Risk management of drilling waste discharges in the marine environment - a holistic approach
Sadiq, R.; Husain, T.; Veitch, B.; Bose, N.

This publication could be one of several versions: author's original, accepted manuscript or the publisher's version. / La version de cette publication peut être l’une des suivantes : la version prépublication de l’auteur, la version acceptée du manuscrit ou la version de l’éditeur.

Publisher's version / Version de l'éditeur:


Access and use of this website and the material on it are subject to the Terms and Conditions set forth at https://nrcresearcharchive.nrc-cnrc.gc.ca/eng/copyright
L’accès à ce site Web et l’utilisation de son contenu sont assujettis aux conditions présentées dans le site https://publications-cnrc.canada.ca/fra/droits

LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D’UTILISER CE SITE WEB.

Questions? Contact the NRC Publications Archive team at PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca. If you wish to email the authors directly, please see the first page of the publication for their contact information.

Vous avez des questions? Nous pouvons vous aider. Pour communiquer directement avec un auteur, consultez la première page de la revue dans laquelle son article a été publié afin de trouver ses coordonnées. Si vous n’arrivez pas à les repérer, communiquez avec nous à PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca.
Risk management of drilling waste discharges in the marine environment - a holistic approach

NRCC-45388

Sadiq, R.; Husain, T.; Veitch, B.; Bose, N.

January 2003

Offshore drilling operations generate wastes associated with rock cuttings and spent drilling fluids during the well drilling phase. The wastes contain toxic substances and are harmful to the marine ecosystem. Discharge limitations and guidelines in different jurisdictions of the world are being developed. Compared to conventional oil-based fluids, the wastes generated from synthetic-based fluids (SBFs) have lower toxicity, lower bioaccumulation potential and faster biodegradation rates. Despite these environmentally benign characteristics, SBF's associated wastes still have a certain amount of pollutants due to contamination with formation oil and the presence of trace heavy metals in barite, which may pose environmental risk. The objectives of this paper are to determine the fate of SBFs waste in the marine environment and integrate methodologies of ecological and human health risk assessment using a holistic risk management model. Various discharge options representing different treatment levels are used to make a risk-cost trade-off analysis to illustrate the risk management process.

A steady state non-equilibrium water-sediment interaction fate model with probabilistic input parameters was used to determine the concentration of pollutants in sediment pore water. A chemical specific approach was used in the fate modeling. The total toxicity of the drilling waste depends on the toxicity of its individual constituents (base fluid, heavy metals, and organic pollutants). Barite contributes most significantly to the toxicity of drilling waste. The environmental risk assessment for the ecological community and human health was determined based on contaminant fate modeling exposure concentrations. Uncertainty in the quantification of risks was incorporated into multi-criteria decision-making (MCDM). The risks to the marine ecological community and humans were converted into an environmental risk index, which was then compared to the costs of different offshore treatment options, and of loss due to ecological damage. An analytical hierarchy process using fuzzy composite programming was employed to determine the best management alternative for the discharge of drilling waste in the marine environment.

Key words: Offshore, drilling waste, SBFs, fate modeling, fuzzy composite programming, ecological and human health risk assessments.
the well. Disposal of rock cuttings and used mud constitutes one of the most significant waste discharges associated with offshore drilling. The drilling fluids, or circulating muds, are broadly classified into three groups:
1. Water-based drilling fluid (WBF): conventional drilling mud with water as a base fluid
2. Oil-based drilling fluid (OBF): diesel, mineral, or some other oil as its continuous phase
3. Synthetic-based drilling fluid (SBF): synthetic material like polyesters and vegetable esters as its continuous phase

The SBF mud system consists of a synthetic base fluid, weighting agent (barite) and some other additives. Since 1990, the oil and gas extraction industry has developed many synthetic and non-synthetic materials as base fluids to provide drilling performance characteristics comparable to traditional OBFs with the lower environmental impacts and greater worker safety of WBFs. These characteristics have been achieved through lower toxicity, elimination of polynuclear aromatic hydrocarbons (PAHs), faster biodegradation rate, and lower bioaccumulation potential of pollutants [U.S. EPA 1999a].

The discharge of OBF rock cuttings into the North Sea has been prohibited by the Norwegian regulatory authority. As a result, all such cuttings must be either re-injected downhole, or shipped to the shore for treatment and disposal. Discharge of SBFs is restricted and is permitted only on a case by case basis. The regulatory authorities on the East Coast of Canada have recently moved from 15% (by dry weight) drilling muds on cuttings allowed at discharge to a target of 6.9% (on wet cuttings).

The United States Environmental Protection Agency (U.S. EPA) has identified different options to reduce the discharge of drilling waste into the marine environment. Current industry practice for managing and treating SBF cuttings before discharge is to process the cuttings through solids separation equipment, which consists of primary and secondary shale shakers and occasionally a centrifuge. Based on current industry data, the efficiency of solids separation equipment results in a long-term average of 10.2% (by wet weight) retention on cuttings. However, using new treatment technology, the retention of fluids can be reduced to approximately 4% under certain conditions [U.S. EPA 2000a; 2000b].

The disposal of drilling fluids in the ocean environment is of major concern for two main reasons: economical loss associated with expensive synthetic drilling fluid discharged with rock cuttings and probable adverse ecological impacts. To determine the fate of contaminants associated with drilling waste, several studies have been conducted in the past. The U.S. EPA [2000a] developed a methodology for assessing surface water and pore water quality impacts by using the Offshore Operator’s Committee (OOC) model as described by Brandsma [1996]. In this analysis it is assumed that discharged contaminants immediately leach into the water column or into the pore water. Instead of SBFs waste as a whole, constituent organic priority pollutants and heavy metals were studied in this analysis. Some other modeling attempts have been conducted based on particle tracking techniques (e.g., Seaconsult [2000]). A set of models for the dispersion and drift of drilling wastes and suspended sediment in the benthic boundary layer has been developed by Hannah et al. [1997] who applied these models to the Georges Bank, Canada.

Thibodeaux et al. [1986] developed a model for the fate and transport of chemical contaminants originating from offshore drilling bottom deposits. This model was limited to the transport of the soluble constituents from the cuttings and mud deposits. It does not take into account particulate transport and chemical and biochemical transformations that degrade contaminants within the sediment zone or boundary layer. In the North Sea OSPAR (Oslo and Paris) convention area, the Chemical Hazard Assessment and Risk Management (CHARM) model was developed to help stakeholders, including regulators, operators and chemical suppliers, with a risk management module [Thatcher et al. 1999]. The CHARM model categorizes wastes into different application groups, such as production waters and WBFs. The OBFs and SBFs are not addressed in this model due to limited information on input parameters such as biodegradation and bioaccumulation characteristics.

SBFs are hydrophobic in nature and tend to sink to the bottom with little dispersion. Therefore, the main research focus has been on determining the toxicity in the sedimentary phase as opposed to the aqueous phase. Many studies, including Candler and Leuterman [1997] and Rabke and Candler [1998], have reported the toxicity response of SBFs for different organisms. In addition to the toxicity of the base fluid, the drilling waste contains organic priority pollutants and heavy metals that adversely affect the ecological community [U.S. EPA 1999a]. The CHARM model calculates ecological risk by taking the ratio of two parameters: the predicted environmental concentration to the predicted no-effect concentration (PEC/PNEC). This method is similar to the U.S. EPA approach where predicted concentration is compared with Federal Water Quality Criteria [U.S. EPA 1999b].

Another aspect of environmental risk assessment of drilling waste is human exposure through consumption of contaminated commercial fish. Marine organisms are exposed to pollutants through direct uptake (bioconcentration) and consumption of lower trophic level organisms (biomagnification). Bioaccumulation of chemicals in aquatic food chains, which is a combined effect of the above two processes, is an important phenomenon in aquatic organisms and affects their predators, especially humans and fish-eating wildlife [Campfens & Mackay 1997]. The consumption of contaminated organisms may pose a threat to human health. A deterministic analysis for human exposure and related non-carcinogenic and carcinogenic health risk through consumption of finfish and shrimps is presented in the U.S. EPA studies [1999b; 2000a].

Cost comparisons of different discharge options for water quality, and in the case of zero discharge the non-water quality environmental impacts, are provided in the U.S. EPA study [2000a]. The risk management module of the CHARM model is not well accepted by stakeholders, although it compares various alternatives for risk reducing measures. The basis of risk management in the CHARM model is to combine the risk
of individual substances into a single risk estimate. The several management alternatives can be compared on the basis of their cost and risk reduction strategy. Some other researchers (e.g., Stansbury et al. [1989]) used fuzzy composite programming for management of dredged material, which accommodated conflicting objectives - environmental risk and cost - in their analysis.

To develop a decision support system for management of drilling waste discharges in the marine environment, a risk-based approach was planned. This research integrates the contaminant fate modeling, ecological and human health risk assessment and risk management methodologies [Sadiq 2000; 2001]. A risk management methodology, fuzzy composite programming (FCP), is formulated and applied to optimize drilling waste discharges as an illustrative case study in the following sections.

2. FUZZY COMPOSITE PROGRAMMING (FCP) - A RISK MANAGEMENT TECHNIQUE

Decision-making is an integral part of all design and management issues. The main concern in decision-making is that decision problems are diverse in nature and usually have conflicting criteria. Many attempts have been made to incorporate the uncertainty of attributes into decision-making, which involves probability theory and/or fuzzy set theory. Fuzzy set theory is an important tool for modeling uncertainty or imprecision arising from human perception. Human judgment is involved in decision-making, so a rational approach to decision-making takes into account human subjectivity. A traditional multiple criteria decision-making (MCDM) problem can be expressed in a matrix form

\[
\begin{align*}
A_1 & = \begin{pmatrix}
X_{11} & X_{12} & \cdots & X_{1n} \\
X_{21} & X_{22} & \cdots & X_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
X_{m1} & X_{m2} & \cdots & X_{mn}
\end{pmatrix}
\end{align*}
\]

where

- \( A_i \) = 1, 2, ..., \( m \) are possible courses of action or alternatives
- \( Xi \) = 1, 2, ..., \( n \) are attributes, or performance criteria
- \( X_{ij} \) = performance or rating of alternative \( A_i \) with respect to attribute or criterion \( Xi \)

In real life problems, it is common that \( X_{ij} \) are not assessed precisely due to unquantifiable, incomplete, and non-obtainable information and partial ignorance. These limitations in MCDM methods lead to fuzzy-based approaches. To perform MCDM using fuzzy-based methods, two main steps are followed:

1. The aggregation of the performance scores with respect to all the attributes for each alternative; and
2. the rank ordering of the alternatives according to aggregated scores. These two steps are referred to as final rating and ranking order, respectively. In fuzzy MCDM problems, the performance scores of the alternatives are compared and rank orders of fuzzy numbers are determined, which in some cases is not a trivial task. Both phases are integral parts of fuzzy MCDM.

(a) Grouping of Attributes

FCP is an extension of compromise programming [Bogardi & Bardossy 1983]. In this approach, analytical hierarchy process (AHP) and fuzzy arithmetic are used. Many researchers have used this approach in environmental related issues and risk management problems (e.g., James & Lee [1992]; Lee [1992]; Lee et al. [1991]; and Stansbury et al. [1989]). A detailed description of this technique is given in this section. FCP is used to assist decision-makers in solving problems of multiple attributes and conflicting objectives. FCP organizes the problem into the following format

1. Identification of management alternatives
2. Definition of basic indicators
3. Grouping them into more generalized indicators
4. Defining weights, balancing factor, the best and worst values of the indicators and
5. Estimation and ranking of the alternatives

FCP is a step-by-step procedure of regrouping a set of various basic indicators to form a single indicator [Bogardi & Bardossy 1983]. FCP may use a composite structure of the basic indicators selected for risk management of drilling waste. In addition to cost and technical feasibility, risks to both human and non-human populations can also be taken as basic indicators. Carcinogenic and non-carcinogenic human health and ecological risks can also be considered.

The first step in FCP is the normalization of the basic indicators. This is necessary because all basic indicators have different units and are difficult to compare in their respective units. At the first level, human cancer and non-cancer risks are determined for different contaminants, which are grouped into cancer and non-cancer human risk indices (figure 1). Similarly, ecological risks are determined for different contaminants to get ecological risk indices.

At level 2, the human health cancer and non-cancer risks are grouped as a human health risk index. The level 2 human and ecological risk indices are grouped to form the environmental risk at level 3. The same procedure is repeated for the cost and the technical feasibility of treatment operations. The grouping for different attributes is performed in steps, until we get the total risk index, total cost and technical feasibility of operations to make a trade-off analysis among conflicting objectives. This trade-off analysis for different alternatives can be done at all hierarchy levels. The system index value at level 4 represents the contribution of the final risk index, total cost and final technical feasibility of operations. Figure 1 shows the framework of FCP in a step-by-step procedure for risk management of drilling waste discharges.
The values of the basic indicators can be designated by fuzzy numbers to characterise their uncertainties. By defining $Z_i(x)$ as a fuzzy number of the $i^{th}$ basic indicator with a triangular membership function of $\mu(Z_i(x))$, various management alternatives under uncertainty can be evaluated. The confidence level for an uncertain value can be determined using observed or measured variability. Since units of basic indicators are different, the actual value of each basic indicator should be transformed into an index, $S_{i,h}(x)$, using the best or the worst value of the indicator as shown in figure 2 [Lee et al. 1991]. Using the index values of basic indicators, the level 2 index values, $L_{j,h}(x)$, of composite indicators can be defined by

$$L_{j,h}(x) = \left\{ \sum_{i=1}^{n_j} wi_j [S_{i,h,j}(x)]^{p_j} \right\}^{1/\sum wi_j} \quad (2)$$

where

- $n_j$ = number of elements in second level group $j$
- $S_{i,h,j}(x) = \text{basic value for } i^{th} \text{ basic indicator in the second level group } j \text{ of basic indicators with membership of } h$
- $wi_j = \text{weight reflecting the importance of each basic indicator } (\sum wi_j = 1)$ and $p_j$ is the balancing factor for group $j$

Further, the index values $L_{k,h}(x)$, of the third level composite indicators can be calculated by using the index values for the second level composite indicators. This procedure is repeated to the final step, which compares three index values of the 4th level indicators: environmental risk, cost and technical feasibility.

The selection of weights ($w$) and balancing factors ($p$) depends on a single or group of decision-makers. The weights represent the relative importance of each indicator as viewed by a decision-maker, whereas the balancing factors account for maximum deviation of the indicators and limit the ability of one indicator to substitute for another. A weighting technique is used to group basic indicators into more general groups. The weights are allotted in each group based on their relative importance. The process, called an analytical hierarchy process (AHP), is used to determine the weight of each indicator in a group by a paired comparison of each of the indicators [Saaty 1988; Lee 1992].

![Diagram](image-url)

**Figure 1.** The framework of FCP for drilling waste risk management.
To determine the ranking for various management alternatives, assume \( L(x) \) as a fuzzy number, which is represented by a final composite indicator of alternative \( x \). With the help of two index values, \( L_{h=1}(x) \) and \( L_{h=0}(x) \), the membership function, \( \mu[L(x)] \), of the fuzzy number can be calculated approximately. For \( m \) management alternatives there are \( m \) fuzzy numbers, \([L(x), x = 1, 2, ..., m]\), to which any ranking method can be applied. The Chen [1985] ranking method determines the ranking of \( m \) fuzzy numbers by maximizing and minimizing sets. This method has been extensively used in ranking alternative studies [Lee 1992; Stansbury et al. 1989]. The methodology of FCP allows the incorporation of complex social, ecological and economic information into the fuzzy decision-making process. The details of weighting schemes and fuzzy ranking methods are given in the following sections.

(b) Weighting of Basic Attributes

MCDM methods require information about the relative importance of attributes or criteria. It is usually established by a set of preference weights, which are normalized to a sum of 1. In case "n" criteria, a set of weights can be written as

\[
\sum_{j=1}^{n} w_j = 1
\]

Therefore, the MCDM problem (equation 1) becomes

\[
\begin{align*}
A_1 &\begin{pmatrix}
X_1 & X_2 & \ldots & X_n
\end{pmatrix}^T W \\
A_2 &\begin{pmatrix}
X_{11} & X_{12} & \ldots & X_{1n}
\end{pmatrix}^T w_1 \\
&\quad \vdots \\
A_m &\begin{pmatrix}
X_{m1} & X_{m2} & \ldots & X_{mn}
\end{pmatrix}^T w_n \\
D = &\begin{pmatrix}
X_1 & X_2 & \ldots & X_n
\end{pmatrix}^T \sum_{j=1}^{n} w_j
\end{align*}
\]

Saaty [1988] has proposed AHP to estimate the relative weight of each attribute in a group based on a paired comparison. To compare criterion "i" with "j" the decision-maker can assign values \( a_{ij} \) from table 1. He proposed the following steps to assign the weights:

1. If \( a_{ij} = r \), then \( a_{ji} = (1/r) \), where \( r \neq 0 \) and \( i \neq j \)
2. If \( i = j \), then \( a_{ij} = a_{jj} = 1 \)
3. Construct matrix \( A_{ij} = (a_{ij} / (1..n); j = 1, ..., n) \)

It is further shown that the eigen vector corresponding to the maximum eigen value of matrix \( A \) is a cardinal ratio scale for the criteria compared [Saaty 1988]. The eigen value problem can be solved by:

\[
A \cdot W = \Phi_{max} \cdot W
\]
Where $\Phi_{\text{max}}$ is a scalar corresponding to the maximum eigenvalue and the unit vector “W" corresponding to $\Phi_{\text{max}}$ gives the preference weights.

<table>
<thead>
<tr>
<th>Intensity of importance</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>3</td>
<td>Weak importance</td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
</tr>
<tr>
<td>7</td>
<td>Demonstrated importance</td>
</tr>
<tr>
<td>9</td>
<td>Absolute importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>Intermediate values</td>
</tr>
</tbody>
</table>

Table 1. Linguistic measures of importance (Saaty 1988).

A double weighting scheme is proposed in FCP. The second type of weighting used in FCP is the balancing factor ($p$). The balancing factor is assigned to groups of indicators to reflect the importance of the maximal deviations of an indicator value and the corresponding best value for that indicator. The larger the value, the greater is the concern with respect to the maximal deviation. When $p = 1$, all deviations are equally weighted, for $p = 2$, each deviation receives its importance in proportion to its magnitude [Torno et al. 1988].

(c) Converting Linguistic Terms into Fuzzy Numbers

For those basic indicators that are expressed by linguistic terms (e.g., good, poor or excellent) a numerical approximation is proposed to convert linguistic terms into corresponding fuzzy numbers. Chen and Hwang [1992] have defined eight scales to convert linguistic terms into fuzzy numbers and one of the most important scales is shown in figure 3. This scale contains five levels. The linguistic terms for this scale are “very low”, “low”, “medium”, “high”, and “very high”. The same linguistic terms may contain different meaning in different scales. The “high” in this scale means [(0.6,0), (0.75,1.0), (0.9,0)], that is, the most likely value (when the membership function $\mu(x)$ is 1) is at 0.75 and the largest likely interval is between 0.6 and 0.9 (when the membership function, $\mu(x)$ is 0). Similarly all other linguistic terms can also be defined from figure 3.

(d) Converting Statistical Data into Fuzzy Numbers

For those basic indicators that are expressed by statistical data, the most crucial step is to determine the membership functions. There are many guidelines on developing membership functions for fuzzy sets. The fuzzy sets based on statistics are perhaps one of the most naturally fuzzy sets that can be used [Civanlar & Trussel 1986]. The statistical data can be represented by histograms, which can be used for approximation of a probability density function (PDF). Consequently, the fuzzy sets using this histogram can follow the rule that $\max[\mu(x)] = 1$. A similar approach is used by Guyonnet et al. [2000] for comparing MC simulation results and fuzzy arithmetic as two methods of measuring uncertainties.

Jooste [2001] developed a simple methodology for risk estimation of co-occurring stressors in an aquatic ecosystem based on fuzzy sets. He used the lowest 5th, median and the highest 95th percentiles for defining triangular fuzzy numbers. Sadiq [2001] adopted a similar approach for converting probability data into triangular fuzzy numbers. The confidence intervals of the lowest 1% and highest 99% were used to define the largest likely interval of the fuzzy number. The mode of the data was used to define the most likely value of the fuzzy number with a membership function value of 1. Figure 4 shows this methodology for developing a triangular fuzzy number from statistical data.

![Figure 3. Conversion of linguistic terms into numerical scores [Chen and Hwang 1992].](image-url)
RISK MANAGEMENT OF DRILLING WASTE DISCHARGES - A HYPOTHETICAL CASE STUDY

The risk management formulation discussed in this section is now applied to risk management of drilling waste discharges case study.

3. RISK MANAGEMENT OF DRILLING WASTE DISCHARGES - A HYPOTHETICAL CASE STUDY

The risk management methodology developed above was applied to a hypothetical case study of an oilfield on the East Coast of Canada. The contaminant fate modeling, ecological and human health risk assessment, and cost estimation models were integrated to show the significance of adopting a holistic risk management methodology for the selection of the best management alternative for drilling waste disposal in the marine environment.

Various discharge scenarios representing management alternatives were selected based on regulatory discharge requirements and efficiency of state-of-the-art solid control devices. Based on these selected discharge scenarios, the loading rates for contaminants present in the drilling waste stream were estimated. The fate models were employed in estimating the predicted environmental concentration in the pore water. In the next step, the ecological and human health risk assessment models were used for risk characterization, based on estimated exposure concentrations (EC). In the end, a tradeoff analysis was performed to decide the best management alternative for the discharge of drilling waste from risk reduction, cost saving, and technical feasibility viewpoints. A methodology framework for this integrated approach is shown in figure 6. A step-by-step description of each module is given below.

(a) Contaminant Fate Modeling

Contaminant fate modeling consists of drilling waste characterization, discharge scenarios definition, estimation of pollutant loading rates and estimation of pollutant concentrations using fugacity/aquivalence models.

(f) Characterization of Drilling Waste

The waste stream discharged from drilling operations that use SBFs or other non-aqueous drilling fluids consists of three main components: drilling fluid, drill cuttings, and formation oil. The U.S. EPA [1999a] has analyzed pollutant reduction options, compliance costs, and non-water quality environmental impacts, which are based on the drilling waste characteristics data given in table 2. Formation oil is the only source of organic priority pollutants in the SBF cuttings waste.
SBFs contain 47% synthetic base fluid, 33% barite, and 20% water by weight; and 0.2% formation oil of SBF (by volume).

<table>
<thead>
<tr>
<th>Priority pollutant organics</th>
<th>mg pollutant/ml formation oil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naphthalene</td>
<td>1.43</td>
</tr>
<tr>
<td>Fluorene</td>
<td>0.78</td>
</tr>
<tr>
<td>Phenanthrene</td>
<td>1.85</td>
</tr>
<tr>
<td>Phenol</td>
<td>6.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Metals</th>
<th>mg/kg of barite</th>
<th>Metals</th>
<th>mg/kg of barite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arsenic (As)</td>
<td>7.1</td>
<td>Lead (Pb)</td>
<td>35.1</td>
</tr>
<tr>
<td>Cadmium (Cd)</td>
<td>1.1</td>
<td>Mercury (Hg)</td>
<td>0.1</td>
</tr>
<tr>
<td>Chromium (Cr)</td>
<td>240.0</td>
<td>Nickel (Ni)</td>
<td>13.5</td>
</tr>
<tr>
<td>Copper (Cu)</td>
<td>18.7</td>
<td>Zinc (Zn)</td>
<td>200.5</td>
</tr>
</tbody>
</table>

Table 2. Waste characteristics of SBF-cuttings.

(ii) Discharge Scenarios and Pollutant Loading Rates

A hypothetical oilfield comprised of 32 wells — and the associated discharge — was considered on the Grand Banks of Newfoundland. The elements of greatest concern in these wastes were base fluid, heavy metals, and formation oil, although the cuttings themselves were also a concern because of their smothering effect on the benthic community. The hypothetical oilfield encompassed an affected area of 67 km². The wells were assumed to be uniformly distributed over that area. The affected impact area ($A_w$) for a single well was 2.09 km². The radius of impact area ($R$) for a single well was approximately 816 m. The depth of the water column was 95 m. The wells were assumed to be drilled only by SBFs (esters). The esters are the most commonly used and environmentally benign synthetic based drilling fluids [U.S. EPA 2000a]. Pollutant loading rates of heavy metals, base fluid (ester) and organic priority pollutants were calculated based on deep development model well data as suggested by U.S. EPA [2000a; 2000b].

Five discharge scenarios were selected as potential management alternatives for drilling waste disposal in the marine environment. These alternatives included 10% (current practice in Gulf of Mexico), 8.5% (obtainable with the current technology), 7.0%, 5.5% and 4.0% (BAT proposed). These alternatives represent the percentage of base fluid attached to the drill cuttings. The major components of drilling wastes are drill cuttings, base fluid, barite and water. The weights and volumes of these components were calculated based on ester percentage attached to the cuttings. The volume and weight of dry drill cuttings were estimated using borehole volume and the density of dry cuttings.

The quantities of each component were estimated to determine the weight and volume of total drilling waste for a given discharge option. The total volume of base fluid discharged for the 10% discharge option was estimated to be 57 m³ per well. The amount of formation oil was estimated based on an assumption that it is 0.2% volume fraction of the SBF, which is 140 kg for the 10% discharge option. The weight of barite discharged under the 10% discharge option is approximately 32,000 kg. The barite discharged in the marine environment contributes trace heavy metals, which pose a threat to ecological entities.

The amounts of heavy metals depend on the quantity of barite discharged for each option. The effluent concentrations of heavy metals in a drilling waste stream ($C_e$) were estimated based on the weight fractions of metals in the barite, whereas organic pollutant concentrations depend on the volume fraction of formation oil present in the SBF. The volume fraction of SBF was calculated by dividing the volume of SBF with the total volume of drilling waste for a given discharge option [Sadiq 2001].

The total quantities of pollutants were estimated by multiplying the total volume of the drilling waste with the $C_e$ of each pollutant present in the drilling waste stream for a given option. An average time of one-month is assumed to estimate the loading rates for each pollutant [U.S. EPA 2000a]. The loading rates calculated for all pollutants are provided in mg/hr, except for ester, which is given in kg/hr. Table 3 provides a summary of pollutant loading rates estimated for different discharge scenarios.
Pollutants | 10% | 8.5% | 7.0% | 5.5% | 4.0% |
--- | --- | --- | --- | --- | --- |
As | 311 | 254 | 201 | 152 | 107 |
Cd | 48 | 39 | 31 | 24 | 17 |
Cr | 10,495 | 8,573 | 6,796 | 5,146 | 3,612 |
Cu | 818 | 668 | 530 | 401 | 282 |
Hg | 4.4 | 3.6 | 2.8 | 2.1 | 1.5 |
Ni | 590 | 482 | 382 | 290 | 203 |
Pb | 1,535 | 1,254 | 994 | 753 | 528 |
Zn | 8,768 | 7,162 | 5,677 | 4,299 | 3,018 |
*Naphthalene* | 3319 | 270 | 214 | 162 | 114 |
*Ester* | 62 | 51 | 40 | 31 | 21 |

*Naphthalene is considered as the marker for formation oil contamination in the drilling waste. Other PAH are not considered in the analysis.

*Ester (values are in kg/hr)*

| Pollutants | 10% | 8.5% | 7.0% | 5.5% | 4.0% |
--- | --- | --- | --- | --- | --- |
As | 311 | 254 | 201 | 152 | 107 |
Cd | 48 | 39 | 31 | 24 | 17 |
Cr | 10,495 | 8,573 | 6,796 | 5,146 | 3,612 |
Cu | 818 | 668 | 530 | 401 | 282 |
Hg | 4.4 | 3.6 | 2.8 | 2.1 | 1.5 |
Ni | 590 | 482 | 382 | 290 | 203 |
Pb | 1,535 | 1,254 | 994 | 753 | 528 |
Zn | 8,768 | 7,162 | 5,677 | 4,299 | 3,018 |
*Naphthalene* | 3319 | 270 | 214 | 162 | 114 |
*Ester* | 62 | 51 | 40 | 31 | 21 |

Table 3. Pollutant loading rates (E, mg/hr) for one month for different discharge scenarios [Sadiq 2001].

(iii) Application of Fate Models

Generally, physical processes are employed in the fate modeling of drilling waste, however other processes including chemical, biological and ecological are not incorporated. The transport of drilling waste involves advection, dispersion, flocculation, deposition, consolidation, erosion, and resuspension. The impacts of these processes on the fate of drilling waste depend on the characteristics of the waste and the hydrodynamics of the receiving water bodies [Khondaker 2000].

Fugacity/aquivalence based models have been applied for detergent chemicals, PCBs, and heavy metals to determine their fate in rivers and lakes [Mackay 1991]. In these models, a steady state solution describes conditions that will be reached after prolonged exposure of the system to constant input conditions. The use of fugacity as an equilibrium criterion is suitable for chemicals that can establish measurable concentrations in the vapor phase. It is not applicable to some metals, organometals, ionic compounds, or some organics such as polymers whose vapor pressure is negligible. To model the behavior of these chemicals, another equilibrium criterion known as the aqueous equivalent concentration (aquivalence) criterion is used [Mackay & Diamond 1989]. A model developed in terms of equivalence is ultimately similar to models written in terms of concentration or fugacity. Steady state non-equilibrium fugacity and equivalence models were employed in this study for organics and heavy metals, respectively. The formulation of these models can be seen in Sadiq et al. [2001a-d].

The model inputs were defined by statistical distributions to incorporate uncertainty and variability. Monte Carlo (MC) simulation is one of the most widely used methodologies to account for parameter variability in contaminant transport and fate modeling. The robustness and capability of MC simulation methods are not limited by the non-linearity of the problem. A Latin Hypercube Sampling (LHS) based MC simulation was used to estimate the concentrations in the water column and pore water [Sadiq et al. 2000a-d]. The predicted environmental concentration (PEC) is defined as the highest 95th percentile value on the cumulative distribution function (CDF) of estimated concentration profile. The PEC values were adjusted for exposure probability (p) and bioavailability (BF) to estimate the exposure concentration (EC) for each pollutant in various discharge scenarios. The bioavailability of contaminants depends on their physico-chemical characteristics and ability of receptors to uptake and intake. It is a complex mechanism but for simplicity BF values are assumed based on the dissolved fraction of pollutants. Similarly, exposure probability also depends on receptor movement and their ability to uptake contaminants. A single exposure probability value was assumed based on the ratio of contaminated area to total area under study. Table 4 summarizes pore water exposure concentrations for various discharge scenarios. These exposure concentrations were used for ecological and human health risk assessments, which are basic indicators in FCP.

Water column concentrations are not reported in this paper as they were below background concentrations due to the hydrophobic nature of drilling waste.
where $X_m = \text{average of the lognormally transformed data} = 2.85$

$S_m = \text{standard deviation of the lognormally transformed data} = 1.74$

$y = \text{variable to describe the normal probability curve} = \ln(HQ)$. 

$$
\text{Risk} = \int_{y=0}^{\ln(HQ)} \left( \frac{1}{S_m \sqrt{2\pi}} e^{-\frac{(y-X_m)^2}{2S_m^2}} \right) dy
$$

Table 4. Exposure concentration in pore water (EC, $\mu g/L$) for different discharge scenarios.

<table>
<thead>
<tr>
<th>Pollutants</th>
<th>10%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>As</td>
<td>0.23</td>
<td>0.19</td>
<td>0.15</td>
<td>0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>Cd</td>
<td>0.17</td>
<td>0.14</td>
<td>0.11</td>
<td>0.08</td>
<td>0.06</td>
</tr>
<tr>
<td>Cr</td>
<td>2.05</td>
<td>1.68</td>
<td>1.33</td>
<td>1.01</td>
<td>0.71</td>
</tr>
<tr>
<td>Cu</td>
<td>1.01</td>
<td>0.83</td>
<td>0.66</td>
<td>0.50</td>
<td>0.35</td>
</tr>
<tr>
<td>Hg</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Ni</td>
<td>2.01</td>
<td>1.65</td>
<td>1.31</td>
<td>0.99</td>
<td>0.70</td>
</tr>
<tr>
<td>Pb</td>
<td>2.19</td>
<td>1.78</td>
<td>1.42</td>
<td>1.07</td>
<td>0.75</td>
</tr>
<tr>
<td>Zn</td>
<td>2.35</td>
<td>1.92</td>
<td>1.52</td>
<td>1.16</td>
<td>0.81</td>
</tr>
<tr>
<td>Naphthalene</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Ester</td>
<td>17.68</td>
<td>14.45</td>
<td>11.50</td>
<td>8.70</td>
<td>6.10</td>
</tr>
</tbody>
</table>

Table 5. PNEC response criteria values ($\mu g/L$) used to determine the risk of adverse effects.
The risks estimated for each pollutant were grouped together as statistically independent events i.e.,

\[ \text{Risk} (A + B) = \text{Risk} (A) + \text{Risk} (B) - \text{Risk} (A) \cdot \text{Risk} (B) \] (9)

Similarly,

\[ \text{Risk} (A + B + C) = \text{Risk} (A) + \text{Risk} (B) + \text{Risk} (C) - \text{Risk} (A) \cdot \text{Risk} (B) - \text{Risk} (B) \cdot \text{Risk} (C) - \text{Risk} (A) \cdot \text{Risk} (C) + \text{Risk} (A) \cdot \text{Risk} (B) \cdot \text{Risk} (C) \] (10)

And so on.

Thatcher et al. [1999] and Jooste [2000] have adopted similar methodologies for grouping risk in the case of multiple stressors. The risk estimated from equation 8 is in the form of an empirical distribution function (EDF). Therefore composite ecological risks estimated from the series of equations (e.g. equations 9 and 10) are also in the form of an empirical distribution function.

The EDFs of composite ecological risk values were converted into minimum, maximum likely (mode, MLV) and maximum values (see figure 4). The minimum, MLV and maximum risk values were used to develop a triangular fuzzy number. Figure 7 shows the minimum, MLV and maximum values for each discharge scenario, where these values represent the lowest 1%, mode and the highest 99% of the EDF [Jooste 2001]. The cumulative ecological risk varied over a wide range from 0.18 to 0.63 for the 10% discharge option, with an MLV of 0.25. It reduced to 0.04 to 0.33 for the 4% discharge option with an MLV of 0.13. The base of the triangular fuzzy number represents the uncertainty in the estimates. The apex of the triangle represents the MLV. The highest uncertainty in the ecological risk estimates can be observed for the 10% discharge option and the least uncertainty is observed for the 4.0% discharge scenario.

(c) Human Health Risk Assessment

Human health is the other major component of environmental risk assessment. Human health risk assessment involves exposure to contaminated fish caught at the impacted site. The pore water exposure concentrations (EC) of each contaminant were employed to estimate the fish tissue concentration, which were further used as human exposure concentrations through consumption of contaminated fish. The fish tissue concentration was estimated by multiplying EC by bio-concentration factors (BCF) and lipid content of fish (L). Human health risk consists of cancer and non-cancer risk estimates. The chronic daily intakes (CDI) were calculated for each contaminant individually. For cancer risk, CDI was multiplied by the slope factor (SF) (arsenic is the only proven bio-concentration factors (BCF) and lipid content of fish in this study) to estimate the unit risk over the life span of a person. Similarly, for the estimation of non-cancer risks, reference doses (RfD) were divided by CDI for each contaminant to determine a hazard index \( HI \). In the end, the \( HI \)s for all contaminants were summed up to determine the composite hazard index \( HIE \).

\[ \sum HI = HIE \] (11)

The cancer and non-cancer risk estimates are reported in table 6. The minimum, MLV and maximum values for various discharge scenarios are reported. The minimum values correspond to the lowest 1% and maximum values correspond to the highest 99th percentile value of the estimates, whereas the MLV is the highest frequency value, which corresponds to the mode value (see figure 4).

The highest estimated value of \( HIE \) for the 10% discharge scenario was 0.086. This value is approximately 12 times lower than the safety level of 1. Similarly, the unit risk values are very small, much lower than 1 in a million, which is conventionally used as a regulatory measure for human health risk assessment. Although all scenarios represent safe situations from a human health risk viewpoint, the purpose of this study was to make a comparative evaluation of various discharge scenarios based on risk estimates. Therefore these values were used in the risk management section for comparing the different alternatives.

(d) Cost Estimation

The cost components considered in this study are treatment cost, cost of drilling fluid lost during discharge, ecological and human health damage costs. To compare management alternatives or discharge options, the cost estimates were normalized over one year and values are reported in $/day. The information available for the cost estimates is scant in the literature. The information available is only through published reports, which are not in the public domain. The cost estimation requires judgment and generally the estimates are site specific. The summary of cost estimates for different activities is provided in table 7. A plot of total cost estimates for various discharge scenarios is shown in figure 8. Details of the cost estimation analysis can be seen in Sadiq [2001].

(e) Technical Feasibility

The third attribute for risk management is the technical feasibility of the treatment options or management alternatives. The technical feasibility of various alternatives was defined based on three basic indicators: ease of operation (EO), status of the technology (ST), and control measures required (CM). These are not necessarily the only indicators to compare various treatment alternatives; rather they cover the basic information about each treatment option. For example, the ease of operation may include the total number of hours of operation, capacity of the treatment unit, and exposure of workers to drilling fluid. Similarly, the status of technology can encompass the efficiency of the treatment device, availability of skilled labor, and space requirements. The control measures include maintainability of the treatment units, and safety of workers. All of these sub-indicators need a detailed study to incorporate information from vendors, regulators and literature.

The technical feasibility basic indicators were defined qualitatively. The numerical scores are assigned from 0 to 1. The scales are assumed as fuzzy numbers to incorporate vagueness and fuzziness in human judgment. The MLV of
each scale represents the membership function of 1. The base of the fuzzy number represents uncertainty in human judgment. Figure 3 illustrates these five qualitative levels to compare technical feasibility basic indicators.

Figure 7. Ecological risk estimates for various discharge scenarios.

Figure 8. Total cost estimates for various discharge scenarios.
Table 6. Human health risk assessment for various scenarios.

<table>
<thead>
<tr>
<th>Items</th>
<th>Parameter</th>
<th>10.0%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-cancer (HI)</td>
<td>Min.</td>
<td>0.007</td>
<td>0.005</td>
<td>0.004</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>MLV</td>
<td>0.016</td>
<td>0.014</td>
<td>0.014</td>
<td>0.009</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>0.086</td>
<td>0.073</td>
<td>0.062</td>
<td>0.044</td>
<td>0.033</td>
</tr>
<tr>
<td>Cancer (Unit risk)</td>
<td>Min.</td>
<td>1.24 x 10^-10</td>
<td>9.15 x 10^-17</td>
<td>8.26 x 10^-17</td>
<td>6.39 x 10^-17</td>
<td>4.53 x 10^-17</td>
</tr>
<tr>
<td></td>
<td>MLV</td>
<td>5.54 x 10^-12</td>
<td>4.31 x 10^-15</td>
<td>5.18 x 10^-16</td>
<td>1.73 x 10^-16</td>
<td>1.87 x 10^-16</td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>3.49 x 10^-15</td>
<td>2.95 x 10^-15</td>
<td>2.35 x 10^-15</td>
<td>1.64 x 10^-15</td>
<td>1.16 x 10^-15</td>
</tr>
</tbody>
</table>

Table 7. Cost ($/day) estimates for various discharge scenarios.

<table>
<thead>
<tr>
<th>Items ($/day)</th>
<th>Parameter</th>
<th>10.0%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment cost</td>
<td>Min.</td>
<td>201</td>
<td>235</td>
<td>297</td>
<td>356</td>
<td>413</td>
</tr>
<tr>
<td></td>
<td>MLV</td>
<td>353</td>
<td>437</td>
<td>452</td>
<td>541</td>
<td>587</td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>705</td>
<td>784</td>
<td>792</td>
<td>876</td>
<td>902</td>
</tr>
<tr>
<td>Ecological damage cost</td>
<td>Min.</td>
<td>27</td>
<td>21</td>
<td>18</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>MLV</td>
<td>39</td>
<td>41</td>
<td>35</td>
<td>27</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>94</td>
<td>83</td>
<td>76</td>
<td>64</td>
<td>50</td>
</tr>
<tr>
<td>Economic loss due to disconnection</td>
<td>Min.</td>
<td>245</td>
<td>198</td>
<td>157</td>
<td>119</td>
<td>84</td>
</tr>
<tr>
<td></td>
<td>MLV</td>
<td>339</td>
<td>274</td>
<td>217</td>
<td>165</td>
<td>116</td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>460</td>
<td>372</td>
<td>295</td>
<td>223</td>
<td>157</td>
</tr>
</tbody>
</table>

Table 8. The qualitative scales assigned to rank technical feasibility indicators.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>10.0%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Status of Technology (ST)</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Ease of Operation (EO)</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Control Measures Requirements (CM)</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Based on figure 3, the ST, EO and CM were rated for various discharge scenarios. As described earlier in section 2 (c), this qualitative scaling needs significant information before assigning any scale. The scales were assigned based on a simple comparative evaluation. The scales 1 and 5 were not assigned for any indicator because the scale 1 represents a poor level, which is not the case for any alternative. Even in the case of ST, scale 1 could not be assigned to the 10% discharge option, because it represents a current discharge practice in the U.S. offshore. Similarly, scale 5 represents an excellent level, which could be assigned to EO in the case of the 10% discharge option or for the 4% discharge option for ST. It is avoided because there are some other technologies, like a thermal treatment option, which were not evaluated in this study, but might warrant a better scale rating. Based on these considerations, the scales were assigned to technical feasibility attributes for various discharge options as given above in table 8.

(f) Fuzzy Composite Programming (FCP)

(i) Normalization of Basic Indicators

Figure 1 showed that at the first level, the human health cancer and non-cancer risks were grouped together to make a human health risk index. Similarly the three basic indicators - ease of operation, status of technology, and control measures - were grouped to get the technical feasibility index. At the second level, the human health risk and ecological risk were grouped together to make a general group of the environmental risk reduction index. At the final stage, environmental risk reduction, technical feasibility and total cost saving indices were grouped to obtain a system improvement index.

The higher the risk value the less desirable that alternative will be. Similarly, if the total cost is more, that option will not be desirable. Contrary to that, if some basic indicators have a higher value (e.g., ease of operation), it may considered a better option. To avoid this confusion, all basic indicators were
normalized based on two criteria, either WORST > BEST (e.g., risk, cost etc.) or BEST > WORST (e.g., technical feasibility). These two criteria were used to normalize the basic indicators into unitless numbers scaling from 0 to 1. The method is illustrated in figure 2. The BEST and WORST values were selected among the estimated values for different discharge options.

After defining the BEST and WORST criteria values for each basic indicator, the values were normalized. All normalized basic indicator values were unitless and were scaled from 0 to 1, in which a higher value meant a better option. The risk and cost estimates became a risk reduction index and a cost saving index, respectively. Table 9 summarizes the normalized values of risk reduction and cost saving indices. The technical feasibility indicators are already scaled from 0 to 1. The estimated normalized values of all basic indicators are reported in unitless terms so that they can be grouped accordingly using FCP methodology.

(ii) Weighting Schemes for Basic Indicators

After normalizing the basic indicators, the next step in FCP is to define the weights for different attributes. A double weighting scheme was used. The first type of weighting (w) is based on one-to-one comparison of attributes. The AHP process defined the relative importance of each attribute and grouped them into a generalized group. For example, human cancer risk and non-cancer risks were proportioned as 2:1 by importance, at the first level. Similarly, human health risk was given more priority than ecological risk by giving double weight to human health risk. At the highest level, the environmental risk reduction and cost saving were given three times more weight in comparison to the technical feasibility. Table 10 summarizes the calculated weights for all attributes at various levels. The second type of weight is the balancing factor (p); it was assigned to groups of indicators to show the importance of the maximal deviations [Torno et al. 1988].

(iii) Tradeoff Analysis

After assigning weights to basic indicators and more generalized groups at higher levels, a tradeoff analysis was performed. The analysis was repeated for each management alternative or discharge option. FCP can be used for comparing two attributes at any level, e.g. at level 3. Figure 9 shows a comparison of the environmental risk reduction and the cost saving indices for different discharge options.

The plot shows the largest likely interval, or range, of the fuzzy number (base of the triangle, when the membership function, \( \mu = 0 \)) in two dimensions. The x-axis shows the largest likely interval, or range, of the environmental risk reduction index and the y-axis shows the largest likely interval of the cost saving index. For the 10% discharge option, the largest likely intervals are joined with the MLV. This can form a pyramid if it is viewed in 3-D. The MLVs of two indices are also provided for each option given by the x and y components. The larger base of the pyramid shows higher uncertainty in the indices. The 10% discharge option has the largest base for the cost saving index. The 4% discharge option shows more uncertainty in the cost saving index than the environmental risk reduction index. The MLV of cost saving and environmental risk reduction indices are at (0.93, 0.72). The ideal point in this type of comparison would be (1.0, 1.0) which is practically very difficult to achieve.

The environmental risk reduction index can also be compared with the technical feasibility index. Figure 10 shows that the base (or largest likely interval) of the 5.5% discharge option is larger than the other options, but the environmental risk reduction index uncertainty is maximum for the 10% discharge option. The 7.0% discharge option shows the best results from a technical feasibility viewpoint. If the system improvement index is based on only technical feasibility and environmental risk reduction viewpoints, then the 7.0% discharge option may be the best option, as its MLV is closest to the ideal point (1.0, 1.0). But this option shows higher uncertainty in the environmental risk reduction index than the 4.0% and 5.5% discharge options. The environmental risk reduction index was assigned three times more weight than the technical feasibility index, which reduces the chance of the 7.0% option to be selected as the best discharge option.

Similarly, the cost saving index can be compared with the technical feasibility index. Figure 11 shows that the 7.0% option is the best option if the cost saving and the technical feasibility indices are the major criteria. The MLV of the 7.0% discharge option is closest to the ideal point (1.0, 1.0).

After estimating the technical feasibility, cost saving, and environmental risk reduction indices, they are grouped as a system improvement index. This final index is in the form of a fuzzy number. For all discharge options, the system improvement indices are compared in figure 12. The ideal point of (1.0, 1.0) is also shown for comparison. The 7.0%, 5.5% and 4.0% discharge options look very close to each other. The MLV of the 7.0% and 4.0% discharge options are approximately the same (0.80), but the largest likely interval of the 7.0% discharge option (0.62) is bigger than the 4.0% discharge option (0.51). The larger base represents higher uncertainty in the estimates.

(iv) Ranking Alternatives

Figure 12 shows that selection of the best alternative is not an easy task, because some alternatives are very close to each other. The Chen [1985] ranking method was used to rank these discharge scenarios outlined in section 2(e). In Chen's ranking method [Chen 1985] the utility value \( U(x) \) was determined for each fuzzy number as described before. The highest utility value represents the best management alternative. Table 11 summarizes the system improvement index values for these discharge scenarios. The utility values were calculated for the system improvement index for each scenario. A conclusion can be drawn from this ranking method that the 4.0% is the best management alternative in our hypothetical case study, followed by the 7.0% and then the 5.5% discharge option.

(vi) Sensitivity Analysis

The ranking of various discharge options was the last step in deciding which option is the best management alternative. The
The process of ranking alternatives involved assumptions and human judgments for assigning weights to various attributes. To confirm the ranking order achieved in the previous section, sensitivity analysis was performed in which various weighting schemes were employed and the entire FCP procedure was repeated. Table 12 summarizes the trials in which new weights and importance values were assigned to the last three groups. The first trial results have already been discussed in which risk reduction and cost saving indices were given three times more weight than the technical feasibility index. The second trial represents the case in which technical feasibility is not considered, rather risk reduction and cost saving indices were assumed to be the selection criteria for the best management alternative. Similarly in the third trial, the environmental risk reduction index was given 1.5 times more weight than the cost saving index. This trial represents the pro-environment scenario. In the last trial, the weights of environmental risk reduction and cost saving indices are reversed, which is a pro-cost saving scenario.

Table 9. Normalized values of the basic indicators used in fuzzy composite programming.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Values</th>
<th>10.0%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHRc (Reduction)</td>
<td>Min. 0.0000</td>
<td>0.1568</td>
<td>0.3309</td>
<td>0.5371</td>
<td>0.6764</td>
<td></td>
</tr>
<tr>
<td>Human health cancer risk MLV</td>
<td>Max. 0.9772</td>
<td>0.9866</td>
<td>0.9892</td>
<td>0.9946</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>HHRc (Reduction)</td>
<td>Min. 0.0000</td>
<td>0.1514</td>
<td>0.2788</td>
<td>0.5060</td>
<td>0.6370</td>
<td></td>
</tr>
<tr>
<td>Human health non-cancer risk</td>
<td>Max. 0.9507</td>
<td>0.9651</td>
<td>0.9772</td>
<td>0.9892</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>ER (Reduction)</td>
<td>Min. 0.0000</td>
<td>0.1259</td>
<td>0.2129</td>
<td>0.3487</td>
<td>0.5103</td>
<td></td>
</tr>
<tr>
<td>Ecological risk</td>
<td>Max. 0.7723</td>
<td>0.8425</td>
<td>0.8753</td>
<td>0.9605</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Cost (Saving)</td>
<td>Min. 0.0000</td>
<td>0.1430</td>
<td>0.2236</td>
<td>0.2383</td>
<td>0.2186</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max. 0.9469</td>
<td>0.9647</td>
<td>0.9657</td>
<td>0.9870</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>EO</td>
<td>Min. 0.6000</td>
<td>0.6000</td>
<td>0.6000</td>
<td>0.3000</td>
<td>0.3000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max. 0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.7000</td>
<td>0.7000</td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>Min. 0.3000</td>
<td>0.3000</td>
<td>0.6000</td>
<td>0.6000</td>
<td>0.6000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max. 0.7000</td>
<td>0.7000</td>
<td>0.7500</td>
<td>0.7500</td>
<td>0.7500</td>
<td></td>
</tr>
<tr>
<td>CM</td>
<td>Min. 0.6000</td>
<td>0.6000</td>
<td>0.6000</td>
<td>0.3000</td>
<td>0.1000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max. 0.9000</td>
<td>0.9000</td>
<td>0.9000</td>
<td>0.7000</td>
<td>0.4000</td>
<td></td>
</tr>
</tbody>
</table>

Table 10. Weights estimated for basic indicators and more generalized groups.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Importance value</th>
<th>w</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human Cancer Risk</td>
<td>2</td>
<td>0.67</td>
<td>1</td>
</tr>
<tr>
<td>Human Non-cancer Risk</td>
<td>1</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Human Health Risk</td>
<td>2</td>
<td>0.67</td>
<td>2</td>
</tr>
<tr>
<td>Ecological Risk</td>
<td>1</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Status of Technology</td>
<td>1</td>
<td>0.33</td>
<td>2</td>
</tr>
<tr>
<td>Ease of Operation</td>
<td>1</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Control Measures Requirements</td>
<td>1</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Technical Feasibility</td>
<td>1</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>Environmental Risk Reduction</td>
<td>3</td>
<td>0.43</td>
<td>2</td>
</tr>
<tr>
<td>Cost Saving</td>
<td>3</td>
<td>0.43</td>
<td></td>
</tr>
</tbody>
</table>

Table 9. Normalized values of the basic indicators used in fuzzy composite programming.
Figure 9. Comparison of environmental risk reduction and cost saving indices.

Figure 10. Comparison of environmental risk reduction and technical feasibility indices.
Figure 11. Comparison of cost saving and technical feasibility indices.

Figure 12. The system improvement index for comparison of various discharge options.
<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Min.</th>
<th>MLV</th>
<th>Max.</th>
<th>$U_T(x)$</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.0%</td>
<td>0.1935</td>
<td>0.6859</td>
<td>0.9154</td>
<td>0.3634</td>
<td>5</td>
</tr>
<tr>
<td>8.5%</td>
<td>0.2354</td>
<td>0.7431</td>
<td>0.9353</td>
<td>0.4698</td>
<td>4</td>
</tr>
<tr>
<td>7.0%</td>
<td>0.3259</td>
<td>0.8010</td>
<td>0.9496</td>
<td>0.6437</td>
<td>2</td>
</tr>
<tr>
<td>5.5%</td>
<td>0.3829</td>
<td>0.7460</td>
<td>0.9573</td>
<td>0.6280</td>
<td>3</td>
</tr>
<tr>
<td>4.0%</td>
<td>0.4534</td>
<td>0.7951</td>
<td>0.9630</td>
<td>0.7208</td>
<td>1</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Trials</th>
<th>Weighting schemes</th>
<th>Environmental risk reduction index</th>
<th>Cost saving index</th>
<th>Technical feasibility index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trial 1</td>
<td>Importance value</td>
<td></td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Trial 2</td>
<td>Importance value</td>
<td></td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Trial 3</td>
<td>Importance value</td>
<td></td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Trial 4</td>
<td>Importance value</td>
<td></td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 12. Different weighting schemes for sensitivity analysis.

<table>
<thead>
<tr>
<th>Trials</th>
<th>Final utility Index</th>
<th>10.0%</th>
<th>8.5%</th>
<th>7.0%</th>
<th>5.5%</th>
<th>4.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trial 1</td>
<td>$U_T(x)$</td>
<td>0.3634</td>
<td>0.4698</td>
<td>0.6437</td>
<td>0.6280</td>
<td>0.7208</td>
</tr>
<tr>
<td>Rank</td>
<td></td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Trial 2</td>
<td>$U_T(x)$</td>
<td>0.3789</td>
<td>0.5948</td>
<td>0.7192</td>
<td>0.7273</td>
<td>0.8074</td>
</tr>
<tr>
<td>Rank</td>
<td></td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Trial 3</td>
<td>$U_T(x)$</td>
<td>0.3684</td>
<td>0.4680</td>
<td>0.6437</td>
<td>0.6515</td>
<td>0.7426</td>
</tr>
<tr>
<td>Rank</td>
<td></td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Trial 4</td>
<td>$U_T(x)$</td>
<td>0.3563</td>
<td>0.4562</td>
<td>0.6362</td>
<td>0.5755</td>
<td>0.6655</td>
</tr>
<tr>
<td>Rank</td>
<td></td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 13. Summary of sensitivity analysis results for ranking management alternatives.

The second trial results showed that the 5.5% option improved its ranking from third to second position. The 5.5% option was at second position in this trial due to its better technical feasibility index value. The 4.0% discharge option was again shown to be the best discharge option among the alternatives. The third trial represented the situation in which...
the environmental reduction index was given more weight than the cost saving index. The environmental risk reduction index was maximum for the 4.0% discharge option. Therefore a utility index of the 4.0% discharge option was improved from 0.72 to 0.74. Approximately. The ranking orders show that the 4.0% discharge option was the best option and the 5.5% was second, followed by the 7.0% discharge option, although the second and third ranks have no appreciable differences in their utility values. The 10.0% discharge option was the least desirable option among all management alternatives. In the final trial the cost saving index was given 1.5 times more weight than the risk reduction scenario. The results showed that the 4.0% discharge option was the best management alternative but the 7.0% improved its ranking again from 3 to 2 in comparison to the 5.5% discharge scenario. The utility value of 7.0% discharge scenario was appreciably higher than the 5.5% discharge alternative. The 10.0% discharge option was still the least desirable option, followed by the 8.5% discharge option.

A summary of the ranking for various weighting schemes is provided in table 13. Overall, the 4.0% discharge option is the best management alternative. The second best option lies somewhere between the 5.5% and 7.0% discharge options, which encompasses the recent revisions to the regulations on the East Coast of Canada. The better management alternatives were those options in which treatment technology was sophisticated enough to substantially reduce the ecological damages without compromising the cost of treatment.

Our case study involves some simplified assumptions and uncertain data for various attributes. The intention here is not to decide about any particular discharge scenario as the best management alternative rather the authors are of the opinion that this methodology can lead to better decision-making when real data are used.

4. SUMMARY AND CONCLUSIONS

A holistic approach was adopted for risk management of offshore petroleum drilling waste discharges in the marine environment. The research focused on development of a fuzzy composite framework for risk management by integrating environmental risk assessment with cost estimation and technical feasibility of various treatment options. The approach was applied to a hypothetical case study of drilling waste discharges on the East Coast of Canada.

A risk management methodology using FCP was developed. The fuzzy composite programming involved identification of basic indicators, a methodology for grouping basic indicators, weighting schemes, converting linguistic terms and statistical data into fuzzy numbers, and ranking methodologies for management alternatives. To perform tradeoff analysis for the selection of the best management alternative or discharge scenario, cost estimates and technical feasibility parameters were studied in this paper. The basic indicators - risk estimates, technical feasibility, and cost estimates - were defined by triangular fuzzy numbers to incorporate uncertainties. The final utility values of the system improvement indices were calculated through the Chen [1985] ranking method to determine the ranking order of the management alternatives. In this paper, FCP methodology was modified for probabilistic quantitative and fuzzy qualitative data.

The framework for risk management was applied to a hypothetical case study. Five discharge scenarios were defined based on the percent base fluid attached to the wet drill cuttings. These discharge scenarios or management alternatives were 10.0%, 8.5%, 7.0%, 5.5% and 4.0% attached base fluids. Fate models with probabilistic inputs were used to estimate the PEC, which were converted into exposure concentrations using BF and p. The exposure concentrations were used in the human and ecological probabilistic risk assessment models to quantify the risk values. Similarly, cost estimates for treatment, lost drilling fluid, and ecological and human health damages for different discharge scenarios were made. The technical feasibility parameters - status of the technology, ease of operation and control measures required - were defined in qualitative terms. The importance matrix of basic indicators was developed using AHP. All basic indicators were grouped into environmental risk reduction, cost saving and technical feasibility indices to perform a tradeoff analysis. The 4% attached base fluid option was shown to be the best management option when risk and cost were given equal weight and technical feasibility was allotted one-third of the weight. The 7.0% discharge option was the second best alternative and that was followed by 5.5%, 8.5% and 10.0%, respectively. A sensitivity analysis was performed using different weighting schemes to account for human subjectivity and this was found to have some effect on the overall ranking.

To conclude, the risk management method developed here was shown to have utility in terms of guiding decisions, and was sensitive to changes in weights assigned to reflect the values of the decision-maker. It would be useful to solicit more input from different stakeholders into the assigned weights in future applications. It would also be useful to express the results in different ways, such as giving the cost of a treatment option per unit of protection afforded ecological entities.

Further, more types of treatment options could be incorporated into the scheme, and these could be more precisely defined in terms of costs, operability, reliability, and other relevant attributes. Work is underway to address this, and the outcomes are expected to afford greater confidence in the results of subsequent applications.

At present, the fate of discharges is based on some strong assumptions. This is being addressed in part through a laboratory investigation on the settling characteristics of drill cuttings, the results of which will strengthen the fate model. Some aspects of the case study, such as the assumption that discharge is continuous and over a relatively short time period, are not realistic. The aim of the case study was to illustrate the utility of the method, and simplifying assumptions were made in the process. Such assumptions need not be made under a practical application of the model.

In general, there are various approaches to deal with multiple stressors. Data required to treat the total drilling waste and synergistic and antagonistic effects are virtually non-
The approach used here was to use individual contaminant data, an approach in harmony with modeling done of the US EPA and other regulatory agencies. The methodology can readily be adapted to use the other data as it becomes available. The focus of the paper is on decision-making under a risk management framework. Rather than use a specific endpoint to gauge toxicological effects, the entire ecological community was taken as the endpoint.

ACKNOWLEDGEMENTS

The authors acknowledge with gratitude the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC) through a Strategic Projects Grant Offshore Environmental Engineering Using Autonomous Underwater Vehicles.

REFERENCES


Jooste, S. 2000 A model to estimate the total ecological risk in the management of water resources subject to multiple stressors. Water SA, 26(2), 159-166.


