Dynamic Bayesian Network-Based Risk Assessment for Arctic Offshore Drilling Waste Handling Practices

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The increased complexity of Arctic offshore drilling waste handling facilities, coupled with stringent regulatory requirements such as zero "hazardous" discharge, calls for rigorous risk management practices. To assess and quantify risks from offshore drilling waste handling practices, a number of methods and models are developed. Most of the conventional risk assessment approaches are, however, broad, holistic, practical guides or roadmaps developed for off-the-shelf systems, for non-Arctic offshore operations. To avoid the inadequacies of traditional risk assessment approaches and to manage the major risk elements connected with the handling of drilling waste, this paper proposes a risk assessment methodology for Arctic offshore drilling waste handling practices based on the dynamic Bayesian network (DBN). The proposed risk methodology combines prior operating environment information with actual observed data from weather forecasting to predict the future potential hazards and/or risks. The methodology continuously updates the potential risks based on the current risk influencing factors (RIF) such as snowstorms, and atmospheric and sea spray icing information. The application of the proposed methodology is demonstrated by a drilling waste handling scenario case study for an oil field development project in the Barents Sea, Norway. The case study results show that the risk of undesirable events in the Arctic is 4.2 times more likely to be high (unacceptable) environmental risk than the risk of events in the North Sea. Further, the Arctic environment has the potential to cause high rates of waste handling system failure; these are between 50 and 85%, depending on the type of system and operating season. [DOI: 10.1115/1.4033713]

Keywords: Arctic, drilling waste, dynamic Bayesian network, risk assessment, risk influencing factors, waste handling

1 Introduction

Oil and gas producers continue to drive offshore projects into arduous and colder Arctic frontiers, driven primarily by the need to secure future oil and gas reserves [1,2]. As the industry expands into the potentially fragile Arctic environment, the petroleum industry and society in general are faced with new and unforeseen challenges [3]. One of the main challenges and risk sources is the management of drilling waste, which is generated from the drilling activities [4,5]. Current industry practices for managing and disposing of drilling waste are broadly classified into three major categories: (i) offshore discharge—treating and discharging the drilling waste to the ocean (sea), (ii) offshore re-injection—re-injecting the drilling waste offshore into a dedicated re-injection well and/or a dry (dead) well, and (iii) skip-and-ship—hauling the drilling waste back to shore for further treatment and disposal [6]. Figure 1 illustrates the schematic flowchart showing the separation of drill cuttings from drilling fluids and the options for waste disposal.

Drilling waste handling practices pose environmental risks due to the potential for the release or spillage of drilling fluids and cuttings during operation on the well pad or off-site during the transportation of drilling fluid additives or waste drilling fluids and cuttings [4,7,8]. The release or spillage of drilling fluids to the marine environment is of major concern for two main reasons: the economic loss associated with expensive drilling fluid discharge and the potential adverse environmental impacts or marine pollution [4]. To determine the fate of contaminants associated with drilling waste and their environmental impacts, several risk analysis studies have been conducted; see, e.g., Sadiq et al. [4], Melton et al. [9], and Neff [10].

For a long time, traditional risk analysis strategies have been preoccupied with estimating the frequency of an undesirable event and its magnitude to give an overall measure of risk. This type of risk measure is quite useful for prioritizing risks (the larger the number, the greater the risk); however, it is normally impractical and can be irrational when applied blindly [11]. One immediate problem with expressing the risk as a product of frequency and consequence is that, usually, one cannot directly obtain the

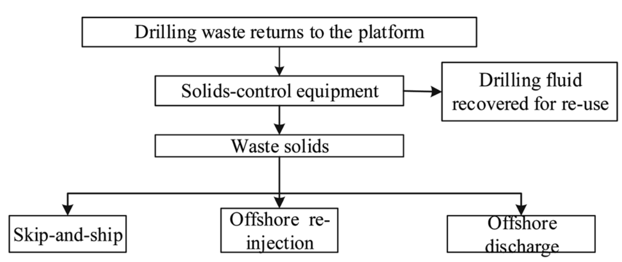

Fig. 1 Schematic flowchart showing separation of drill cuttings from drilling fluids and options for cuttings disposal. Modified from Bernier et al. [42].

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numbers needed to calculate the risk without complete knowledge of the relation between the causes and effects of risk of events [12]. Hence, to avoid the inadequacies of traditional risk assessment approaches and to provide solutions to the problems mentioned above, the application of Bayesian networks (BN) is gaining popularity and has been discussed in several pieces of the literature; see, e.g., Refs. [11–14]. BNs are particularly useful in the risk analysis of offshore waste handling activities, as they allow us to understand the causal relationship as well as to combine any historical data that is available with qualitative data and subjective judgments about the risk of events. For instance, for evaluating waste disposal options, Lee and Lee [14] proposed a probabilistic risk assessment model by connecting the results of probabilistic inference from the BN with the consequence evaluation.

Most of the conventional BN-based risk assessment approaches are, however, broad, holistic, practical guides or roadmaps, developed for off-the-shelf systems for non-Arctic offshore operations. The oil and gas industry operating in the Arctic faces a larger set of risks over and above the "conventional" or "tolerable" risks it would expect to face in other parts of the world due to the demanding physical conditions, the remote location, and extreme weather conditions [1,15]. For instance, an overriding factor that must be accommodated in the analysis of the potential risks, in Arctic offshore drilling waste handling activities, is an extremely cold climate with significant variations in temperature within a short period of time [15].

To address the above-mentioned issues and examine the potential hazards associated with offshore operations in cold regions, several studies have been carried out [8,15,16]. For instance, Guo et al. [16] presented a monitoring and diagnostic analysis for managing risks and uncertainties related to a drill cuttings reinjection process for offshore waste handling in a harsh environment. Ayele et al. [8] suggested a risk-based approach for managing hazards associated with Arctic offshore waste handling practices. However, these risk assessment approaches suffer limitations as they fail to capture and model the time-variant operating environment. Given the fast-changing nature of the arduous Arctic environment, this is considered as a significant drawback [17,18]. Hence, in order to minimize and manage the potential hazards and risk profile during handling of drilling waste in the Arctic offshore, the principles of risk assessment approaches need to be integrated with time series or sequences analysis. The main purpose of this paper is thus to propose a risk assessment methodology based on the DBN for Arctic offshore drilling waste handling practices. The DBN is chosen as the primary modeling structure because of its suitability to model complex time-dependent and uncertain variables.

The rest of the paper is organized as follows: The basic concepts of static BN and DBN are described in Sec. 2. Then, the proposed DBN-based risk assessment methodology for Arctic offshore drilling waste handling practices is presented in Sec. 3. Afterward, the application of the proposed methodology is illustrated, in Sec. 4, using a scenario case study. Finally, some concluding remarks are presented in Sec. 5.

For the purpose of this paper, "the Arctic" is taken simply to mean the Norwegian Arctic, and the starting point of our discussion is the Barents Sea. Further, in this paper, risk is taken to mean the probability times the consequence of an adverse or hazardous event. The risks with which this paper is concerned are all in some way "environmental." They are the actual or potential threat of adverse effects on the marine ecosystem and benthic communities by effluents, emissions, waste, etc., arising out of offshore drilling waste handling activities.

2 Background—A Bird's-Eye View of BN

Bayesian networks, also known as probabilistic networks, belief networks, and causal networks, arise from a concept for reasoning complex uncertain problems, where "network" means a graphical model [14]. In general, a BN 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 [19]. 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 [19]. Parent nodes are nodes with links pointing toward the child nodes. Nodes that are not connected represent variables, which are conditionally independent of each other. The quantitative part of a BN can be represented as a product of the conditional distribution of each node, Z_n, given its parent nodes, parents (Z_n). Each node is described by the conditional probability function of that variable. Then, the joint probability distributions, considering discrete variables, can be expressed as [20]

$$\Pr(z_1, z_2, \ldots, z_N) = \prod_{n}^{N} \Pr\big(z_n|\text{parents}(z_n)\big) \tag{1}$$

where

- $\Pr\big(z_n|\text{parents}(z_n)\big)$ is the conditional distribution mass function of node, Z_n

2.1 DBN.

Dynamic Bayesian network are simply BN for modeling temporal dependencies and/or time series structures [21]. The fundamental assumption in the case of time series modeling is that an event can cause another event in the future, but not vice versa [20]. That means the directed arcs should follow forward in time [21]. Modeling with DBN involves the assumption of the Markov property, i.e., there are no direct dependencies in the system being modeled, which are not already explicitly shown via arcs [19]. In other terms, DBN satisfies the first-order Markovian condition, which is defined as follows: the state of the variable at time t depends only on its immediate past, i.e., its state at time $t-1$. For instance, for a finite or countable sequence of data $\{Z_n,\ n = 0, 1, 2, \ldots\}$, a fixed probability P_{ij} that any variable Z_n will next be in state j, given it is in state i, can be expressed as [22]

$$P_{ij} = P\{Z_{n+1} = j|Z_n = i\} \tag{2}$$

Equation (2) can be interpreted as a conditional distribution of any future state, Z_{n+1}, given the present state, Z_n, is independent of the past states and depends only on the present state.

2.2 Limitation of BN Compared With DBN.

The BN can offer a compact, intuitive, and efficient graphical representation of dependence relations and conditional independence between entities of a domain [23]. However, there are also certain limitations. For instance, BNs cannot take changes in time into consideration; therefore, the BN cannot handle time-variant operating environments and model the networks in time series or sequences. In particular, in the Arctic offshore operation, the effect of the RIFs, such as snowstorms, sea spray icing, negative sea temperature, on the posterior probabilities of the waste handling system failure, and the environmental risks is time-dependent; thus, DBNs are more resourceful tools for handling them. RIFs are factors that potentially affect the barriers and barrier performance [24]. Further, DBN variables can be interlinked to themselves in another time elapse or other variables in the network at a future point in time. In general, the key limitations of the BN compared with the DBN are

- BN's limitation in assigning direction of causation to an interaction from an edge, in the case of equivalence class of BN [25].
- BN's limitation in taking into account temporal dependence or time dimension in reasoning [20].
- BN's limitations regarding functional network inference [19].

3 The Proposed DBN-Based Risk Assessment Methodology for Arctic Offshore Drilling Waste Handling Practices

The proposed DBN-based risk assessment methodology consists of two parts: qualitative and quantitative. The main aim of the qualitative part is to investigate the interaction of the predominant Arctic RIFs, such as snowstorms, atmospheric and sea spray icing, negative air and sea temperature, and their negative synergy effect on the drilling waste handling practices. On the other hand, the focus of the quantitative part is to estimate the posterior probabilities of the environmental risks and quantify the weather-related data of the dynamically changing operating environment of the Arctic by employing time series analysis.

3.1 Part 1—Qualitative Assessment.

Figure 2 illustrates specific steps that help to understand the Arctic operational challenges and to construct a dynamic Bayesian structure for Arctic drilling waste handling practices.

Step 1.1—Evaluation of the peculiar Arctic RIFs: The purpose of this step is to study and investigate the influence of the peculiar Arctic RIFs on the drilling waste handling practices. Further, the interaction of the RIFs, the dependence of these factors on various variables, and their negative synergy effect on the drilling waste handling practices need to be assessed and specified.

Step 1.2—Perform drilling waste handling system identification: In the next step, the main disposal techniques such as discharge of drilling waste into the sea (ocean) and reinjection of the waste into the underground formation need to be evaluated. Further, the key solids-control system needs to be investigated. The solids-control system is a system that separates drill solids from the drilling fluid, thereby allowing it to be recirculated down the drill pipe; it is a key part of the waste handling process [26]. Typically, the primary solids-control treatment system comprises shakers or “shale shakers,” hydro-cyclones, and centrifuges, and secondary treatment system comprises cuttings dryers and thermal desorption [26].

Step 1.3—Evaluating the causal dependencies between the main variables: At this stage, the interactions or causal dependencies between the main variables, i.e., the RIFs, the drilling waste handling practices, and the environmental risks, need to be understood, and then the structure of the DBN has to be decided. In general, a DBN can be used for three kinds of reasoning: (i) causal reasoning—from known causes to unknown effects, (ii) diagnostic reasoning—from known effects to unknown causes, and (iii) a combination of causal and diagnostic reasoning [20].

Step 1.4—Construct a DBN structure: The final stage in the qualitative evaluation is to construct a DBN structure. The main aim of this step is to build the dynamic Bayesian structure that captures the time series nature, which comprises both discrete and continuous variables. During this stage, the key is to focus on the causal relationships among the main variables. Further, in this step, one can bring in a domain expert—a person with special knowledge of the main variables, to provide the judgements because the expert has developed the mental tools needed to make sound evaluations.

3.2 Part 2: Quantitative Assessment.

Figure 3 describes the quantitative part of the proposed DBN-based risk methodology and illustrates the specific steps that should be followed to determine the posterior probability of the environmental risks.

Step 2.1—Transforming RIFs into a Markov chain process: The observations of the peculiar Arctic RIFs separated by relatively short times tend to be similar or correlated [27]. Analyzing and characterizing the nature of these temporal correlations, or relationships through time, can be useful for understanding the dynamic operating environment of the Arctic [27]. One way of modeling this temporal correlation is to make use of a Markov chain stochastic process. Hence, to model the time series or sequences of weather-related data in this stage, the dynamic operating environment of the Arctic needs to be transformed into a Markov chain. The aim of this transformation is to specify the time dependencies between the states and satisfy the first-order Markov property. This step will be explained in detail in the case study section.

Step 2.2—Define the state of discrete nodes: In this step, the state of each discrete node has to be defined. A discrete node (variable) is one with a well-defined finite set of possible values called states. The state can take binary values (such as true or false) or ordered (ranked) values (such as low, medium, or high).

Step 2.3—Assign a marginal probability table (MPT) for root discrete nodes and a conditional probability table (CPT) for other discrete nodes: After specifying the states of discrete nodes, the next step is to quantify the relationships between the connected nodes (variables). In this step, MPT and CPT need to be assigned and defined. For each particular discrete node, all possible combinations of values of those parent nodes must be observed; such a combination is called instantiation of the parent [28]. For instance, for a Boolean network, a variable with n parents requires a CPT with 2^{n+1} probabilities [28]. These probabilities can be estimated or assigned using direct elicitation and/or machine-learning techniques.

Step 2.4—Calculate the discretized conditional probability distributions (CPD) of each continuous node: The next stage is defining the CPDs for each continuous variable. A continuous variable (node) is one, which can take on a value between any other two values, such as air temperature. Typically, there are two approaches for handling continuous variables: static and dynamic discretization. Both approaches try to specify the states of the continuous nodes. A static discretization requires the breakup of the total range of the continuous variables into a finite number of intervals [19]. On the other hand, dynamic discretization produces finer discretization in the regions that contribute more to the structure of the density functions [19].

Step 2.5—Select prior probability distribution for the defined system: In this step, a prior reliability or failure rate distribution function needs to be asserted for the defined solids-control system. This function is the description of the failure rate of the solids-control system, and failure rate is the measure of frequency of a system or component failure [13]. The prior function represents the probability of n or fewer failures during a time interval of $(0, t)$, when all RIFs are equal to zero or absent, in the course of waste handling activities [13]. For instance, assuming that the components fail according to a Poisson process, the probability of n or fewer failures can be calculated as follows [29]:

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

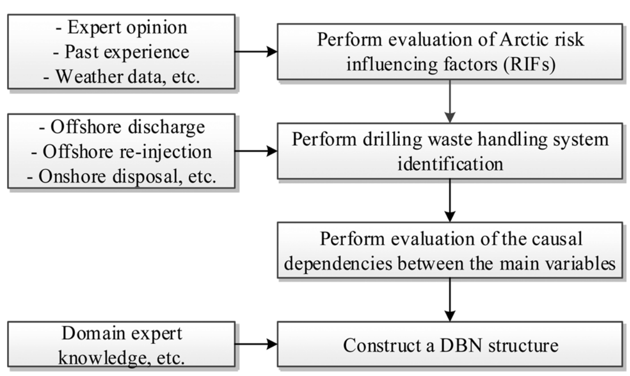

Fig. 2 Qualitative part of the proposed DBN-based risk assessment methodology

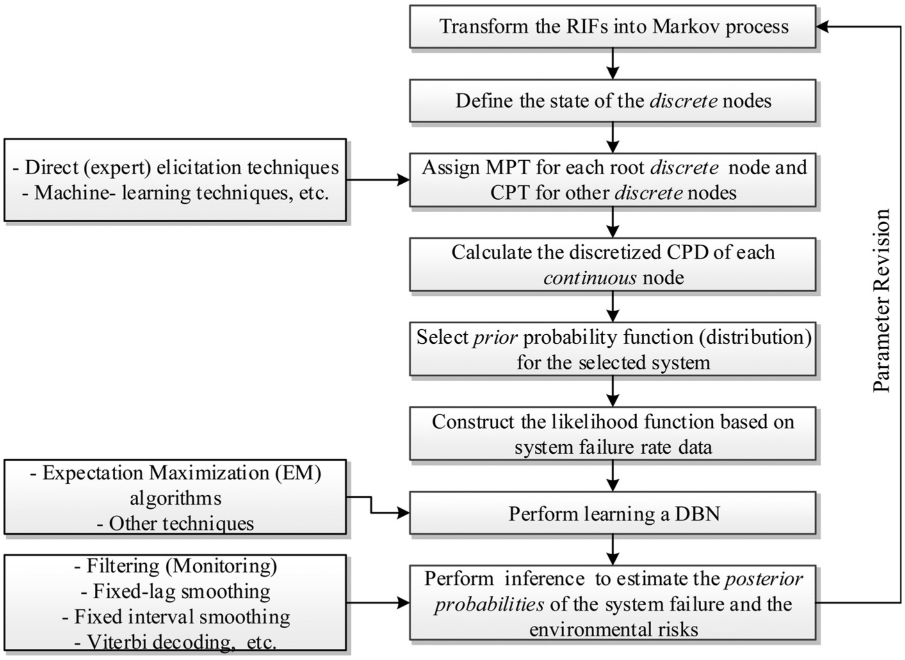

Fig. 3 Quantitative part of the proposed DBN-based risk assessment methodology

where

- $P(W)$ is the probability of n or fewer failures of the solids-control component or system, and
- λ is the failure rate of the solids-control component or system.
- W represents the solids-control component or system.

Step 2.6—Construct the likelihood function, based on the system failure rate data: After observing the RIFs' data and defining the prior probability function, the likelihood function has to be constructed. The likelihood function is generally the joint probability function and can be expressed as a product of conditional probabilities [30]. By considering discrete R time-independent and M time-dependent variables (RIFs), the likelihood function of the solids-control system failure, given the RIFs' observation data, based on Glickman and van Dyk [30] approach, can be expressed as follows [13]:

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

where

- $z_1,\ldots,z_r$ is a set of time-independent RIFs, and
- $z_1(t),\ldots,z_m(t)$ is a set of time-dependent RIFs.

Afterward, by grouping the RIFs into vectors of size $R+M$, the likelihood function of the system failure can be rewritten as follows [13]

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

where

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

By following the same approach and considering the discrete risk variables, the likelihood function of the environmental risk, given system failure, can be expressed as [13]:

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

where

- $p(W_i|E)$ represents the conditional probability of each system or component failure, given environmental risks.
- E represents environmental risks.

Step 2.7—Learning in a DBN: The representation of a real-world problem by a DBN structure often requires the introduction of several nodes, and in such cases, conditional probabilities cannot be exactly determined for all nodes [20]. Even expert knowledge cannot offer us the solution for conditional relationships of several nodes in a particular domain. The next step is thus to learn these CPDs. Learning is the process of estimating the parameters of a DBN in such a way that the estimated parameters best fit to the observed data and make the best fit model for the system [20]. This process is complex and most often based on the expectation maximization [31] or general expectation maximization [32] algorithms for DBNs.

Step 2.8—Computing the posterior distribution or probabilistic inference: The final stage is to perform inference to estimate the posterior probabilities of the drilling waste handling system failure and the environmental risks. Probabilistic inference can be defined as the task of computing the probability of each node in a DBN according to the most recent RIFs to provide posterior probabilities [13]. To predict the future potential risks, the posterior distribution combines prior RIFs' information with actual observed data from weather forecasting [13]. That means the current information about the RIFs will be used to continuously update the potential hazards related to the environmental risks. In other words, the distribution describes the probability that the solids-control system will fail given the RIFs, which have been observed. The posterior distribution of the solids-control system failure, considering discrete RIFs can be expressed as

$$P\left(W|z,z(t)\right)=\frac{P\left(z,z(t)|W\right)P(W)}{P(z,z(t))} \tag{7}$$

In general, $P\left(W|z,z(t)\right)$ measures the reduction of the performance of the solids-control system, i.e., in terms of reliability, due to the adverse impact of both time-independent and time-dependent RIFs. Then, by substituting the likelihood function and applying Bayes' theorem, Eq. (7) can be rewritten as [13]

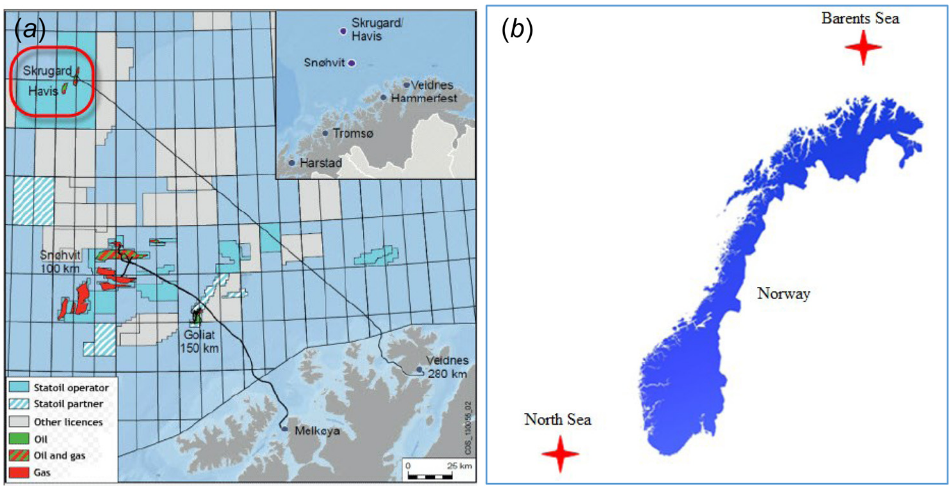

Fig. 4 Johan Castberg oil field: (*a*) Johan Castberg oil field [43] and (*b*) North Sea – reference area, Barents Sea – target area

Table 1 Johan Castberg oil field—key field data

Status	Planned Project
Operator	Statoil AS
Year of discovery	2011
Planned start-year of production	2020
Location	Barents Sea
Water depth	370 m
Main development plan	FPSO/FPU
Estimated oil volume	450—650 million barrels

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

In order to solve Eqs. (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 one [13,27].

By considering the discrete risk variables and following the same approach as above, the posterior probabilities of the environmental risks can be expressed as

$$P(E|W) = \frac{P(W|E)P(E)}{P(W)} \tag{9}$$

where

- $P(E)$ is the prior probability of environmental risks before system failure and observing the RIFs.

Fig. 5 Typical icing phenomena in Arctic (photo courtesy of Ice Engineering Solutions)

Afterward, by employing the likelihood function, Eq. (9) can be rewritten as [13]

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

4 Case Study: Johan Castberg Field Development Project in the Barents Sea

To illustrate the proposed methodology, a holistic risk assessment case study was carried out to assess the environmental risks due to the release of untreated drilling waste because of failure of the shale shaker, which is one of the key solids-control systems. The main assumptions during estimation of probabilities are: (i) a year-round operational window, (ii) there is no winterization or enclosure of the solids-control system to protect the vulnerable areas, and (iii) the system is assumed to be installed in the drilling rig for the Johan Castberg field development project in the Barents Sea. The Johan Castberg field (formerly Skrugard and Havis) is an oilfield development project in the Barents Sea, located about 280 km from Veidnes, northern Norway. Figure 4 illustrates the field location, and key field data are summarized in Table 1.

In general, in the Norwegian part of the Barents Sea, the bottom line principle is that the oil and gas exploration activities shall be at least as safe as in the North Sea [33]. Thus, in this case study, the North Sea is considered as a reference region. The case study

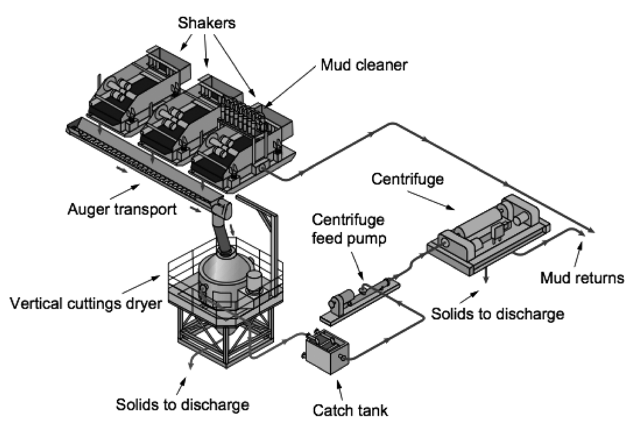

Fig. 6 Solids-control system installed in the rig. Adapted from Bernier et al. [42]. (Reprinted with permission from the International Association of Oil & Gas Producers.)

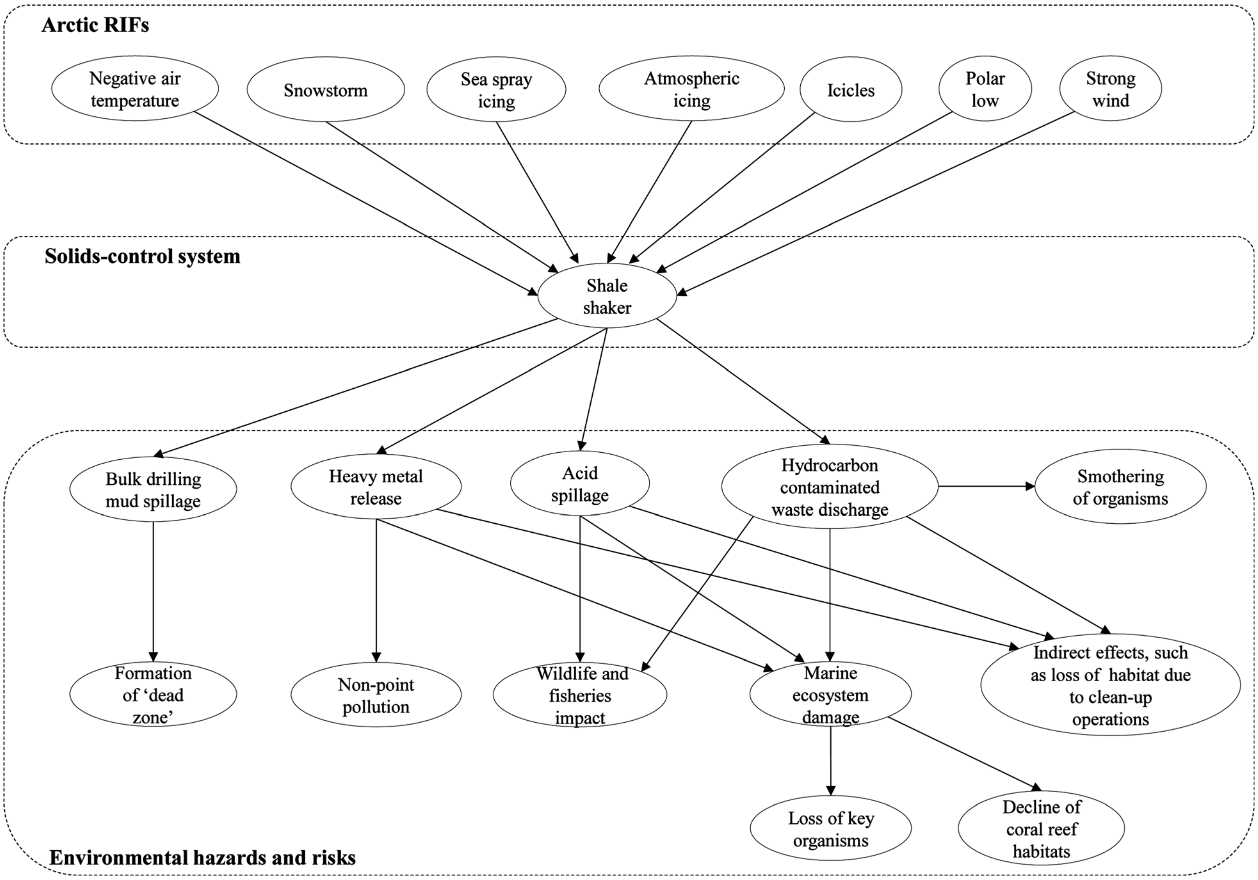

Fig. 7 The original static BN fragment

emphasizes the measurement of the relative effect of the Arctic operating environment against that of the North Sea.

4.1 Part 1—Qualitative Assessment. The first step is to investigate the impact of the predominant RIFs on waste handling practices, particularly on the solids-control system to be installed in the Barents Sea. The peculiar Arctic RIFs are identified and their impacts are briefly discussed below:

- *Negative temperature:* Negative temperature causes the solids-control systems, such as the primary shale shaker, mud cleaner, screw conveyor, and the vacuum pump, to cease to function. In addition, the viscosity of the water

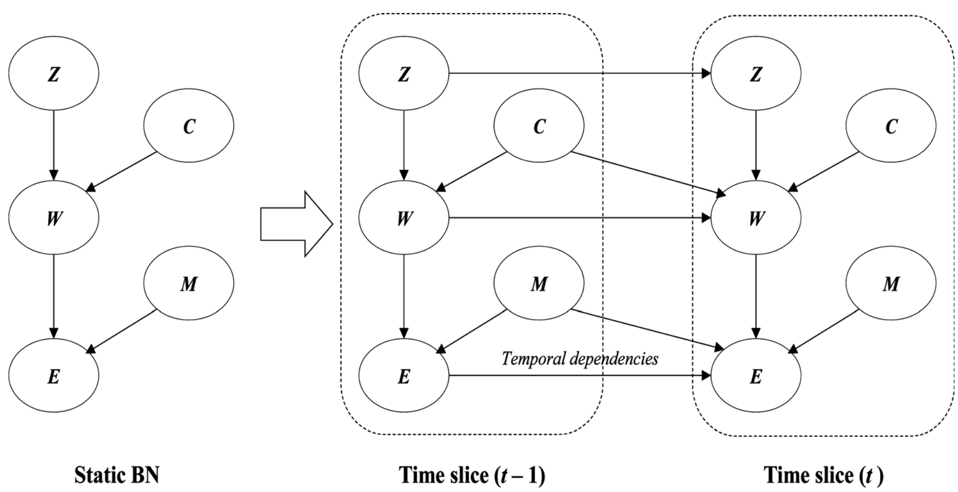

Fig. 8 The extension of the static BN into two time slices of DBNs. *Z* denotes a set of any initiating (trigger) events, which are the risk-influencing factors, and *C* denotes the control measure, which can be a winterization measure—enclosure of the solids-control systems. *W* denotes the main risk event—a system or component failure, which shows that the cause of the trigger *Z* produces the effect *W*. *E* denotes the consequence of the system failure, which is an environmental risk (marine pollution). *M* denotes the mitigating event that prevents any cause *E*, such as rapid emergency response that avoids or reduces the consequence event.

Table 2 The process is in

State	State description
0	If it has been snowing both at time t & at time $t-1$
1	If it has been snowing at time t but not at time $t-1$
2	If it has been snowing at time $t-1$ but not at time t
3	If it did not snow either at time $t-1$ or at time t

increases significantly as the temperature falls [31]. Higher viscosity means slower flow and mixing rates within the solids-control system and, consequently, an increase in the overall energy demand [9,34]. Furthermore, the prevailing low temperature magnifies the embrittlement of the solids-control system, causing failures at loads that are routinely imposed without damage in a warmer climate; it also amplifies the system wear rates as a result of lubricant failure [35].

- *Snowstorms (blizzards):* In the Barents Sea, the mean annual number of days with snowstorms is about 100–120 days, with mean durations of 37.5–45.8 days [36]. During these periods, there is high potential for ice accretion on the waste handling systems and structures. A major snowfall restricts access to waste handling equipment and instruments and hinders the process of collecting, transporting, and treating the drilling waste. Further, working in a snowstorm has the potential to cause an increase in incidents and injuries.
- *Icing:* The potential hazards of icing (atmospheric and sea spray) include system or component failure, and this can cause loss of the system or stoppage of the waste handling process. Typical icing phenomena in the Arctic regions are shown in Fig. 5.
- *Icicles:* 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 fall because of a change in air temperature or a heavy ice deposit, they can damage the nearby waste handling equipment and injure personnel working onsite. Furthermore, structural integrity can be significantly affected, due to the accumulated heavyweight of icicles.

After recognizing the peculiar Arctic RIFs, the next step is to define the key waste handling (solids-control) systems. Figure 6 illustrates a typical solids-control system assumed to be installed on the rig. In general, after returning to the platform, the fluid and suspended cuttings are processed on the rig through screens called "shale shakers" to maximize recovery of the mud. Shale shakers are considered to be the key device of the primary solids-control system; they consist of a series of screens that vibrate in horizontal or elliptical motion [26]. The failure of the shale shaker may then lead to stoppage of the overall system and waste handling process. Thus, the impact of the Arctic operating environment on the drilling waste handling practices will be analyzed by:

- Estimating the conditional and posterior probabilities of failure of the shale shakers due to the predominant Arctic RIFs, and
- Predicting the environmental risks due to the release of untreated waste once the shale shaker fails.

In the next step, the causal dependencies among the main variables are described using reasoning processes. Figure 7 illustrates the original static BN fragment considering the causal dependencies between the main variables, i.e., the Arctic RIFs, solids-control systems, and environmental risks.

Afterward, to consider the time-variant CPD of the potential hazards and risks, the temporal connections within time slices are introduced. Since the results from observations, separated by relatively short time spans, of Arctic RIFs tend to be similar, the DBN for Arctic drilling waste handling practices is assumed to possess an identical structure for every time slice and identical temporal conditional dependencies between the time slices. Such a structure is called a DBN with uniform structure [20]. For uniform DBN structure, the conditional dependencies and states in one time slice are represented as a static BN. Afterward, the DBN structure is built by multiplying the static BNs for each time slice and by adding arcs between states from two consecutive time slices (nodes in BN), if they are temporally dependent [20]. Figure 8 illustrates the extension or "unrolling" of the static BN into two time slice DBNs.

4.2 Part 2—Quantitative Assessment.

Based on the method developed by Ross [22], RIFs can be transformed into a Markovian process as follows. Taking the snowstorm as an example, presume that whether or not it snows at time t depends on preceding weather conditions, i.e., at time $t-1$ and $t-2$. Specifically, presume that if it has been snowing at time t and $t-1$, then it will snow at time $t+1$ with probability α ; if it has been snowing at time t but not at time $t-1$, then it will snow at time $t+1$ with probability β ; if it has been snowing at time $t-1$ but not at time t, then it will snow at time $t+1$ with probability η ; if it has not been snowing at time t and $t-1$, then it will snow at time $t+1$ with probability μ. Then, if we let the state of the snow at time t depend only on whether or not it is snowing at time $t-1$ and $t-2$, then the preceding model is not a Markov chain. This is due to first-order Markov property. Simply, this means that Eq. (2) needs to be fulfilled to be a Markov chain. However, we can transform this model into a Markov chain by saying that the state of the snow at any time t is determined by the weather conditions both at time t and at time $t-1$. Table 2 illustrates the state of the snow and the state description.

The preceding would then represent a four-state Markov chain of the snow having a transition probability matrix, $Q_{\text{snowstorm}}$

$$Q_{\text{snowstorm}} = \begin{bmatrix} P_{00} & P_{01} & P_{02} & P_{03} \\ P_{10} & P_{11} & P_{12} & P_{13} \\ P_{20} & P_{21} & P_{22} & P_{23} \\ P_{30} & P_{31} & P_{32} & P_{33} \end{bmatrix} = \begin{bmatrix} \alpha & 0 & 1-\alpha & 0 \\ \beta & 0 & 1-\beta & 0 \\ 0 & \eta & 0 & 1-\eta \\ 0 & \mu & 0 & 1-\mu \end{bmatrix} \tag{11}$$

The transition probability matrix information can also be expressed in the form of a transition diagram. Figure 9 illustrates the transition diagram that shows the four-state Markov chain of the snow and the probabilities of transition from one state to another.

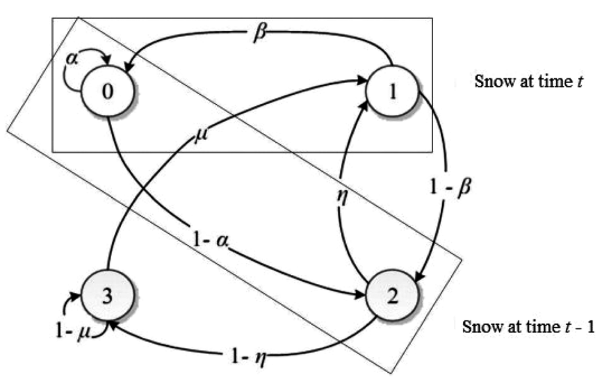

Fig. 9 Probability transition diagram for four-state Markov chain of the snow

The next step is to define the state of the nodes (variables). The recognized RIFs are sorted for both regions—Arctic (AR) and North Sea (NS)—in monthly order (i.e., from January to December), and a sample of the data is shown in Table 3. These RIFs (except the temperature) were scored 0 or 1, for their absence or presence during drilling waste handling activities, respectively.

Table 3 The observed RIFs for Arctic (Barents Sea) and North Sea

	z_1		z_2		z_{3A}		z_{3B}		z_4	
Month	NS	AR	NS	AR	NS	AR	NS	AR	NS	AR
January	2.7	−14.2	1	1	1	1	1	1	1	1
February	2.8	−11.2	1	1	1	1	1	1	1	1
March	2.3	−14.6	1	1	1	1	1	1	0	0
April	4.9	−12.4	0	1	0	1	0	1	0	0
May	7.6	−3	0	1	0	1	0	1	0	0
June	10.9	0	0	1	0	1	0	1	0	0
July	13.6	2.2	0	0	0	0	0	0	0	0
August	14.2	2.7	0	0	0	0	0	0	0	0
September	12.9	1.5	0	1	0	0	0	0	0	0
October	9.8	−2.6	1	1	0	1	0	1	0	0
November	6.1	−7	1	1	1	1	1	1	0	1
December	3.4	−10.1	1	1	1	1	1	1	1	1

z_1, air temperature (°C); z_2, snowstorm; z_{3A}, sea spray icing; z_{3B}, atmospheric icing; and z_4, icicles.

Table 4 States of the main variables

Variable	Description	States
z_1	Negative air temperature	Very low ($T \leq -10\,°\text{C}$) Low ($-10\,°\text{C} < T < 0$) Medium ($T \geq 0\,°\text{C}$)
z_2	Snowstorm	Type III (severe) Type II (mild) Type I (light)
z_3	Icing	Type III (severe) Type II (mild) Type I (light)
z_4	Icicles	H (heavy) M (moderate) L (light)
RRM_i	RRM, which is implemented to prevent or reduce the potential risks	P (poor) performance M (medium) performance H (high) performance
W_i	Prior reliability of the shale shaker (solids-control system)	F (failed) D (degraded) O (fully operating)
E	Environmental risk	H (high) M (medium) L (low)

The minimum temperature (°C) data of the study were collected over a period of 10 years (from 2005 to 2014) on a monthly basis, from the Norwegian Meteorological Institute database. The temperature data were observed at the Hopen Island weather station, located at 76°33'N, 25°7'E, Barents Sea, northern Norway and at the Ekofisk oilfield, 56°32′N, 3°12′E, North Sea, about 320 km southwest of Stavanger, Norway.

For computational convenience, all variables were considered as ranked states and summarized in Table 4. The continuous node, which is air temperature (Z_1), was discretized into ranked states, using static discretization technique [19]. Further, the environmental risk is categorized into three risk levels: (i) low (broadly acceptable) risk—here the level of risk is regarded as negligible and further measures to reduce the risk are not usually required, (ii) medium (tolerable) risk—here the risk is acceptable as long as we keep the risk at that level, and (iii) high (unacceptable) risk—here the risk of an undesired event requires rigorous risk control and reduction measures to bring the risk down to the ALARP (as low as reasonably practicable) level.

Table 6 Sample of the elicited MPT of the root nodes

	March		August	
Marginal probability	AR	NS	AR	NS
$P(z_1 = VL)$	0.91	0.10	0.01	0.01
$P(z_1 = L)$	0.04	0.05	0.10	0.01
$P(z_1 = M)$	0.05	0.85	0.89	0.98
$P(z_2 = \text{Type}-\text{III})$	0.87	0.05	0.01	0.01
$P(z_2 = \text{Type}-\text{II})$	0.08	0.27	0.01	0.01
$P(z_2 = \text{Type}-\text{I})$	0.05	0.68	0.01	0.01
$P(z_3 = \text{Type}-\text{III})$	0.90	0.10	0.01	0.01
$P(z_3 = \text{Type}-\text{II})$	0.06	0.25	0.01	0.01
$P(z_3 = \text{Type}-\text{I})$	0.04	0.65	0.01	0.01
$P(z_4 = H)$	0.84	0.12	0.01	0.00
$P(z_4 = M)$	0.07	0.30	0.01	0.00
$P(z_4 = L)$	0.09	0.58	0.01	0.00
$P(\text{RRM}_i = P)$	0.15	0.15	0.05	0.05
$P(\text{RRM}_i = M)$	0.15	0.15	0.05	0.05
$P(\text{RRM}_i = H)$	0.70	0.70	0.90	0.90
$P(W_i = F)$	0.05	0.02	0.01	0.01
$P(W_i = D)$	0.12	0.10	0.04	0.01
$P(W_i = O)$	0.83	0.88	0.95	0.98

Afterward, the MPTs are estimated based on the direct elicitation [28] of expert judgment. For this purpose, the experts have been selected based on the criteria suggested by Ortiz et al. [37], which states that experts collectively should represent a wide variety of backgrounds and experience. The selected experts are of two types—academics and professionals with hands-on experience, having expertise in risk analysis, waste handling and management, drilling and reliability engineering, meteorology, cold-climate technology, and offshore engineering, with 5–15 years of experience in their respective fields. Then, the selected experts are informed about the operational environment in the reference area, i.e., North Sea, and the target area, i.e., Barents Sea. In total, six experts were asked to provide their degree-of-belief marginal probabilities of the root nodes. Table 5 depicts their corresponding background, i.e., whether they are academic or have hands-on experience. Furthermore, to document the faithfulness of the probabilities given by the experts, calibration, which is a measure of the quality of probability distributions given by experts, has been carried out. For further details about how to use, when to use, and how to elicit the expert judgment, see e.g., Meyer and Booker [38] and Hoffman et al. [39].

Table 5 Domain experts' background

Expert i		1	2	3	4	5	6
Experience (years)		15	10	12	7	9	5
Background		Pro.	Pro.	Pro.	Acad.	Pro.	Acad.
Performance-based weights	Non-normalized	1.000	0.667	0.800	0.467	0.600	0.333
	Normalized	0.259	0.172	0.207	0.121	0.155	0.086

Acad.: academic and Pro.: professional.

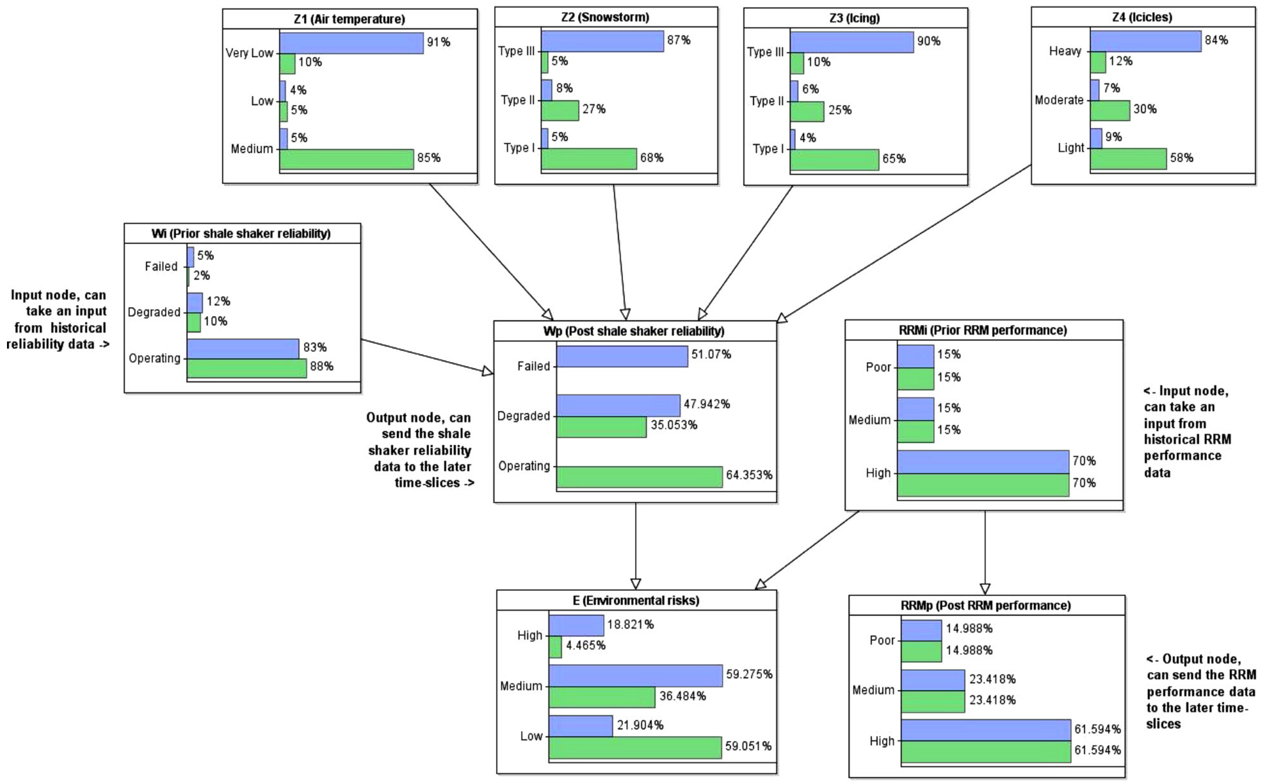

Fig. 10 Estimated posterior environmental risks for the month of March, for both regions: Arctic and North Sea (see online for color version)

Thereafter, the meteorologists are asked to provide their opinions on observing the RIFs in a particular period of the year. Further, to assert a prior reliability or failure rate distribution function, failure rate data need to be available. However, in the Arctic region, there is a shortage of valid failure rate data, particularly for the solids-control systems [17,13]. In the case of shortage of data, the other option is to make use of expert judgment for extrapolating reliability (failure rate) data from other regions, such as the North Sea. Hence, the experts with reliability and cold-climate engineering backgrounds have been asked to provide their opinions on the subjective prior reliability of the shale shaker, in a categorized format. For instance, an expert provides a number, such as the prior reliability of the shale shaker, R in the month of March as 0.80. Following this, they are asked about the degree of decrease in the reliability of the shale shaker and performance of the risk reduction measures (RRMs) due to the operating environment of the Arctic region. Table 6 presents a sample of the elicited (assigned) MPT for the months of March and August—the coldest and warmest months of the year, respectively, for both regions.

Once the MPTs are elicited, DBN learning and probabilistic inference are carried out by employing AgenaRisk [40]—a commercial general-purpose (D)BN software tool. The DBN methodology predicts whether the environmental risk will be high, medium, or low, using information about the predominant RIFs, the reliability of the shale shaker, and the performance of RRMs. The DBN is structured in such a way that it is possible to link together different instances of it to monitor the environmental risk over time. The observed RIFs, together with the "prior" reliability of the shale shaker (i.e., before observing the RIFs), influence the "post" reliability of the shale shaker (i.e., after observing the RIFs). This "post" reliability can then be used as the "prior" reliability in a new instance of the DBN that represents the next time period. The performance of the RRMs and the reliability of the shale shaker after observing the RIFs determine the magnitude of the environmental risk. As with the "post" reliability, the "post" performance of the RRMs can be linked to the same node in the next time period. Figure 10 shows the posterior environmental risk and the conditional system (shale shaker) reliability at *time slice 1* for both regions and for the month of March. In this case study, a *time slice* represents a day.

As shown in Fig. 10, from the inference result of the static BN, the peculiar Arctic RIFs significantly reduce the posterior shale shaker reliability and, consequently, increase the environmental risk. Comparing the posterior reliability, the shale shaker will be 1.5 times more likely to fail in the Arctic region than in the North Sea during the month of March. This means that the peculiar Arctic RIFs increase the failure rate by more than 50%. Similarly, the risk of undesirable events in the Arctic is 4.2 times more likely to be a high (unacceptable) environmental risk than the risk of events in the North Sea.

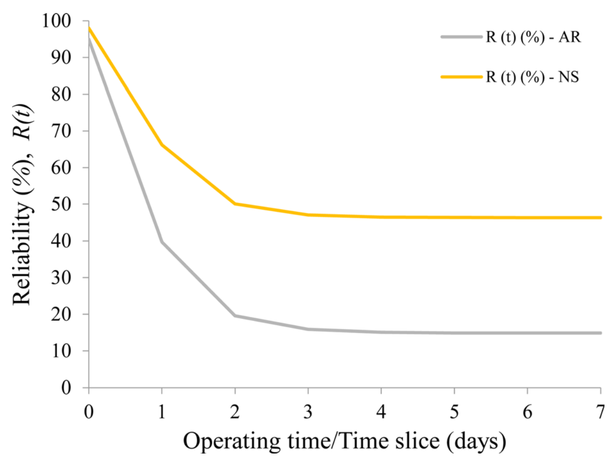

Fig. 11 Post shale shaker reliability versus operating time. The degraded and fully operating states are expressed as posterior reliability and the failed state of the shale shaker is expressed as posterior unreliability (1 − $R(t)$).

In order to capture the time dimension in our DBN methodology so that we can reason about how changes in air temperature, snowstorms, icing, each day affect the level of environmental risk, the DBN fragments are connected together. For instance, to explore how 7 days (i.e., a week) of very low temperatures, severe snowstorm, and icing conditions affect the environmental risks and the posterior shale shaker reliability, the DBN fragments are arranged in chronological order as *time slice 1*, *2*,…, *7*. Then, the link between the DBN fragments is introduced. Afterward, the observation of *Very Low* on the air temperature (z_1) node, *Type III* on the snowstorm (z_2), and *Type III* on the icing (z_3) node is entered. The result of the temporal linking, i.e., the post shale shaker reliabilities as well as posterior environmental risk, for different operating periods (*time slices*), for both regions, is shown in Figs. 11 and 12.

The DBN inference result (Figs. 11 and 12) shows that the reliability of the shale shaker in the Arctic $R_{AR}(t=7)$ is 0.15. However, this reliability in the North Sea, $R_{NS}(t=7)$, is around 0.46. This may be alternatively expressed by saying that the Arctic operating environment increases the failure of the shale shaker by more than three times after a week of operation under a very low temperature, severe snowstorm, and icing conditions. Moreover, in the Arctic, the posterior environmental risk is 46% in the higher (unacceptable) risk group after 3 days of operation under severe

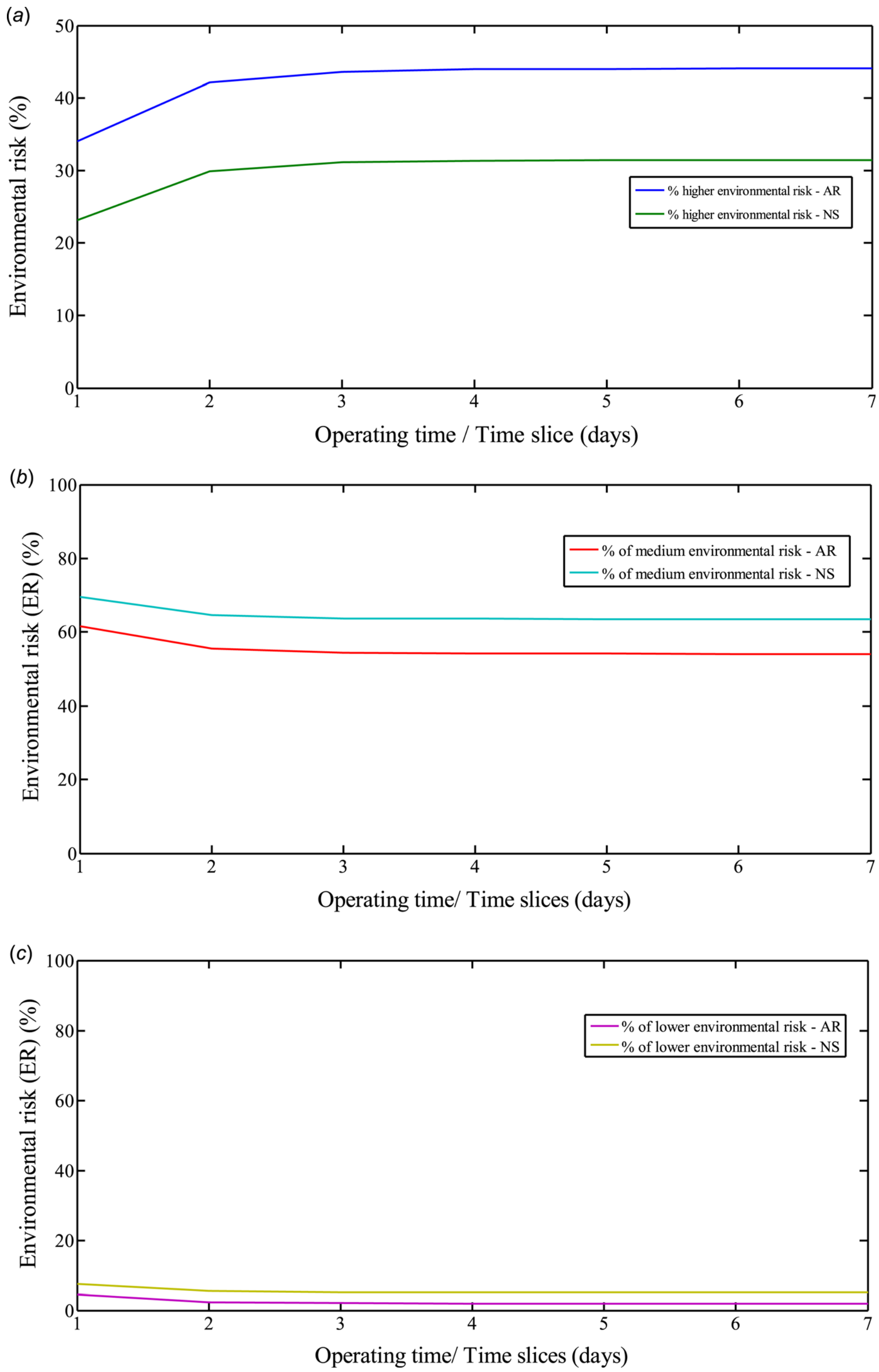

Fig. 12 Environmental risk (ER) (%) versus operating time (days): (*a*) % higher ER versus operating time (days), (*b*) % medium ER versus operating time (days) (*c*) % lower ER versus operating time (days)

conditions. On the other hand, this value is 15% less in the North Sea.

Furthermore, based on the result shown in Figs. 11 and 12, the impact of observing a very low temperature, severe snowstorm, and severe icing conditions is significant for the first 3 days of operating periods. This is due to certain storm conditions in the Arctic, during which humans cannot venture outside, ice or snow cannot be cleared at the rate they are accumulating, ice management cannot operate, and ice detection systems do not function to their full capacity [41]. For the first 3 days, no response can take place. It is the combination of these kinds of situations, which leads to adverse consequences, i.e., high level of environmental risks and higher system failure rates. It is usually possible to deal with one emergency at a time but, if one has multiple RIFs, adequate response can be difficult.

5 Concluding Remarks

This work introduced a methodology for a risk assessment of drilling waste handling practices based on DBN, by considering the peculiar operational conditions of the Arctic. The proposed methodology is particularly important in the Arctic operating environment since there is less experience and data in the region. The methodology consists of two parts: qualitative and quantitative. The qualitative analysis involves the following steps: (i) evaluation of the peculiar Arctic RIFs (to investigate the influence of the peculiar Arctic RIFs on the drilling waste handling practices), (ii) performing drilling waste handling system identification (to investigate the main disposal techniques), (iii) evaluating the causal dependencies between the main variables (to understand the interactions between the main variables), and (iv) constructing a DBN structure (to capture the time series nature). The quantitative part illustrates the specific steps that should be followed to estimate the probability of the environmental-related risks and involves the following steps: (i) transforming RIFs into a Markov chain process, (ii) defining the state of each discrete node, (iii) assigning a MPT for root discrete nodes and a CPT for other discrete nodes, (iv) calculating the discretized CPD of each continuous node, (v) selecting the prior probability distribution for the defined system, (vi) constructing the likelihood function, based on the system failure rate data, (vii) learning in a DBN, and (viii) computing the posterior distribution or probabilistic inference.

The findings are as follows:

- The proposed methodology is beneficial as it outlines a set of steps that assist the risk analyst to estimate the probabilities of the environmental risks due to the release of untreated drilling waste, because of the failure of the drilling waste handling system, by considering the Arctic operating environment.
- Further, by employing the proposed DBN-based risk assessment methodology, the risk barriers and mitigation measures can be allocated based on the level of estimated risk.
- The environmental risk analysis showed that working in the cold Arctic environment has the potential, if not managed properly, to cause 4.2 times higher (unacceptable) level environmental risks than in the North Sea.
- The failure rate (reliability) analysis results showed that the Arctic operating environment increases the drilling waste handling system failure rate by more than 50%, compared with the North Sea.

The inference result can be used for developing a robust risk management procedure that addresses all the peculiar environmental risk sources in the Arctic and ensures the fulfillment of the stringent environmental requirements, such as zero "hazardous" discharge. However, a lack of valid reliability or failure rate data in the Arctic and sub-Arctic environment was a challenge during probabilistic inference or computation of the posterior environmental risks and post-reliability of the solids-control system. Therefore, the results should be interpreted in light of the current state of knowledge about operating experience in the Arctic. Moreover, the resulting risk values from the illustrative case study analysis should be updated as new data/evidence becomes available, preferably in the form of field (hard) data reflecting the actual operational experience in this Arctic region and therefore gradually supplanting the opinions elicited from experts. No elements, however, invalidate the results from the illustrative case study analysis.

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Nomenclature

$L(W|z, z(t))$ = the likelihood function of the system or component failure
$L(E|W)$ = a likelihood function of the environmental risks
$P(E|W)$ = a posterior probability of the environmental risks
$P(W)$ = the probability of n or fewer failures of solids-control system
$P(W|z, z(t))$ = a posterior distribution of the system or component failure
P_{ij} = $P\{z_{n+1} = j|z_n = i\}$ a fixed probability that any variable z_n will next be in state j, given it is in state i
$\mathrm{parents}(z_n)$ = parent set of a node z_n
$\Pr(z_n|parents(z_n))$ = conditional distribution mass function of node z_n
$Q_{\mathrm{snowstorm}}$ = a transition probability matrix of the snowstorm
W_i = prior reliability of solids-control system
z_n = probability distribution of node n
z_1 = air temperature
$z_1, \ldots, z_r$ = a set of time-independent RIFs
$z_1(t), \ldots, z_r(t)$ = a set of time-dependent RIFs
z_2 = snowstorm
z_{3A} = sea spray icing
z_{3B} = atmospheric icing
z_4 = icicles
λ = a failure rate of the solids-control component or system

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