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A hierarchical Bayesian approach to modelling fate and transport of oil released from subsea pipelines

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ABSTRACT

The significant increase in global energy demand has drawn the attention of oil and gas industries to exploration of less-exploited resources. Arctic offshore region is reported to hold a great proportion of un-discovered oil reserves. While this can be a promising opportunity for the industry, more exploration activities will also increase the possibility of oil spill during the entire process including production and transport. A comprehensive risk assessment based on Ecological Risk Assessment (ERA) method is then required during the planning and operation stages of future Arctic oil production facilities. In the exposure analysis stage, ERA needs an evaluation of the oil concentration profile in all media. This paper presents a methodology for predicting the stochastic fate and transport of spilled oil in ice-infested regions. For this purpose, level IV fugacity models are used to estimate the time-variable concentration of oil. A hierarchical Bayesian approach (HBA) is adopted to estimate the probability of time to reach a concentration (TRTC) based on the observations made from a fugacity model. To illustrate the application of the proposed method, a subsea pipeline accident resulting in the release of 100 t of Statfjord oil into the Labrador Sea is considered as the case study.

1. Introduction

There has been increasing attention on the possibility of oil exploration in the Arctic Ocean which is mainly attributed to some parts of this region becoming ice-free due to climate change. According to Khon et al. (2010), the thickness and extent of Arctic ice cover has been declining, with a 40% reduction observed from 1979 to 2007. As a consequence, the Northwest Passage which connects Europe and Asia became ice free for the first time in the summer of 2007 (Giles et al., 2008). These changes, in addition to the rising global energy demand, may facilitate the exploration of the substantial hydrocarbon reserves in the Arctic Ocean becoming the next frontier of oil and gas explorations. Gautier et al. (2009) suggest that about 30% of the world's undiscovered gas and 13% of undiscovered oil reserves can be found in the Arctic region, of which more than 80% is expected to be in offshore locations (Bird et al., 2008). This exploration can bring many opportunities to the energy industry and in turn the world economy, however, the existing risk factors in the region can significantly increase the threat of oil spill during the exploration process and transport (Olsen et al., 2011). DNV (2014) highlights the major risk factors as the extremely low temperatures that influence the properties of the structure material as well as loads caused by the impact from drifting icebergs. In addition to the higher likelihood of accidents in the ice-infested waters, the consequences of an oil spill, such as distortion of the reproduction cycles of species and ecological changes, will be exacerbated in such regions (Afenyo et al., 2016a, 2016b). This is mainly due to the slower decomposition of hydrocarbons in low temperatures making them more available to affect the marine life and greater sensitivity of the Arctic ecosystems which have slower reproduction rates and more simple trophic structures (AMAPA, 2010; DNV, 2014; Jonsson et al., 2010). Moreover, an oil spilled in the Arctic is likely to remain in the environment for a long time, as the logistics challenges diminish the effectiveness of strategies for containing and cleaning up oil spills (Nevalainen et al., 2017). Parameters such as the type and quantity of the spilled oil as well as the seasonal

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variations in the environment can influence the extent of damage to the Arctic which can often be extended to long-term consequences. Camus and Smit (2018) investigated the environmental impacts arising from a potential Arctic oil spill based on a joint review program conducted in 2012 (D.F., 2017). Camus and Smit (2018) suggest that the results of their study provide a better understanding of the effects from such accidents assisting in the development of more effective management strategies. However, this research does not provide any method for quantification of the extent of impact or an approach to estimating the overall risk level.

A comprehensive Ecological Risk Assessment (ERA) method is then required for the entire well delivery process, from feasibility studies to asset management and operations. This assessment is performed to evaluate whether the activities are acceptable with respect to the industry's criteria as well as for developing effective contingency plans (Sanni et al., 2017; Hasle et al., 2009).

The three main steps of ERA are problem formulation, exposure analysis and risk characterisation. Exposure analysis is the key component of risk assessment of an accidental oil release in a marine environment (Anon., 1998). This phase of the analysis assists in estimating the extent of contamination in the environment, identifying the organisms exposed, pathways to exposure and the possible responses of the organisms to the stressor (i.e. hydrocarbons) (Afenyo et al., 2016a, 2016b; Nazir et al., 2008). In order to determine the level of contamination, concentration of the stressors must be estimated. To achieve this objective, many researchers have used fugacity concept (mostly level IV fugacity) as an approach to partition modelling (Nazir et al., 2008; Sadiq, 2001; Yang et al., 2015a, 2015b). A fugacity approach is capable of generating time-series of contaminant concentration in every medium in the environment, by simplifying the analysis due to continuity between the interfaces of the phases. Afenyo et al. (2016a, 2016b) developed a dynamic fugacity model for estimating the exposure of four media, including air, sea water, sediments and ice, to the oil released during Arctic shipping. The proposed model provides a profile for oil concentration in these media, however, it fails to consider the uncertainty of many parameters involved in the model which is essential for accurately estimating the ecological risk associated with the spill accident.

Nazir et al. (2008) developed a methodology for ERA of oil spill from a riser. The developed model is based on level IV fugacity for estimating the oil concentration in water and sediment medium, and utilizes Monte Carlo Simulations (MCS) to incorporate the uncertainty of multimedia input parameters. Similarly, Afenyo et al. (2017) proposed a probabilistic ERA model for Arctic marine oil spills. Their model provides probability distributions of the exposure concentration in different media as well as 95% percentile risk. However, due to the adoption of conventional methods that only propagate the uncertainty in input variables to model outputs, the probabilistic dependency of concentration on those inputs is neglected.

Unlike classical statistical methods, Bayesian techniques are useful for probabilistic risk assessment (PRA) applications 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 statistics have been adopted by several researchers for the conduct of probabilistic analyses (Yang et al., 2013; Yu et al., 2017), probabilistic risk assessment (Bhandari et al., 2015; Yeo et al. 2016) and maintenance scheduling of offshore structures (Abbassi et al., 2016; Arzaghi et al. 2017; Pui et al., 2017; Bhandari et al., 2016). Advances in Bayesian statistics such as developments of hierarchical Bayesian modelling (HBM) have brought them to a wider audience for solving complex engineering problems (Kelly and Smith, 2009). This method can be carried out using open source Markov Chain Monte Carlo (MCMC) software packages such as OpenBUGS.

The main objective of this study is to develop a probabilistic methodology for the fate and transport modelling of oil released from subsea pipelines in a marine environment. The results of this research provide the necessary information for conducting a comprehensive ERA and the development of oil spill contingency plans. A fugacity based model is utilized to predict the multimedia fate of oil upon the generation of an oil slick on the surface. An HBA is then adopted to incorporate the uncertainty of the parameters involved in fugacity model, and estimate the level of oil concentration dependent on these parameters. A case study is carried out to demonstrate the application of the proposed methodology through predicting the time taken to reach specific oil concentrations in the Arctic region in ice-infested waters.

1.1. Fugacity model

Fugacity (f) is known as the tendency of a chemical to escape from a phase and has the unit of pressure. The concept of fugacity is used as a substitute for chemical potential which is a criterion for thermodynamic equilibrium describing the fate of chemicals in a multiple media system. The relationship between concentration and fugacity is given in Eq. (1), proposed by Mackay and Paterson (1981):

$$C = Z \times f \tag{1}$$

where C is the concentration of chemical (mol/m^3), f is the fugacity (Pa) and Z is the fugacity capacity (mol/m^3 Pa). Fugacity capacity, Z, represents the tendency of a medium to absorb a chemical. Therefore a medium with a larger Z will have a higher concentration of chemicals due to more tendency to absorb (Yang et al., 2015a, 2015b). Mackay (2001) proposes four levels of fugacity-based models with different applications. Although level III models are used most, because of less complexity and requiring less data, the present study adopts level IV model as it is more realistic and can estimate the time-dependent behavior of the chemicals. The model proposed by Yang et al. (2013) is used as the basis for the developed probabilistic framework. More detailed discussions on fugacity models can be found in (Mackay, 2001; Nazir et al., 2008; Yang et al., 2015a, 2015b).

1.2. Hierarchical Bayesian modelling (HBM)

Observations of physical processes are regarded as *data* and may be subjected to different sources of uncertainty. *Information* can be achieved through the process of evaluation, manipulation and organizing data which eventually adds to *knowledge*. Statistical inference is defined as obtaining a conclusion based on the gained knowledge (Kelly and Smith, 2009). HBM is an advanced probabilistic approach to performing inference based on real-world observations. Bayes' theorem is considered for carrying out Bayesian inference, given in Eq. (2):

$$\pi_1(\theta|x) = \frac{f(x|\theta)\pi_0(\theta)}{\displaystyle\int_\theta f(x|\theta)\pi_0(\theta)\,d\theta}, \tag{2}$$

where θ is the unknown parameter of interest, $f(x|\theta)$ is the likelihood function, $\pi_0(\theta)$ is the prior distribution of θ and $\pi_1(\theta|x)$ is the posterior distribution of θ. The term hierarchical in HBA represents the use of multistage prior distributions. As suggested by Kelly and