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An ecological risk assessment model for Arctic oil spills from a subsea pipeline

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ABSTRACT

There is significant risk associated with increased oil and gas exploration activities in the Arctic Ocean. This paper presents a probabilistic methodology for Ecological Risk Assessment (ERA) of accidental oil spills in this region. A fugacity approach is adopted to model the fate and transport of released oil, taking into account the uncertainty of input variables. This assists in predicting the 95th percentile Predicted Exposure Concentration ($PEC_{95\%}$) of pollutants in different media. The 5th percentile Predicted No Effect Concentration ($PNEC_{5\%}$) is obtained from toxicity data for 19 species. A model based on Dynamic Bayesian Network (DBN) is developed to assess the ecological risk posed to the aquatic community. The model enables accounting for the occurrence likelihood of input parameters, as well as analyzing the time-variable risk profile caused by seasonal changes. It is observed through the results that previous probabilistic methods developed for ERA can be overestimating the risk level.

1. Introduction

The significant rise in global energy demand has increased the attention of oil and gas industry to exploiting the hydrocarbon reserves in less explored areas. This includes the Arctic Ocean, containing about 13% of the world's undiscovered oil reserves (Bird et al., 2008; Giles et al., 2008). Despite the unique opportunity, the socio-environmental impact of exploration activities is an important aspect to be taken into account in decision making. Over the past few years, the concerns around oil spill accidents in the Artic region have prompted the stakeholders, including the governments of countries in those regions and the International Maritime Organisation (IMO), to review and amend existing regulations with respect to marine pollution (Chang et al., 2014; Orszulik, 2008). This is due to the major risk factors associated with the region which will definitely influence the likelihood (e.g. exerted loads from drifting icebergs) and consequences (e.g. slower decomposition of hydrocarbons in lower temperatures) of possible oil release accidents (AMAP, 2010; DNV, 2014; Jonsson et al., 2010). These are the two components of risk that must be analysed for the amendment of in place policies as well as for the development of contingency plans.

There may be a significant risk posed by underwater release of oil (El-Gheirani et al., 2017; Pula et al., 2006). The toxicity of chemicals can also adversely affect marine organisms with possible long-term consequences. There has been a great deal of research conducted on the Ecological Risk Assessment (ERA) of waste from offshore oil production platforms (Karman and Reerink, 1998; Sadiq, 2001; Sadiq et al., 2003). However, this aspect of subsea oil spill has recently achieved even greater attention. Nazir et al. (2008) developed a methodology for ERA of oil spill from a riser. The proposed model is based on US EPA framework and adopts a fugacity-based approach to estimate exposure to contaminants in the marine environment. A Monte-Carlo Simulation (MCS) was applied to incorporate the uncertainty of multimedia input parameters, and the analysis of stressor effect on the organisms was achieved by using toxicity data adopted from literature. Their method characterizes the ecological risk by transforming risk quotient (RQ) into probability distributions. French-McCay (2011) presents a biological effects model coupled to an oil trajectory and fate model for supplying the required spatial and temporal estimation of oil component concentrations. In this method, the long-term effects are quantified using food web modelling and MCS is performed for evaluating the risk of a spill scenario.

In the Arctic oil spill context, there have been several attempts towards ERA based on both qualitative and quantitative approaches. Afenyo et al. (2017) proposed a probabilistic ERA model specifically for Arctic marine oil spills. In their model, a combination of dispersion

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fugacity-based fate modelling and MCS is used to develop probability distributions for the exposure concentration and to predict the 95th percentile risk. The presented probabilistic approach propagates the uncertainty of input variables through the model. However, the probabilistic dependency of risk on those inputs is neglected. Moreover, the proposed methods do not provide a platform for the assessment of environmental risk with respect to important influencing parameters such as seasonal conditions.

Unlike classical probabilistic methods, Bayesian techniques are promising for probabilistic risk assessment (PRA) applications. This is mainly because they are able to deal with a wide range of information types and provide useful estimation of model parameters when the data is sparse or the correlation between them is hard to perceive (Siu and Kelly, 1998). Bayesian network has been adopted by several researchers for conducting PRA (Bhandari et al., 2015; Khakzad et al., 2013a; Yeo et al., 2016). Nevalainen et al. (2017) have used BN for analyzing the ecological impacts of oil spills on the Arctic environment and for providing a holistic view of such accidents. The authors assert that a food web approach be used as a more appropriate choice for ERA. In their model the influence of input parameters such as oil spill size and season on the acute and long-term ecological impacts are incorporated into the BN. However, it is suggested that the model must be enhanced with the quantification of problem variables. This is essential from a quantitative risk assessment viewpoint as well as for utilising the optimum capacity of BN.

The main objective of this study is to develop a probabilistic methodology for conducting ERA of an oil spill accident in the Arctic. A fugacity model is utilized to simulate the fate and transport of released oil and to predict the exposure concentration in different media. A BN is established, based on the US EPA framework, to estimate the risk posed by release of oil from a subsea pipeline, on the environment containing a wide range of organisms. To demonstrate the application of the proposed methodology, a case study of the Kara Sea is selected.

1.1. Ecological Risk Assessment (ERA)

A framework is suggested by the United States' EPA for conducting ERA. The main steps of this framework are i) problem formulation, ii) exposure analysis, iii) risk characterization and iv) risk management and communication (Sadiq et al., 2003). The problem formulation phase focuses on aggregating information, involving the assessment of endpoints, and planning for the risk analysis. The endpoints are selected based on the criteria provided by guidelines. In the case of underwater oil spills, marine organisms will be influenced by toxic chemicals with a concentration above an acceptable threshold. It is recommended by previous researchers that selecting a food web is more realistic than assessment with single species or groups as an endpoint (Husain et al., 2002; Nevalainen et al., 2017). However, this is a challenging task since the toxicity data of an entire food web is hard to obtain, particularly from the Arctic ecosystem. The present study therefore chooses the endpoints based on the availability of toxicity data in the literature. In the analysis step, the aim is at assessing the exposure and corresponding effects on the endpoints. The risk characterization phase uses the obtained results from the previous steps for mapping the risk profile posed by the presence of contaminant(s) in the studied environment. This assists in developing risk mitigation strategies or contingency plans to be shared with the stakeholders (Nazir et al., 2008). The present paper focuses on developing a quantitative ERA model using US EPA framework. In the next section a brief discussion on fundamentals of BN is presented. In Section 2, the proposed methodology is explained in detail followed by a numerical example in Section 3. Lastly, the concluding remarks of this paper are provided in Section 4.

1.2. Bayesian network (BN)

BN is a directed acyclic graph used for reasoning under uncertainty by considering the causal relationships. These relationships are represented by directed arcs, among a number of random variables that are represented by chance nodes. BN estimates the joint probability distribution of a set of random variables using the conditional independencies and the chain rule, given in Eq. (1).

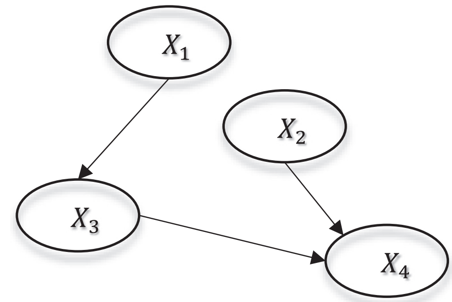

Fig. 1. Schematic of a BN.

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid pa(X_i)) \tag{1}$$

where $pa(X_i)$ is the parent set of variable X_i. As an example, the joint probability distribution of the random variables X_1–X_4 illustrated in Fig. 1 is estimated by $P(X_1, X_2, X_3, X_4) = P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_2, X_3)$.

BN is capable of updating the estimated probabilities when new information becomes available about any of the random variables (i.e. evidence to chance nodes). For instance, if the variable X_2 in Fig. 1 is known to be in state e, the joint probability distribution is updated based on the Bayes' theorem, given by Eq.(2):

$$P(X_1, X_3, X_4 \mid e) = \frac{P(X_1, X_3, X_4, e)}{\sum_{X_1, X_3, X_4} P(X_1, X_3, X_4, e)} \tag{2}$$

Dynamic Bayesian Networks (DBNs) represent stochastic processes and can be used for modelling the temporal behaviour of a set of random variables (Arzaghi et al., 2017). They divide the time line into a series of time slices each of which are connected from nodes in time slice $t - \Delta t$ to the node in time slice t, as shown in Fig. 2. This figure illustrates a schematic of DBN for which the joint probability distribution of its variables can also be estimated using Eq. (1).

An extensive outline of BN and probabilistic knowledge elicitation is provided by Barber (2012) and Pearl (1988). BN has a wide range of applications in risk and reliability assessment of engineering problems. Further details on using BN in different engineering applications can be found in previous research (Abbassi et al., 2016; Abaei et al., 2018; Abimbola et al., 2015; Eleye-Datubo et al., 2006; Khakzad et al., 2013b; Pui et al., 2017).

2. Methodology: Ecological Risk Assessment using BN

The proposed methodology provides a model based on US EPA framework of probabilistic analysis of ecological risk posed by release of oil from a subsea pipeline in the Artic region. This method can be adopted to improve the preparedness for more oil and gas industrial activities in the Arctic region and for amending the safety policies and regulations currently in place. The model can also help in preparing risk mitigation plans for oil release accidents. An overview of the proposed methodology is illustrated in Fig. 3, incorporating the key elements covered in each stage.

2.1. Exposure analysis

Exposure analysis is the key component of ERA of an accidental oil release in marine environment, which estimates the extent of