Risk assessment of Arctic drilling waste management operations based on Bayesian networks

Y.Z. Ayele, J. Barabady,
[1]Department of Engineering and Safety, UiT The Arctic University of Norway, Tromsø, Norway

E.L. Droguett
Center for Reliability and Risk, Mechanical Engineering Department, University of Maryland, College Park, MD, USA

1. INTRODUCTION

Oil and gas producers continue to push offshore projects into the arduous and colder Arctic frontiers, driven primarily by the need to secure future oil and gas reserves [1]. However, offshore Arctic projects have a high degree of technical and social complexity. The technological challenges of drilling at remote location coupled with the extreme weather conditions makes the operation of drilling waste handling in this environment very demanding and risky [2]. Furthermore, due to the sensitive environment to disruption, on one hand, but harsh and unforgiving on the other, the environmental impacts as a result of inappropriate handling of the drilling waste can take longer to heal and cost more to remediate [3, 4].

The competence to reduce the adverse impacts of unwanted events during the drilling waste handling activities depends in part upon the effectiveness of our rigorous safety plan and clear understanding of the effect of the Arctic operating environment on the system [5]. In addition, to ensure an environmentally sound and economically feasible waste handling system, identification and assessment of the peculiar Arctic risk influencing factors (RIF's) play a crucial role [6, 7]. The main goal is to manage the major risk elements related to the drilling waste handling activities and prevent the pollution of the Arctic marine environment. The other focus is to assess whether or not the level of risk is acceptable (tolerable) as per the statutory legislations and the company risk acceptance criteria.

The application of Bayesian Network (BN) to risk assessment and decision-making in the offshore operation, are getting popularity and have been discussed in several literatures [8]. For instance, Aven and Rettedal [9] proposed a "fully Bayesian approach" for quantifying the major risks in offshore industry, with a focus on observable quantities and use of subjective probabilities. For assessing and quantifying ecological risks in catchment management, Pollino, et al. [10] developed a methodology by using parameterization and evaluation of a Bayesian network. Lee and Lee [11] proposed probabilistic risk assessment model, for evaluating waste disposal options, by connecting the results of probabilistic inference from the Bayesian network with the consequence evaluation.

However, most of the BN based risk models used in offshore industries are developed for off-the-shelf systems, for non-Arctic offshore operation. Further, the available models have been mainly focused in identifying the hazard and quantifying the risk and lack particularly the consideration of the effect of the operating environment on the risk profile. This is considered as a big drawback, especially in a complex operational environment such as the Arctic region [12, 13]. Typically, the hazards and risks associated with Arctic offshore drilling waste handling operations will differ vastly depending on the ice conditions, negative sea and air temperature, and factors affecting visibility such as heavy fog, blowing snow, and lengthy period of darkness [2, 5, 7, 14]. In the Barents Sea – part of the Norwegian Arctic, weather related factors are estimated to cause more than 90 percent of fatal accidents during crane lifting, including drilling waste container lifting [15]. Further, in some areas of the Arctic region, environmental and climatic factors causes nearly 65 – 70 percent of extra costs during drilling and drilling waste handling activities [16]. Hence, offshore drilling waste handling strategies, in the hostile Arctic region, must take account of the unique risks due to icing, ice loading, remoteness, very low temperatures, wind-chill effects, and etc., in addition to the ‘conventional’ or ‘tolerable’ risks [1, 7, 13].

Hence, to consider the complex and fast-changing nature of the Arctic during risk assessment, this paper proposes a Bayesian Network based risk model (BN-B-RM) for Arctic drilling waste handling practices. Bayesian belief networks are particularly useful in risk analysis as they do not require complete knowledge of the relation between causes and effects [8]. The paper seeks to determine the probabilities of the potential hazards, risks, and consequences of the unwanted events by considering the peculiar Arctic risk influencing factors (RIF’s) such as snowstorms, atmospheric and sea spray icing, negative air and sea temperature. The rest of the paper is organized as follows: Section 2 presents the basic concepts of static and hybrid Bayesian network. Section 3 investigates the unique Arctic risk influencing factors that affects the handling of drilling wastes in the Arctic region. Section 4 presents the proposed Bayesian Network based risk assessment model (BN-B-RM). Section 5 illustrates Arctic drilling waste handling scenario case study and Secion 6 provides the conclusion.

2. STATIC AND HYBRID BAYESIAN NETWORK – BASIC CONCEPTS

Static Bayesian networks (BN) are a probabilistic graphical model consists of a qualitative part, a directed acyclic graph (DAG), where the nodes represent random variables and a quantitative part, a set of conditional probability functions [17]. The nodes can be discrete or continuous, and may or may not be observable and the arcs (from parent to child) represent the conditional dependencies or the cause-effect relationships among the variables [17]. Parent nodes are nodes with links pointing towards the child nodes. Nodes that are not connected represent variables which are conditionally independent of each other. Further, when BN contain discrete and continuous variables (nodes) generally it is called a hybrid Bayesian network (HBN).

Figure 1 shows the basic qualitative part of a Bayesian network, for Arctic drilling waste handling practices, and illustrates the conditional independencies and dependencies of the main random variables. The variables considered, in this paper, are: risk influencing factors (RIF’s), drilling waste handling systems or component, health risks, safety risks, and environmental risks. For instance, a shale shaker (a component of waste handling system) ceases to function or fail when there is freezing temperature and ice accretions (which are the RIF’s). Then, the shale shaker failure may lead to drilling waste chemical spills (i.e. environmental hazards) and may have many different occupational hazards, i.e. health and safety hazards.

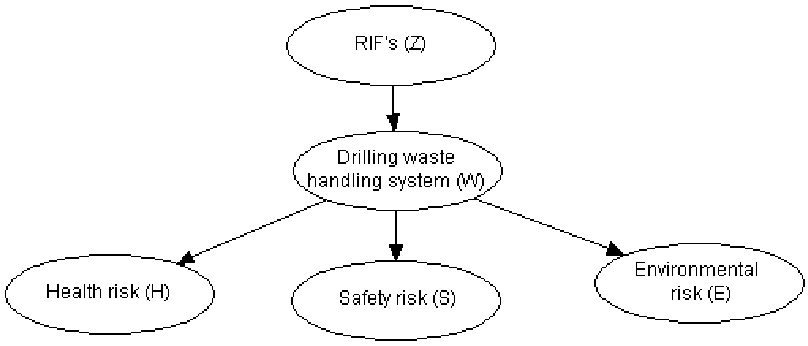

Figure 1. Basic Bayesian Network representing conditional dependencies

- *Risk influencing factors (designated as Z) includes: negative air and sea temperature, severe snowstorms, wind-chill effect, atmospheric and sea spray icing, icicles, visibility reducing factors, and polar lows.*
- *Drilling waste handling system (W) comprises offshore discharge, offshore re-injection, and skip- and ship.*
- *Health risk (H) is a chance or probability that a waste handling worker will experience health effect due to direct and indirect effect of RIF's.*
- *Safety risk (S) is a likelihood that a waste handling personnel experience physical injures due to RIF's effect and system failures.*
- *Environmental risk (E) is a chance or likelihood of the pollution of the Arctic marine environment because of accident. Mainly, due to indirect effect of the RIF's.*

The *quantitativ*e part of a Bayesian network structure can be represented as a product of conditional distribution of each node X_i given its parents nodes $parents\ (X_i)$. Each node is described by the conditional probability function of that variable. Then, the joint probability distributions, considering *discrete* variable, can generally be expressed as:

$$\Pr(X_1, X_2, ..., X_n) = \prod_i^n \Pr(X_i \mid parents(X_i)) \tag{1}$$

Where:

- $\Pr\{X_i \mid parents(X_i)\}$ is the conditional distribution mass function of node X_i .

In general, for the case of drilling waste handling operations, the probability of waste handling system or component failure (*W)* (i.e. a child node) is conditionally dependent on the RIF's (*Z*) (i.e. a parent node). In addition, the probability of the health risks (*H*), the safety risks (*S*) and the environmental risks (*E*) are conditionally independent to each other, given the system or component failures (*W*) and the RIF's (*Z*). However, this doesn't mean that *H*, *S* and *E* are totally independent. Hence, for the given static BN structure (i.e. Figure 1), assuming that all variables are *discrete*, the joint probability function, as a product of conditional probabilities then can be expressed as:

$$P(Z,W,H,S,E) = P(Z)P(W \mid Z)P(H \mid W)P(S \mid W)P(E \mid W) \tag{2}$$

where:

- *P(Z)* is the marginal probability function of *Z*, and
- *P(W|Z)*, *P(H|W)*, *P(S|W)*, and *P(E|W)* are conditional probability function of *W*, *H*, *S*, and *E*, respectively. A detailed explanation of the marginal and conditional probabilities is included in Section 4.

3. RISK INFLUENCING FACTORS (RIFs) IN THE ARCTIC

Aven [18] defines risk influencing factors (RIF's) as factors that potentially affect the barriers and barrier performance. In general term a barrier is a measure which is put in to prevent the release of a hazard or the occurrence of a top event once the hazard is released, and barriers may be physical or non-physical [6]. In the Arctic offshore dilling waste handling operations, the predominant RIF's are the climatic and environmental conditions. The predominant RIF’s in the Arctic region are identified and briefly discussed below.

3.1 Negative Temperature

Negative temperatures reduce the performance of drilling waste handling system, ranging from primary shale shaker and mud cleaner to screw conveyor. In addition, for most drilling activity in the Arctic region, wells are recommended to be drilled with water-based drilling fluids. To meet the drilling-performance demands, thus the water must be kept from freezing or the system ceases to function [19]. In worst case, the primary shale shaker, mud cleaner, screw conveyor, and the vacuum pump can be destroyed by the pressure of ice expansion. Moreover, the viscosity of water increases significantly as temperature falls. Higher viscosity mean slower flow and mixing rates within the waste handling systems, and consequently increased the overall energy demand [19].

3.2 Wind-chill effect

The wind-chill effect is the perceived decrease in air temperature felt by the body on exposed skin due to the flow of air [13]. In general, the effect of the wind-chill will increase with high wind speed and in the worst case it can be expected to have outdoor working restrictions, for waste handling personnel, for some specified period of time [20]. Lengthy period of exposure to cold wind without adequate protection can lead frostbite, hypothermia, and in worst case it can cause freezing to death [20].

3.3 Icing, Snowstorm, Icicles and Polar lows

Figure 2 illustrates the typical icing phenomena in the Arctic regions. Icing has various potential hazards, such as slipping hazards and disabling winches and cranes by locking cables in continuous hard ice [21]. These locking effects on the crane have high-level potential hazards, and can significantly affect the waste handling activities. Further, the falling ice can cause fractures, bruises, lacerations, dislocations, as well as permanent injuries for personnel’s working at the waste handling site [22].

Figure 2. Typical icing phenomena in Arctic (Photo courtesy of ice engineering solutions)

Moreover, significant amount of snowstorms restricts access to drilling waste handling equipment and instruments and hinders the process of collecting, transporting, and treatment of the drilling waste. Further, working in the snowstorm has the potential to cause an increased incidences and injuries, such as hypothermia, infections from frost bite, and increases the risk to persons with known asthma or cardiovascular disease [20].

Furthermore, icicles can pose potential safety hazards for personnel’s and structural hazards for waste handling equipment’s. An icicle is a spike of ice formed when water dripping or falling from an object freezes; and it normally has a very sharp edge. When icicles falls as a result of change in air temperature or heavy ice deposit, it can cause serious injury for personnel involved in the waste handling activities or damages the near-by waste handling equipment's.

Polar lows are the other RIF and generally they are a phenomenon formed when cold air flow over warmer water and leads to an atmospheric instability [23]. In the Barents Sea, polar lows occur frequently up to 15 times monthly and generally in the period from October to May [23]. They are known to possess heavy snowstorms and icing as their typical feature. These typical characteristics are source of various potential hazards, during waste handling activities.

3.4 Visibility reducing factors

These factors include heavy fog, blowing snow, lengthy period of darkness; and they are the main contributors for the poor visibility during offshore waste handling activities in the Barents Sea. Poor visibility are the biggest contributors to the overall risk of fatal accidents in the Arctic offshore operations [24].

4. BAYESIAN NETWORK BASED RISK ASSESSMENT MODEL (BN-B-RM)

A step-by-step approach for implementing the Bayesian network based risk assessment, for Arctic drilling waste handling operations, is provided in Figure 2. The proposed methodology has 7-steps and it starts with identifying the predominant risk influencing factors (RIF's) under Arctic conditions.

4.1 Step 1: Identify the peculiar risk influencing factors (RIFs) in the Arctic region

The purpose of this step is to study and investigate the effect of the predominant RIF's, which are induced by the unique Arctic operating environment, on the drilling waste handling operations. Further, the interaction of the RIF's, the dependability of these factors on various variables, their negative synergy effect on the drilling waste handling systems needs to be assessed and specified [21, 25, 26].

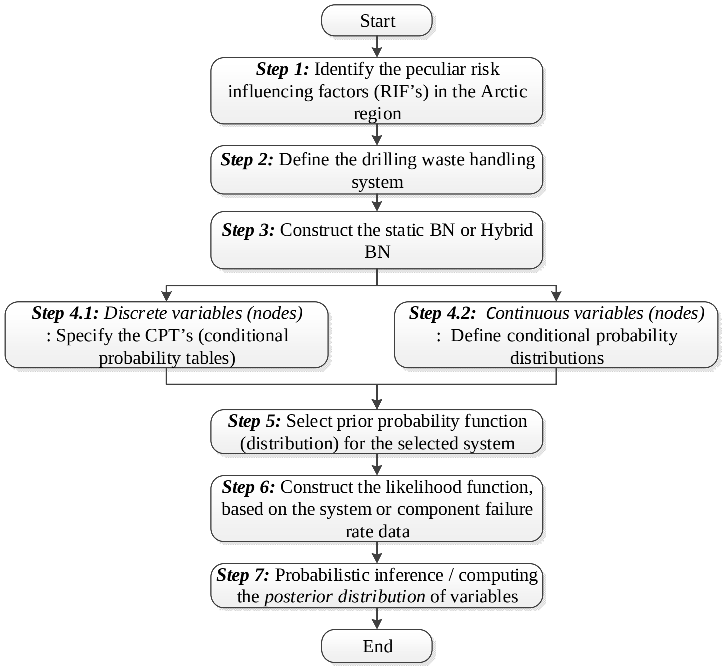

Figure 2. Proposed Bayesian network based risk assessment model (BN-B-RM) for Arctic drilling waste handling operations.

4.2 Step 2: Define the drilling waste handling system

In this step, suitable waste handling system should be defined, by considering the operating environment of the Arctic region. In general, the most common drilling waste handling systems in the Arctic region are: *i)* offshore discharge (i.e. treating and discharging the drilling wastes to the ocean (sea)), *ii)* offshore re-injection (i.e. re-injecting the drilling waste offshore both in a dedicated reinjection well and/or in a dry (dead) well), and *iii)* skip- and ship (i.e. hauling the drilling waste back to shore for further treatment and disposal) [4].

4.3 Step 3: Construct the static BN or Hybrid BN

The aim of this step is to build the static BN, which comprises *only* discrete or continuous variables, or hybrid BN, consist of *both* discrete and continuous variables. When deciding on the structure of the network, the key is to focus on the causal relationships between the main variables [27].

4.4 Step 4: Discrete vs continuous variables

After specifying the BN or HBN structure, then the quantification of the relationships between the connected nodes (variables) is the next step.

Step 4.1: Discrete variables (nodes): A discrete variable (node) is one with a well-defined finite set of possible values, called states [28]. For instance, icing (one of the RIF's), taking zero for the absence or one for the presence, during the drilling waste handling operations, can be regarded as a discrete variable. When a variable is discrete, then the CPT's (conditional probability tables) needs to be assigned. That means, for each particular discrete node, all possible combinations of values of those parent nodes needs to be observed; and such combination is called *instantiation* of the parent [27]. In general, for a Boolean network, a variable with *n* parents requires a CPT with 2^{n+1} probabilities [27].

Step 4.2: Continuous variables (nodes): A continuous node (variable) is one which can take on a value between any other two values, such as negative air and sea temperature [28]. In this step, for each continuous node, the conditional probability distributions (CPD's), needs to be defined. Table I illustrates some popular CPD's which can be used to define the continuous node. Sometimes you want to treat a continuous variable as a discrete variable. In such situations, it is possible to break up the total range of the continuous variable into a number of intervals, and commonly this process is known as *discretizing* the variable [28].

Table I. Example of CPD's, adopted from Murphy [29]

Child/Parent	Discrete	Continuous
Discrete	Tabular, noisy-OR, decision tree	Probit, logistic, softmax
Continuous	Conditional Gaussian	Linear Gaussian

4.5 *Step 5: Select prior probability function (distribution) for the selected system or component*

Once the drilling waste handling system or component is defined, then a *prior* probability function or distribution needs to be asserted. This function is the representation of the failure rate of the waste handling system or component; and failure rate is the measure of frequency of system or component failure. The *prior* function describes the probability of *n* or fewer failures during a time interval of (0, *t*), when all RIF's are equal to zero or absent (i.e. ''normal'' operating environment), during waste handling operations. For instance, by assuming that the components fail according to a Poisson process, the probability of *n* or fewer failures, can be estimated by the following equation [30]:

$$P(W) = \sum_{i=0}^{n} \frac{(\lambda t)^n}{n!} \exp(-\lambda t) \tag{3}$$

where:

- *P (W)* is the probability of *n* or fewer failures, and λ is a failure rate of the waste handling component.

4.6 *Step 6: Construct the likelihood function, based on the system or component failure rate data*

After defining the *prior* probability function and observing the RIF's data, then the likelihood function, has to be constructed. Likelihood function generally is the joint probability function (JPF) and it can be expressed as a product of conditional probabilities [31]. Hence, by considering *discrete* time-independent and time-dependent RIF's, the likelihood function of the system failure, based on Glickman and van Dyk [31] approach, can be expressed as follows:

$$L(W \mid z, z(t)) = p(z_1, \ldots z_r, z_1(t), \ldots z_m(t) \mid W) \tag{4}$$

where:

- $z_1, \ldots z_r$ is a set of time-independent RIF's, and
- $z_1(t), \ldots z_m(t)$ is a set of time-dependent RIF's.

Then, by grouping the RIF's into vectors of size $R+M$, Equation (4), can be re-written as follows:

$$L(W \mid z, z(t)) = \prod_{i=1}^{n} p(z_i, z_i(t) \mid W) \tag{5}$$

where:

- n is a vector of size $R+M$.

By following the same approach, the likelihood function of the health, safety, and environmental risk can be estimated. Taking the environmental risk as an example and by considering the *discrete* risk variables, likelihood function of the environmental risk can be expressed as:

$$L(E \mid W) = \prod_{i=1}^{n} p(W_i \mid E) \tag{6}$$

where:

- E is representing the environmental risks, as a result of the waste handling system failure. The same approach can be applied to determine the health and safety risks.

4.7 Step 7: Probabilistic inference/ computing the posterior distribution of variables

Probabilistic inference is the task of computing the probability of each node in BN, according to the most recent RIF's to provide posterior probabilities. The *posterior* distribution combines prior RIF's information with actual observed data from weather forecasting to predict the future potential hazards and/or risks. That means the current information about the RIF's will be used to continuously update the potential hazards relating to the health, safety, and environment. Simply, the distribution describes the probability that the waste handling system will fail, given the predominant RIF's has observed. The posterior distribution of the system or component failure, considering *discrete* RIF's (variables), based on Glickman and van Dyk [31] approach, can be expressed as:

$$P(W \mid z, z(t)) = \frac{P(W)P(W \mid z, z(t))}{\int p(W)\, p(z, z(t) \mid W) d_{\lambda}} \tag{7}$$

By substituting the likelihood function and applying Bayes' theorem, Equation (7) can be re-written as:

$$P(W \mid z, z(t)) = \frac{P(W)L(W \mid z, z(t))}{P(z, z(t))} \propto P(W)L(W \mid z, z(t)) \tag{8}$$

To solve, Equation (7) and (8), we can first multiply the prior distribution by the likelihood, and then determine the marginal constant that forces the expression to integrate to 1 [31].

As we did above, by following the same approach and considering the *discrete* risk variables, the posterior probabilities of the environmental risk can be expressed as:

$$P(E \mid W) = \frac{P(E)P(E \mid W)}{\int p(E)\, p(W \mid E) d_{E}} \tag{9}$$

Afterwards, by employing the likelihood function, Equation (9) can be re-written as:

$$P(E \mid W) = \frac{P(E)L(E \mid W)}{P(W)} \tag{10}$$

Sometimes, it is demanding and cumbersome to collect failure rate data in the Arctic. Such kind of situations can hinder selecting the prior probabilities and constructing the likelihood function. Thus, the other option, in the case of data shortage, is to make use of inference algorithms.

5. AN ILLUSTRATIVE CASE STUDY

To illustrate the proposed model, a shale shaker, which is one of the key components of the offshore discharge waste handling system, is chosen to estimate its conditional probability of failure due to the predominant Arctic RIF's and predict the probability of the environmental risks, in the case of failure of the shale shaker. In general, offshore discharge is a series of pre-treatment of drilling fluid and cutting, and finally disposing the waste into the sea (ocean). As part of these treatment process, the fluid and suspended cuttings are processed on the rig through screens called "shale shakers" to maximize recovery of the mud [32]. The failure of the shale shaker may then lead to stoppage of the overall system and waste handling process. Hence, to estimate the probabilities of the potential risks of the failure of the shale shaker, the proposed approach is implemented.

Simply, our main objective (inquiry) is to determine the unconditional probability of the environmental risk. The main assumptions during estimation of probabilities are: a year-round operational window and there is no winterization or enclosure of the waste handling components to protect the vulnerable areas, and the system is installed in the drilling rig, which operates in the Barents Sea, northern Norway. The system failures due to other factors, such as failures due to maintenance error, design defect, and operating procedures are ignored.

The *first* step is to investigate and identify the predominant RIF's in the Barents Sea. The recognized RIFs are sorted in monthly order (i.e. from January to December) and a sample of the data is shown in Table II. These RIFs (except the temperature) were scored zero or one, for the absence or presence during drilling waste handling activities. The minimum temperature (ºC) data of the study were collected over a period of 10 years (from 2005 – 2014) on the monthly basis, from Norwegian Meteorological Institute database. The temperatures are observed in the Hopen Island weather station, located at 76º33'N and 25º7'E, northern Norway. Figure 4 shows the monthly minimum temperature profile.

Table II. The predominant risk influencing factors (RIF's) in the Barents Sea

Month	Air temperature (ºC), Z_1	Snowstorm , Z_2	Wind-chill effect, Z_3	Icing		Icicles , Z_5	Visibility reducing factors, Z_6	Polar lows ,Z_7
				Sea spray, Z_{4A}	Atmospheric, Z_{4B}			
January	-14.2	1	1	1	1	1	1	1
February	-11.2	1	1	1	1	1	1	1
March	-14.6	1	1	1	1	0	1	1
April	-12.4	1	1	1	1	0	1	1
May	-3.0	1	1	1	1	0	0	1
June	0.0	1	1	1	1	0	0	0
July	2.2	0	1	0	0	0	0	0
August	2.7	0	1	0	0	0	0	0
September	1.5	1	1	0	0	0	0	0
October	-2.6	1	1	1	1	0	1	1
November	-7.0	1	1	1	1	1	1	1
December	-10.1	1	1	1	1	1	1	1

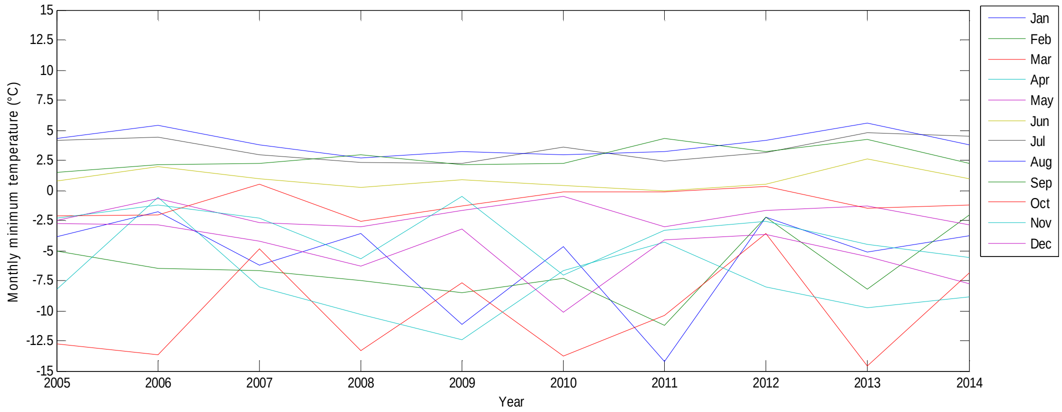

Figure 4. The monthly minimum temperature profile

The *second* step is to define the drilling waste handling system or component. As discussed above, the probability of failure of the shale shakers under Arctic environment will be analysed. In practice, there are two series of shale shakers – primary and secondary, installed in the rig. The primary shakers use coarse screens to remove only the larger drilling cuttings; and secondary shakers use fine mesh screens to remove much smaller particles [33]. For simplification, only primary shakers are considered in our case study.

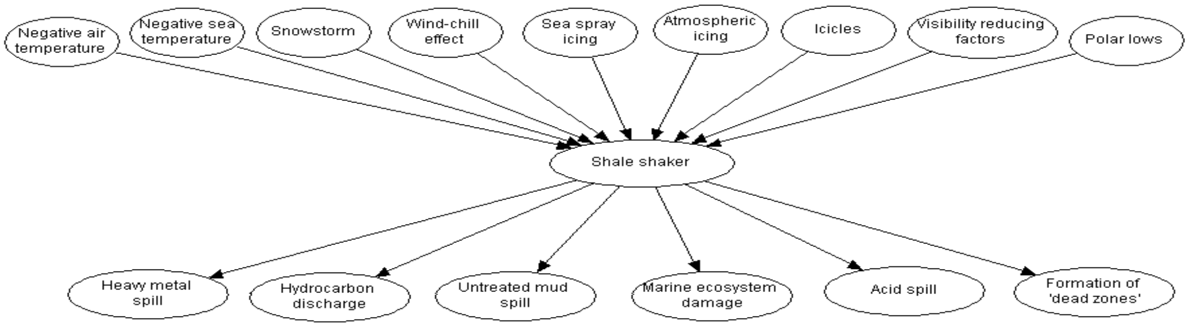

Figure 5. The original HBN fragment

The *third* step is to construct the BN structure. Figure 5 illustrates the original HBN fragment considering the predominant RIF's, the waste handling component (i.e. the shale shaker), and the potential environmental risks – when the shale shaker ceased to function. To simplify estimation of the probabilities, the original HBN is abridged and shown in Figure 6. Atmospheric icing, as a discrete RIF, and air temperature, as a continuous RIF, are considered in the abridged HBN. In addition, marine ecosystem damage is considered as one of the main environmental risks, and is included in the HBN.

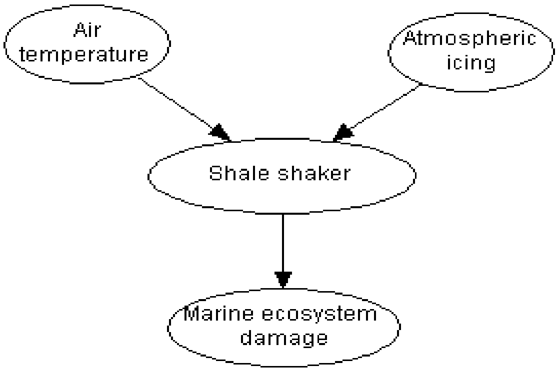

Figure 6. A hybrid Bayesian network

The *fourth* step is to define the state of the nodes (variables) and assign the CPT's. The *discrete* node, which is atmospheric icing (Z_4), is a Boolean node, representing true (*1*) or false (*0*) alternatives. Simply, true/ false means presence/absence of the atmospheric icing, during that specific observation period. Since the atmospheric icing (Z_4) and air temperature (Z_1) are *root nodes* (i.e. node without parents) marginal probabilities need to be assigned. To estimate the marginal probabilities of Z_4, for each month, a direct elicitation technique [27] is considered, where an expert provides a number, such as the probability of observing Z_4 in the month of January is 0.90. In addition, for simplification, the *continuous* node, which is air temperature (Z_1), is *discretized*, and take the values [*Low (0 to -10ºC), Very Low (<-10ºC), and Medium (≥ 0.1 ºC)*]. Then, to determine the probabilities that the Z_1 will be low, $P(Z_1=L)$, very low, $P(Z_1=VL)$ and medium, $P(Z_1=M)$, the raw temperature data are used as an input into a MATLAB probability estimation command. Afterwards, marginal probabilities tables (MPT) are assigned.

Further, the other *discrete* nodes – the shale shaker (W) and marine ecosystem damage (E), are also considered as a Boolean node, representing two states. The shale shaker states are failed (T) or not failed (F); and for marine ecosystem damage, not acceptable (T) or acceptable (F). Thereafter, a CPT has been assigned using a direct elicitation technique. That means the CPT takes the following possible joint values, for each month:

$$\begin{Bmatrix} \langle P(W=T \mid Z_1=T, Z_4=L)\rangle, \langle P(W=T \mid Z_1=T, Z_4=VL)\rangle, \\ \langle P(W=T \mid Z_1=T, Z_4=M)\rangle, \langle P(W=T \mid Z_1=F, Z_4=L)\rangle, \\ \langle P(W=T \mid Z_1=F, Z_4=VL)\rangle, \langle P(W=T \mid Z_1=F, Z_4=M)\rangle, \\ \langle P(E=T \mid W=T\rangle \end{Bmatrix} \tag{11}$$

For instance, $P(W=T \mid Z_1=T, Z_4=L)$ describes the probability that the shale shaker will fail given icing condition and low temperature. The MPT and CPT results are presented in Table III.

To proceed with step 5 and 6, failure rate data need to be available. However, in the Arctic region, there is a shortage of valid failure rate data [12, 13]. Hence, in the case of shortage of data, the other option is to make use of inference algorithms. As mentioned above, our inquiry is to get the *posterior* probability of environmental risk, P (E), i.e. the probability of environmental risk being not acceptable. Then, to determine, $P(E)$ the following *inference algorithm* can be used:

$$P(E) = \sum_{Z_1, Z_4, W} P(E \mid W) P(W \mid Z_1, Z_4) P(Z_1) P(Z_4) \tag{12}$$

Table III. MPT for icing & air temperature and CPT for system failure and marine ecosystem damage

Month	Jan.	Feb.	Mar	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.

Marginal probabilities												
$P(Z_4=T)$	0.90	0.90	0.90	0.80	0.80	0.50	0.01	0.01	0.01	0.85	0.95	0.95
$P(Z_4=F)$	0.10	0.10	0.10	0.20	0.20	0.50	0.99	0.99	0.99	0.15	0.05	0.05
$P(Z_1=L)$	0.80	0.90	0.40	0.80	0.80	0.10	0.10	0.10	0.10	0.8	0.85	0.90
$P(Z_1=VL)$	0.20	0.10	0.60	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.15	0.10
$P(Z_1=M)$	0.00	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.20	0.00	0.00
Conditional probabilities												
$P(W=T\|Z_4=T, Z_1=L)$	0.85	0.85	0.60	0.65	0.65	0.35	0.05	0.05	0.05	0.70	0.80	0.85
$P(W=F\|Z_4=T, Z_1=L)$	0.15	0.15	0.40	0.35	0.35	0.65	0.95	0.95	0.95	0.30	0.20	0.15
$P(W=T\|Z_4=T, Z_1=VL)$	0.55	0.40	0.85	0.50	0.50	0.25	0.05	0.05	0.05	0.50	0.30	0.30
$P(W=F\|Z_4=T, Z_1=VL)$	0.45	0.60	0.15	0.50	0.50	0.75	0.95	0.95	0.95	0.50	0.70	0.70
$P(W=T\|Z_4=T, Z_1=M)$	0.40	0.40	0.40	0.35	0.35	0.30	0.01	0.01	0.01	0.35	0.40	0.40
$P(W=F\|Z_4=T, Z_1=M)$	0.60	0.60	0.60	0.65	0.65	0.70	0.99	0.99	0.99	0.65	0.60	0.60
$P(W=T\|Z_4=F, Z_1=L)$	0.35	0.40	0.15	0.30	0.30	0.05	0.05	0.05	0.05	0.15	0.30	0.30
$P(W=F\|Z_4=F, Z_1=L)$	0.65	0.60	0.85	0.70	0.70	0.95	0.95	0.95	0.95	0.85	0.70	0.70
$P(W=T\|Z_4=F, Z_1=VL)$	0.15	0.05	0.40	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.15	0.10
$P(W=F\|Z_4=F, Z_1=VL)$	0.85	0.95	0.60	0.80	0.80	1.00	1.00	1.00	1.00	1.00	0.85	0.90
$P(W=T\|Z_4=F, Z_1=M)$	0.05	0.05	0.05	0.05	0.05	0.01	0.01	0.01	0.01	0.10	0.05	0.05
$P(W=F\|Z_4=F, Z_1=M)$	0.95	0.95	0.95	0.95	0.95	0.99	0.99	0.99	0.99	0.90	0.95	0.95
$P(E=T\|W=T)$	0.47	0.43	0.49	0.41	0.41	0.19	0.03	0.03	0.03	0.36	0.40	0.40
$P(E=F\|W=T)$	0.53	0.57	0.51	0.59	0.59	0.81	0.97	0.97	0.97	0.64	0.60	0.60

Table IV presents the estimated *posterior* probability of environmental risk, for each month. The maximum environmental risk, i.e. the worst marine ecosystem damage can be anticipated during the month of January to March with $P(E)$ equals to 0.35. That means during these months, the probability of system (shale shaker) failure will be higher due to the high probability of icing formation and low and very low temperature conditions. Thus, the system failure consequently leads to higher environmental risks. Figure 7 further illustrates the posterior environmental risks (marine ecosystem damage) for each operating months. For instance, $P_1(E)$, for the month of January, can be calculated as follows (note that the MP and CP can be read from Table III):

$$P_1(E) = P(E=T\,|\,W=T) * P(W=T\,|\,Z_4=T, Z_1=L) * P(Z_4=T) * P(Z_1=L) \tag{13}$$

$$P_1(E) = 0.47 * 0.85 * 0.80 * 0.90 = 0.29 \tag{14}$$

Table IV. Posterior environmental risk probabilities

	Month	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
Unconditional prob.	$P_1(E)$	0.29	0.30	0.11	0.17	0.17	0.00	0.00	0.00	0.00	0.17	0.26	0.29
	$P_2(E)$	0.05	0.02	0.22	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.02	0.01
	$P_3(E)$	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.02	0.00	0.00
	$P_4(E)$	0.01	0.02	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.01	0.01	0.01
	$P_5(E)$	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

$P_6(E)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$P(E)= \sum P_i(E)$	**0.35**	**0.34**	**0.35**	0.23	0.23	0.03	0.00	0.00	0.00	0.20	0.28	0.31

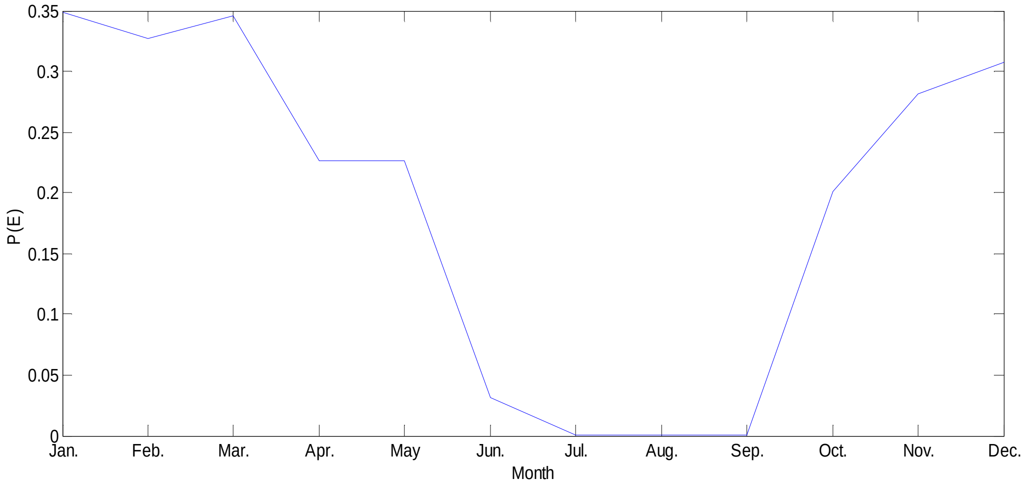

Figure 7. *P(E)* vs Operating months

6. CONCLUDING REMARKS

The sensitive environment, the remoteness, and the demanding physical conditions of the Arctic create special challenges for drilling waste handling activities. Further, drilling waste treatment facilities are not readily available in the region. In the absence of drilling waste treatment and disposal facilities in this fragile ecosystem, a major concern could be the assurance of the fulfilment of health, safety, environment, and quality (HSEQ) requirements. To reduce the overall environmental footprint and ensure the rigorous HSEQ requirements in the Arctic, prior to initiating drilling operations, attention should be paid to prediction of probabilities of the potential HSE risks, and consequences of waste handling system failures.

The proposed Bayesian network based risk assessment model (BN-B-RM) can help the user to investigate the probability of HSE risks as well as system failure, by considering the peculiar risk influencing factors which are caused by the operating environment of the Arctic region. The step-by-step approach is outlined, to facilitate the prediction of the HSE risks. By employing the proposed BN-B-RM approach, the risk barriers and mitigation measures can be allocated based on the level of estimated risk. The illustrative case study shows that the peculiar Arctic risk influencing factors has significant impact, especially during winter period, in the overall risk picture, in the course of drilling waste handling practices in the region.

ACKNOWLEDGEMENTS

The work has been funded by The Research Council of Norway and ENI Norge AS through the EWMA (Environmental Waste Management) project, facilitated at UiT The Arctic University of Norway. The financial support is gratefully acknowledged.

We would like to thank the Center for Reliability and Risk, University of Maryland, College Park, for making Mr. Yonas's stay as a research scholar possible.

7. REFERENCES

[1] A. S. Martin, "Deeper and Colder: The Impacts and Risks of De epwater and Arctic Hydrocarbon Development," Sustainalytics. 2012.

[2] T. Svensen and K. Taugbol, "Drilling Waste Handling in Challenging Offshore Operations," in *SPE Arctic and Extreme Environments Conference and Exhibition*, 2011.

[3] D. F. Boesch and N. N. Rabalais, *Long-term environmental effects of offshore oil and gas development*: CRC Press, 2003.

[4] Y. Z. Ayele, A. Barabadi, and J. Barabady, "Drilling waste handling and management in the High North," in *Industrial Engineering and Engineering Management (IEEM), 2013 IEEE International Conference on*, 2013, pp. 673-678.

[5] J. R. Hasle, U. Kjellén, and O. Haugerud, "Decision on oil and gas exploration in an Arctic area: Case study from the Norwegian Barents Sea," *Safety Science,* vol. 47, pp. 832-842, 2009.

[6] T. Aven, S. Hauge, S. Sklet, and J. E. Vinnem, "Methodology for incorporating human and organizational factors in risk analysis for offshore installations," *International Journal of Materials & Structural Reliability,* vol. 4, pp. 1-14, 2006.

[7] K. Øien, "Remote operation in environmentally sensitive areas: development of early warning indicators," *Journal of Risk Research,* vol. 16, pp. 323-336, 2013.

[8] W. Røed, A. Mosleh, J. E. Vinnem, and T. Aven, "On the use of the hybrid causal logic method in offshore risk analysis," *Reliability Engineering & System Safety,* vol. 94, pp. 445-455, 2009.

[9] T. Aven and W. Rettedal, "Bayesian frameworks for integrating QRA and SRA methods," *Structural safety,* vol. 20, pp. 155-165, 1998.

[10] C. A. Pollino, O. Woodberry, A. Nicholson, K. Korb, and B. T. Hart, "Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment," *Environmental Modelling & Software,* vol. 22, pp. 1140-1152, 2007.

[11] C.-J. Lee and K. J. Lee, "Application of Bayesian network to the probabilistic risk assessment of nuclear waste disposal," *Reliability Engineering & System Safety,* vol. 91, pp. 515-532, 2006.

[12] A. Barabadi, O. T. Gudmestad, and J. Barabady, "RAMS data collection under Arctic conditions," *Reliability Engineering & System Safety,* vol. 135, pp. 92-99, 2015.

[13] Y. Z. Ayele, A. Barabadi, and J. Barabady, "A risk-based approach to manage the Occupational Hazards in the Arctic drilling waste handling practices," in *Safety and Reliability: Methodology and Applications - Proceedings of the European Safety and Reliability Conference, ESREL 2014*, 2015, pp. 1329-1334.

[14] Y. Z. Ayele, A. Barabadi, and J. Barabady, "Effectiveness Assessment for Waste Management Decision-support in the Arctic Drilling. ," in *IEEE International Conference on Industrial Engineering and Engineering Management*, 2014

[15] S. Røsnes, "Risk Indicator Model - Appliaction to Dropped Loads due to Crane Operations," M.Sc., University of Stavanger, 2011.

[16] A. Martin, "Drilling waste handling," 2004.

[17] D. Marquez, M. Neil, and N. Fenton, "Improved reliability modeling using Bayesian networks and dynamic discretization," *Reliability Engineering & System Safety,* vol. 95, pp. 412-425, 2010.

[18] T. Aven, *Risk Analysis - Assessing Uncertainties Beyond Expected Values and Probabilities*. West Sussex: John Wiley & Sons Ltd., 2008.

[19] D. R. Freitag and T. T. McFadden, *Introduction to cold regions engineering*: Asce Press, 1997.

[20] T. Risikko, T. M. Mäkinen, A. Påsche, L. Toivonen, and J. Hassi, "A model for managing cold-related health and safety risks at workplaces," *International journal of circumpolar health,* vol. 62, 2003.

[21] C. C. Ryerson, "Ice protection of offshore platforms," *Cold Regions Science and Technology,* vol. 65, pp. 97-110, 2011.

[22] T. Haavasoja, V. Haavisto, M. J. Turunen, P. Nylander, and Y. Pilli-Sihvola, "A field trial of vehicle grip compared to RWS data," *Vaisala News,* vol. 159, pp. 28-30, 2002.

[23] G. Noer, Ø. Saetra, T. Lien, and Y. Gusdal, "A climatological study of polar lows in the Nordic Seas," *Quarterly Journal of the Royal Meteorological Society,* vol. 137, pp. 1762-1772, 2011.

[24] F. A. C. Nascimento, A. Majumdar, W. Y. Ochieng, and S. R. Jarvis, "A multistage multinational triangulation approach to hazard identification in night-time offshore helicopter operations," *Reliability Engineering & System Safety,* vol. 108, pp. 142-153, 2012.

[25] T. Cameron. (2013, 12.12). *Working in Cold Environments: Thermal Comfort Through Design & Control*. Available: http://www.safetyrisk.net/working-in-cold-environments

[26] K. F. Jones and E. L. Andreas, "Sea spray concentrations and the icing of fixed offshore structures," *Quarterly Journal of the Royal Meteorological Society*, vol. 138, pp. 131-144, 2012.

[27] K. B. Korb and A. E. Nicholson, *Bayesian artificial intelligence*: CRC press, 2010.

[28] Norsys. (2015, 02/20). *Discrete vs. Continuous*. Available: http://www.norsys.com/WebHelp/NETICA/X_CY_discrete_vs_continuous.htm

[29] K. P. Murphy, "A variational approximation for Bayesian networks with discrete and continuous latent variables," in *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, 1999, pp. 457-466.

[30] J. Hassan, F. Khan, and M. Hasan, "A risk-based approach to manage non-repairable spare parts inventory," *Journal of Quality in Maintenance Engineering*, vol. 18, pp. 344-362, 2012.

[31] M. E. Glickman and D. A. van Dyk, "Basic Bayesian Methods," in *Topics in Biostatistics*, ed: Springer, 2007, pp. 319-338.

[32] GEM, "Exploration drilling in the Faroe-Shetland channel: Environmental impact assessment," 2001.

[33] DOE. (2000, 12.05). *The Drilling Waste Management Information System : Fact Sheet - Thermal Treatment Technologies*.