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Research article

# A probabilistic approach for a cost-benefit analysis of oil spill management under uncertainty: A Bayesian network model for the Gulf of Finland

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ABSTRACT

Large-scale oil accidents can inflict substantial costs to the society, as they typically result in expensive oil combating and waste treatment operations and have negative impacts on recreational and environmental values. Cost-benefit analysis (CBA) offers a way to assess the economic efficiency of management measures capable of mitigating the adverse effects. However, the irregular occurrence of spills combined with uncertainties related to the possible effects makes the analysis a challenging task. We develop a probabilistic modeling approach for a CBA of oil spill management and apply it in the Gulf of Finland, the Baltic Sea. The model has a causal structure, and it covers a large number of factors relevant to the realistic description of oil spills, as well as the costs of oil combating operations at open sea, shoreline clean-up, and waste treatment activities. Further, to describe the effects on environmental benefits, we use data from a contingent valuation survey. The results encourage seeking for cost-effective preventive measures, and emphasize the importance of the inclusion of the costs related to waste treatment and environmental values in the analysis. Although the model is developed for a specific area, the methodology is applicable also to other areas facing the risk of oil spills as well as to other fields that need to cope with the challenging combination of low probabilities, high losses and major uncertainties.


## 1. Introduction

Marine, coastal and freshwater ecosystems around the world have been altered by human activities for centuries, but the rate of change has accelerated in recent decades. Intensified impacts of drivers like habitat change, pollution, and overexploitation of species have resulted in adverse effects on biodiversity and ecosystem goods and services (Millennium Ecosystem Assessment, 2005). To counteract this trend, societies are eager to find means to restore and maintain the good status of ecosystems.

In a world of limited resources, it is evident that environmental problems need to be combated as effectively as possible. Common approaches for assessing the economic efficiency of proposed environmental projects are cost-effectiveness analysis (CEA) and cost-benefit analysis (CBA). CEA aims at reaching a given target with minimum costs, while CBA compares monetized costs and benefits to assess the economic efficiency of a project or to identify the economically optimal level of action.

Although the logic of CBA is fairly straightforward, i.e. to compare the expected gains with the expected losses, there are many issues that need to be addressed particularly when applying the method in the context of environmental problems (Hanley, 1992; Pearce, 1998). For instance, the valuation of environmental impacts is challenging, especially when non-market goods, such as recreation, biodiversity or landscapes, are involved. This challenge can be overcome, at least partly, by using economic valuation methods that quantify the benefits of environmental improvements (or the damages from deterioration) either by posing direct questions on willingness to pay (WTP) (Bateman et al., 2002) or by observing actual behavior (Bockstael and McConnell, 2007).

Uncertainty poses another challenge for CBA analyses of environmental problems (Boardman et al., 2014; Pearce, 1998). Uncertainty originates from various sources: natural systems are stochastic by nature, and as they involve myriad of interacting

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factors forming complex entities, the knowledge of the system is imperfect. The situation is even more complex if the occurrence of undesirable events is highly uncertain, and the potential outcomes are dependent on several varying factors and thus exhibit large range. In this case the decision-maker has to consider the ultimate question: “How much to invest in mitigation preparedness, if there is a possibility that the adverse impacts will never materialize?”

This holds true for oils spills resulting from tanker accidents. These incidents can result in substantial costs and losses (Allo and Loureiro, 2013; Garza-Gil et al., 2006; Grigalunas et al., 1986; Loureiro et al., 2006). Direct costs result from offshore oil combating operations, shoreline clean-up activities, and logistic and treatment costs of recovered oil. In addition, oil spills usually inflict losses to fisheries and tourism sectors, and have negative impacts on recreational and environmental values (Alvarez et al., 2014; Carson et al., 2003; Loureiro et al., 2009; Loureiro and Loomis, 2013), some of which can be quantified in monetary terms. Although several studies have estimated the costs and monetary damages caused by oil spills, there are very few analyses that have examined the economic efficiency of improving oil spill preparedness by comparing the associated costs and benefits (Cohen, 1986).

In recent decades, Bayesian networks (BNs) have gained popularity in the field of environmental research and management (e.g. Aguilera et al., 2011; Landuyt et al., 2013; Varis and Kuikka, 1999). BNs are models that describe the system with probabilistic variables and links between them. As BNs express uncertainty explicitly, they suit well for modeling problems where uncertainty has a fundamental role (Kelly et al., 2013). Bayesian networks can be extended to influence diagrams by adding decision and utility nodes into the networks (Howard and Matheson, 2005). Further, BNs are able to integrate various types of data (e.g. Uusitalo, 2007), including monetary data, and thus offer a potential tool also for cost-benefit analysis under uncertainty. Previously BNs have been applied to CBAs related to eutrophication management by Ames et al. (2005), Barton et al. (2005, 2008), to pesticide management by Henriksen et al. (2007), and to integrated pond management by Landuyt et al. (2014).

In this paper we present a BN-based modeling approach that we use to conduct a probabilistic cost-benefit analysis of the management measures capable of reducing the harm from oil spills. Our study is focused on the Gulf of Finland (GoF), the easternmost basin of the Baltic Sea, but the methodology is applicable also to other marine and freshwater areas facing the risk of oil spills. The GoF has witnessed a multifold increase in the volume of transported oil since the early 2000s (Finnish Environment Institute, 2013), and, as part of the Baltic Sea, it has been designated as a Particular Sensitive Sea Area (PSSA) (Russian waters excluded) by the International Maritime Organization (IMO). As it is evident that a major oil accident in the GoF could result in substantial costs, our aim is to study whether there are economically reasonable management measures given the high uncertainty related to the frequency as well as the consequences of future tanker accidents. The primary aim of the model lies in the CBA, but the model can also be used to estimate the costs resulting from a single tanker accident.

## 2. Methodology: Bayesian networks and influence diagrams

Bayesian networks are graphical models for reasoning under uncertainty (Jensen and Nielsen, 2007). Each variable is associated with a probability distribution describing the probability of the variable being in a certain state. Variables not dependent on any other variable have a single probability distribution, whereas variables dependent on one or more variables have a conditional probability table (CPT). A CPT describes the probability of each state of the variable conditioned on every possible combination of the states of the parent nodes, i.e. the nodes on which the variable is directly dependent. If new information is fed into the network e.g. by instantiating one variable to a certain state, the states of the other variables are updated accordingly, based on the rules of the probability calculus and the Bayes' theorem. This propagation of new knowledge enables BNs to be used for both cause-to-effect and effect-to-cause reasoning. Various techniques can be used to quantify probability distributions within a BN. These include e.g. observed data, simulation results and expert knowledge (Uusitalo, 2007). A more detailed description of the methodology related to BNs can be found e.g. from Fenton and Neil (2013) and Jensen and Nielsen (2007).

With decision and utility nodes BNs can be extended to influence diagrams (Howard and Matheson, 2005). This enhances their use as decision support tools. As influence diagrams calculate expected utilities related to different states of the system, they can be used to find the optimal combination of decisions under uncertainty. Further, influence diagrams enable the calculation of value of information (VoI; Raiffa and Schlaifer, 1961), which describes the expected increase in expected utility that could be achieved if new information was acquired before making a decision.

BNs are applied in various fields of research including e.g. medicine (Forsberg et al., 2011), forensics (Biedermann and Taroni, 2012), social sciences (Haapasaari and Karjalainen, 2010), and engineering (Langseth and Portinale, 2007). They have gained popularity also in environmental management context, where BNs have been applied e.g. in fisheries (Kuikka et al., 1999; Levontin et al., 2011), water resources management (Bromley et al., 2005; Molina et al., 2010) as well as in other fields of ecology and environmental science (see e.g. reviews by Aguilera et al. (2011), Landuyt et al. (2013) and McCann et al. (2006)). In recent years they have been increasingly employed in studies related to maritime accidents and oil spill risk management (Aps et al., 2009; Carriger and Barron, 2011; Goerlandt and Montewka, 2014; Helle et al., 2011; Hänninen, 2014; Hänninen and Kujala, 2012, 2014; Juntunen et al., 2005; Lecklin et al., 2011; Lehikoinen et al., 2013), and Montewka et al. (2013) have presented a BN for estimating the clean-up costs of oil spills.

## 3. Structure of the model

The model includes altogether 55 variables relevant for the CBA: 2 decision variables, 40 random variables, and 13 utility variables. Further, as the calculation with utility variables is based on expected benefits and costs, additional 10 random variables were included in the model to demonstrate the uncertainty related to each cost and damage type.

The model consists of the main model and one sub-model which is used to calculate the monetary damages to the environment (Fig. S1 in Supplementary Material). Marginal distributions and conditional probability tables for the variables were formed based on several resources and techniques such as existing statistics, expert knowledge, other models (simulation models, BN models as well as other types of models) and published papers, and the cost data were gathered from literature or the experts working with oil combating issues in the Finnish Environment Administration or in regional rescue departments. The description of variables, as well as the data and techniques used to populate the network, are presented in detail in Supplementary Material. The model was built with Hugin Researcher 7.6 software (Madsen et al., 2005; www.hugin.com). In the following we give a general overview of the model and the main assumptions related to it, after which decision and utility variables are described in more detail.

A simplified representation of the model is presented in Fig. 1.