree, consisting of Basic Events (Basic Events), Intermediate Events, and Top Events, will be converted to Root Nodes, Intermediate Nodes, and Leaf Nodes, respectively, in BN. The numerical mapping, which consists of Event Occurrence Probability and Boolean Gates in the Fault Tree, will be converted into Prior Probability of Root Nodes and Conditional Probability Tables (CPT) in BN. Figure 2 illustrates an example of converting the FT Diagram to BN.

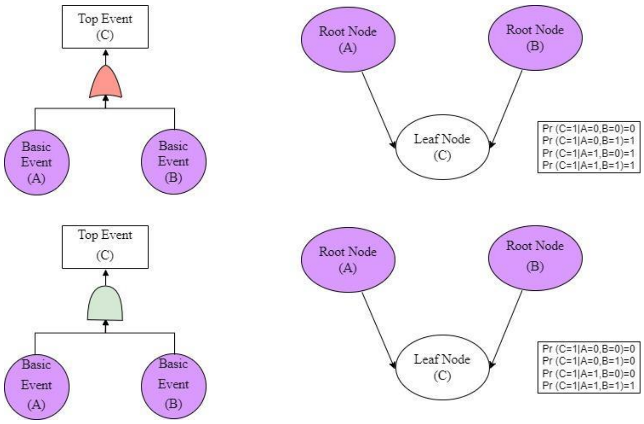

Figure 2. Example of conversion from Fault Tree Diagram to Bayesian Network

3. RESULTS

3.1 Table Format and Arrangement

In This Analysis, FTA was developed in the previous analysis [2], as shown in Figure 3**.** In Figure 3**,** the Basic events represented as a circle illustrate the root cause of the "Survey Equipment Loss" top event. The rectangle shape illustrates the intermediate event from a Basic event to another intermediate event or directly to the top event. The gap between the Basic event and intermediate event, intermediate to intermediate event, or intermediate event to top event is connected by an 'OR' gate, representing a triangle and half oval shape between them.

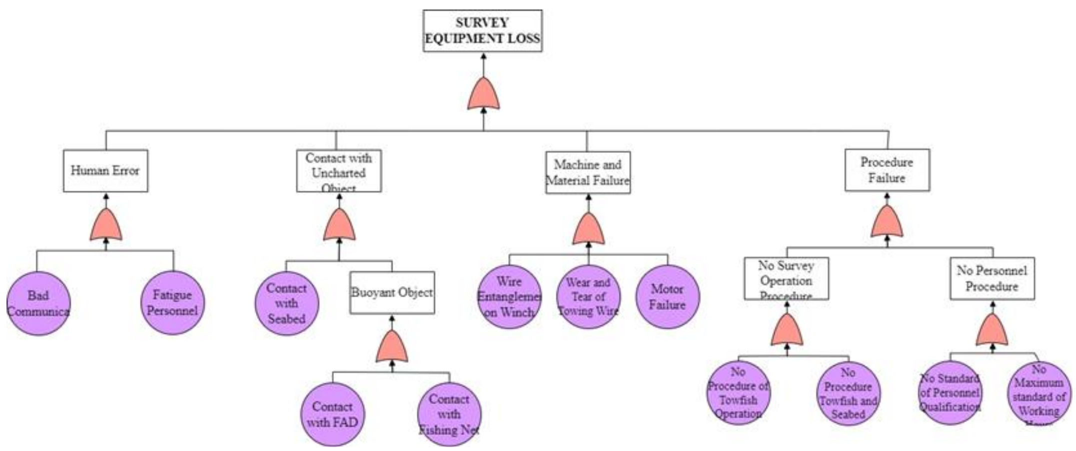

Figure 3. Fault Tree Diagram of Survey Equipment Loss

From the provided Fault Tree Diagram, as depicted in Figure 3, four categories contributing to Survey Equipment Loss top event have been obtained, including Human Factor, Contact with Uncharted Object, Machine and Material Failure, and Procedure Failure. From those categories, twelve Basic events are obtained. According to Table 1, which shows the probability of each Basic event, the highest contributor of the Basic event causing top event failure is achieved by Towfish Contact with FAD (X4), No Procedure of Towfish Operation (X9), and Seabed and Towfish distance standard (X10) with the same value of 2.5E-2.

By using the OR gate, the probability of an Intermediate Event is calculated by a summation. For instance, the probability of a "Human Error" Intermediate Event is determined by the sum Basic event of "Bad Communication Causing Human Error" (X1) and the Basic event of "Fatigue Personnel Causing Human Error" (X2). By sum 0.0084 and 0.0084, the probability of Human Error is obtained at 0.0168. The Basic Events X1 and X2 are converted into Root Nodes in BN, while the Intermediate Event of "Human Error is transformed into Intermediate Nodes in BN. Figure 4 provides an example of a converted fault tree diagram of Human Factors from Survey Equipment Loss.

Table 1. Probability of Survey Equipment Loss Basic Event

Basic Event	Occurrence	Frequency of occurrence (118 days)
Bad Communication Causing Human Error (X1)	1	8.4E-3
Fatigue of Personnel Causing Human Error (X2)	1	8.4E-3
Towfish Contact with Seabed (X3)	1	8.4E-3
Towfish Contact with FAD (X4)	3	2.5E-2
Towfish Contact with Fishing Net (X5)	1	8.4E-3
Wire Entanglement (X6)	1	8.4E-3
Wear and Tear of Wire (X7)	1	8.4E-3
Winch Motor Failure (X8)	2	1.7E-2
No Procedure of Towfish Operation (X9)	3	2.5E-2
Seabed and Towfish distance standard (X10)	3	2.5E-2
No Personnel qualification standard (X11)	2	1.7E-2
No working hours standard (X12)	2	1.7E-2

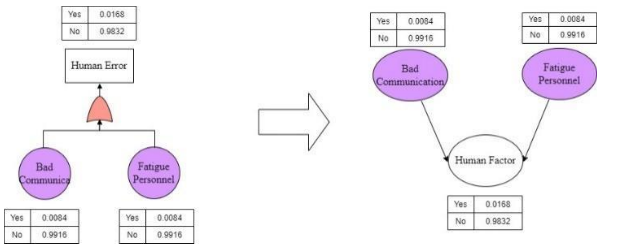

Figure 4. Example of Fault Tree Diagram to Bayesian Network from Human Factor

3.2 Bayesian Network Modelling

Figure 5 shows the BN model converted from FTA. The top event, "Survey Equipment Loss," is transformed into the target nodes, while Intermediate events such as "Human Error," "Contact with Uncharted Object," "Machine Failure," and "Procedure Failure Nodes" are converted into the Intermediate Nodes. Nine basic events are modified into the root nodes. The prior probability of the root nodes is obtained from the probability of occurrence from the FTA.

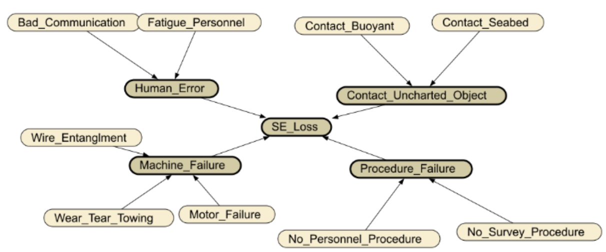

Figure 5. The Bayesian Network of Survey Equipment Loss on Marine Survey Activities

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The model was created using NETICA software, and each node has two states, "Yes" and "No," to determine the status of respective nodes. The "Yes" state means the event's occurrence, while the "No" state represents the non-occurrence condition. One of the most critical inputs for the BN is the CPT for the child nodes. The CPTs are obtained from the logic gates suggested by [10]. For most cases, the CPT value from the logic gates will be amended by incorporating expert judgment since there is a possibility that the "No" states will occur.

Table 2. The Conditional Probability of "Procedure Failure" Node

No Survey Procedure	**Yes**				**No**			
No Personnel Procedure	Yes		No		Yes		No	
Procedure Failure	Yes	No	Yes	No	Yes	No	Yes	No
Probability	1	1	1	1	1	1	1	0

Table 2 states the CPT value from the intermediate nodes "Procedure Failure", which consists of two root nodes, "No Survey Procedure" and "No Personnel Procedure." According to the FTA, the logical gates of the Basic and intermediate events are OR. Therefore, the event "Procedure Failure" will occur whenever one of the Basic events happens (the "Yes" condition occurs). Since the expert opinion is unavailable to amend the CPT, the CPT value remains.

3.3 Results of the Bayesian Network

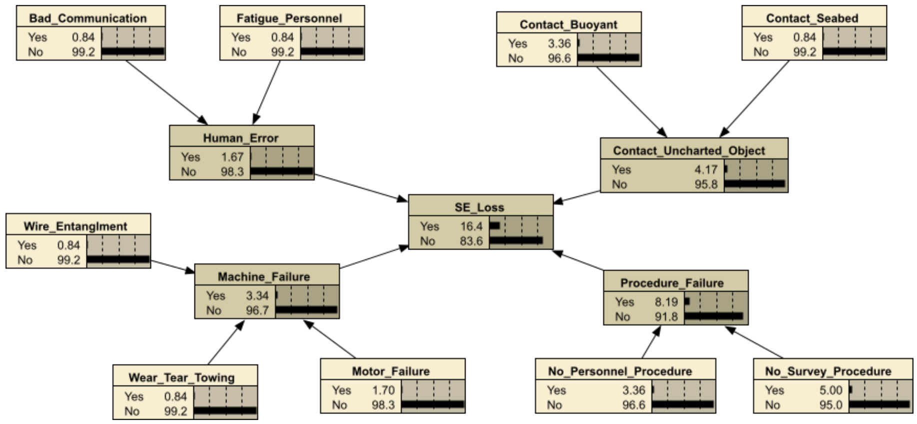

Figure 6. The posterior probability of the BN model

Figure 6 shows the results of the Posterior Probability of the accident Survey Equipment Loss for marine survey operation. The probability of target node "Survey Equipment Loss" is 0.0164 after incorporating the CPT for every possible node. Regarding intermediate nodes, the "Procedure Failure" is the highest probability contributor with 0.0082 compared to the other three. From the accident case, it was found that there is no legitimate procedure for operating and deploying the equipment for survey operations, such as the distance between the seabed and equipment and the procedure for towing, deploying, and lifting the survey equipment. From the BN, it also can be stated that human error has the minimum effect on the survey equipment loss since most of the personnel that operate the equipment have been certified and trained.

3.3.1 Model Validation

Model validation aims to verify whether the network satisfies real-world conditions [30]. In this study, [5],[31], and [32] conducted the three-axiom model validation.

- A specific change in the prior probabilities of each parent node should result in variance in the child node's posterior probabilities.
- The effect of specific changes in the parent node's prior probability on the child node should be consistent.
- If both a and b affect a child node, the probability influence if a and b happen always be greater than the influence level of each node [33]

Since the OR gate rules are applied for axiom three if the "Yes" states occur on one node, the probability of the target nodes should be 100%; therefore, axiom three is not applicable in this study.

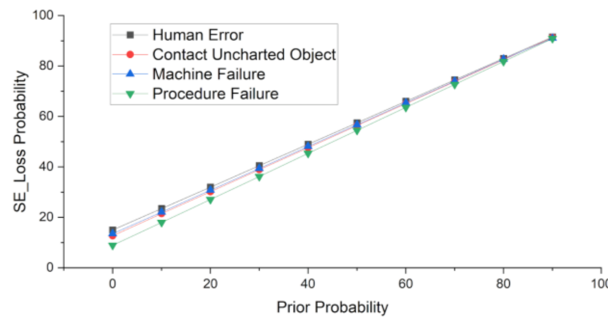

Figure 7. The Probability of Survey Equipment Loss with the variance of the prior probability of its parent nodes

Figure 7 shows the validation results of the change in the posterior probability of the target nodes "Survey Equipment Loss" due to the increasing number of the prior probabilities of the Intermediate nodes. The posterior probability of the target node as a child node increases consistently with the higher number of prior probabilities from the intermediate nodes. Consequently, the model fulfils the requirement for axiom two.

Table 3 shows the validation test for the four nodes from the intermediate level that were analysed. When the probabilities from each intermediate node were increased from 10% to 20%, the probability of intermediate nodes "Human Error," "Contact with Uncharted Object," "Machine Failure," and "Procedure Failure" increased to 32%, 30.2%, 30.8%, and 27.1%, respectively. Therefore, the BN model satisfies the axiom.

Table 3. The increased probability of Survey Equipment Loss from various Intermediate nodes.

	Probability of Survey Equipment Loss	
Intermediate Node Probability	**10%**	**20%**
Human Error	23.5%	32%
Contact with Uncharted Object	21.5%	30.2
Machine Failure	22.1%	30.8%
Procedure Failure	18%	27.1%

3.3.2 Probability Updating

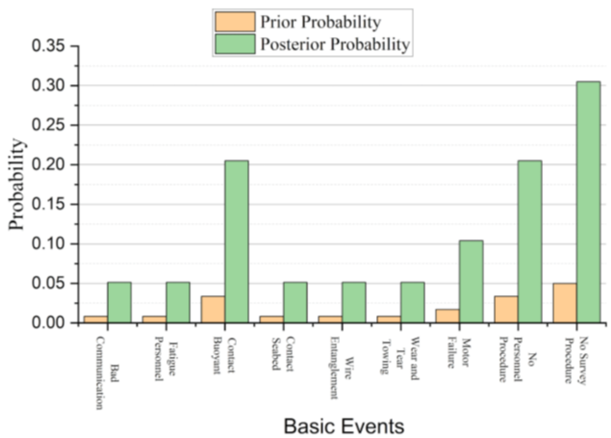

Figure 8. The Comparison Between Prior and Posterior Probability of Basic Events

The probability updating introduces the backward inference from the target nodes into the Basic events. The purpose is to analyse which nodes have a more significant influence when the evidence node happens. The Survey Equipment Loss was settled, as evidenced in this probability updating calculation. Prior probability is obtained from the FTA, while posterior probability is the probability after the target nodes are set as evidence nodes. Figure 8 depicts the difference between the prior and posterior probability of the Basic events. The posterior probability is considered much greater than the priors on every Basic event. The essential event of "No Survey Procedure" is the Basic factor influencing the Survey Equipment with the probability of 0.305.

3.3.3 Sensitivity Analysis

A sensitivity analysis was performed in this study to test the model and identify how each factor is sensitive to the fluctuation of the other factors. The analysis was conducted on the target node “Survey Equipment Loss” by NETICA software. The sensitivity analysis results shown in Table 4 reveal that it is similar to probability updating and model validation. The “Procedure Failure” with 0.245 mutual information is the most sensitive node to the accident of “Survey Equipment Loss” followed by “No Survey Procedure” (0.149) and “Contact with Uncharted Object” (0.116).

Table 4. Sensitivity analysis of the “Survey Equipment Loss” node

Nodes	Mutual Information	Percent
Survey Equipment Loss	0.64349	100
Procedure Failure	0.24504	38.1
No Survey Procedure	0.14097	21.9
Contact with Uncharted Object	0.11599	18
Contact with Buoyant Object	0.0922	14.3
No Personnel Procedure	0.0922	14.3
Machine Failure	0.09175	14.3
Motor Failure	0.04547	7.07
Human Error	0.04473	6.95
Wear and Tear of Towing	0.02218	3.45
Wire Entanglement	0.02218	3.45
Contact with Seabed	0.02218	3.45
Fatigue of Personnel	0.02218	3.45
Bad Communication	0.02218	3.45

3.3.4 Reducing the Probability of Top Event

Prevention and mitigation measures are crucial for eliminating or reducing the probability of the top event, "Survey Equipment Loss," occurring. This study provides several options that will be useful for marine survey companies, Institutions, and Authorities to arrange and plan the risk control option. The analysis was conducted by altering the prior probabilities to zero, assuming nodes on the non-occurrence condition. The first option is to provide a legitimate procedure for survey operation and personnel working hour procedure and improve navigational quality of mapping the survey area for any uncharted objects. These options were assumed based on the three highest values of the sensitivity analysis. The second option is to provide the procedure without improving navigational clearance. The third is eliminating human and machine errors that can influence the accident to occur.

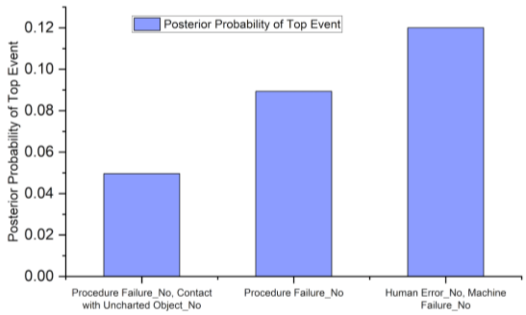

Figure 9. The Posterior Probability of Several Prevention Options

Figure 9 shows the posterior probability of the "Survey Equipment Loss" after applying the prevention options. Option one is the most successful method, reducing the accident probability by 11.44%. In contrast, option three, which involves increasing human error and conducting maintenance of the machine and equipment failure, is the least effective technique, only reducing the probability by 5%.

4. DISCUSSION

This study shows that the integration process from FTA to the Bayesian Network can be done if the data is sufficient. The FTA data is already in the form of an 'AND' Gate or 'OR' Gate with flow levels according to qualitative analysis complemented by the frequency of occurrence data that shows probabilities estimation based on quantitative analysis. Both have been done in previous papers [2], so the FT structure's events were translated into the BN structure's nodes, and conditional probabilities in the BN were constructed via logical gates in the FT structure. Following previous research conducted by [4],[5],[7], which proves that FTA can be developed into a BN if it has sufficient data,

The BN and FTA results are slightly different based on the work done. The difference comes from calculating new probabilities derived from model validation and probability updates based on sensitivity analysis. An adjustment process with the development of data and information is carried out to convert FT into BN, where the number of Basic events is reduced as a probability consideration. This consideration resulted in four intermediate nodes and nine root nodes. In general, the model satisfies both validation methods using axioms. Furthermore, the results show that all posterior probabilities of Basic events (probability after BN) are higher than those of FTA. This process is one of the advantages of the BN method, which can determine the probability of Basic events if the top event occurs.

Contrary to the FTA of survey equipment lost, the BN indicate that the human error factor was the node with the smallest value. By examining the root nodes, it can be seen that bad communication and fatigue from personnel have minimal effect. Therefore, the factors of equipment loss due to fatigue and poor communication can be ignored in the mitigation and prevention processes. However, it should be underlined that the case of human factors having no effect only occurs in cases where all personnel are professional and well-trained.

The findings of this paper may differ from those of other studies due to the need for more data variation. This study is based on a case at the Baruna Jaya Research Vessel. Therefore, what happens in other organisations or ships may differ based on historical data and the root cause of the failure. If the additional data can be obtained from another Institution or Survey company, the results will be more general and can be applied to similar marine survey activities. Despite that, the nature of this study only provides an overview and steps for applying Bayesian networks to marine survey activities to improve their safety.

5. CONCLUSIONS

Accidents and losses in marine surveying activities range from Man Overboard, damaged survey equipment, lost survey equipment, fire, and even fatality. In this study, a previous study that used FSA (Formal Safety Assessment), with the help of FTA, in a risk assessment with a Bayesian network has been developed. Based on the previous study, this study will focus on the most frequent top event, the Loss of Survey Equipment. The previously made FTA was then integrated into a BN so that four intermediate nodes and nine root nodes were found. BN was created with the help of the NETICA application. The additional input given to the child nodes is CPT. The CPT value still refers to the previous FTA because the expert opinion is unavailable. The posterior probability result of the BN model for Survey equipment loss is 0.0164. This BN model was validated and found to fulfil axioms two and one. The probability is then updated by backward inference, so it is found that "No Survey Procedure" is the Basic factor that influences the survey equipment, with a probability of 0.305. The final stage is to analyse the model's sensitivity to identify how each factor is sensitive to the fluctuation of the other factors. The results of sensitivity analysis reveal that similar to probability updating and model validation, the "Procedure Failure" with 0.245 mutual information is the most sensitive node to the accident of "Survey Equipment Loss" followed by "No Survey Procedure" (0.149), and "Contact with Uncharted Object" (0.116). The top contributor to accidents is different from the FTA analysis from the previous study. In addition to the analysis, the technique to reduce the probability of the top event is suggested. According to the sensitivity analysis, the best solution is to provide a legitimate procedure for survey operation and personnel working hour procedure and improve the navigational quality of mapping the survey area for any uncharted objects. This method is expected to reduce the probability of accidents by 11.44%.

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