Journal of Hazardous Materials 213–214 (2012) 421–433

Contents lists available at SciVerse ScienceDirect

Journal of Hazardous Materials

journal homepage: www.elsevier.com/locate/jhazmat

Evaluation of remedial options for a benzene-contaminated site through a simulation-based fuzzy-MCDA approach

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ARTICLE INFO

Article history:
Received 15 June 2011
Received in revised form 6 February 2012
Accepted 8 February 2012
Available online 17 February 2012

Keywords:
Site remediation
Fuzzy set theory
Multi-criteria decision analysis
Benzene
TOPSIS

ABSTRACT

A simulation-based fuzzy multi-criteria decision analysis (SFMCDA) method is developed for supporting the selection of remediation strategies for petroleum contaminated sites. SFMCDA integrates process modeling (using BIOPLUME III) and fuzzy ranking (based on fuzzy TOPSIS) into a general management framework, and can compare various remediation alternatives, in light of both cost-risk tradeoffs and uncertainty impacts. The proposed method is applied to a hypothetical contaminated site suffering from a benzene leakage problem. Six remediation alternatives are taken into consideration, including natural attenuation (NA), pump-and-treat (PAT), enhanced natural attenuation (ENA), and a number of their combinations. Six fuzzy criteria, including both cost and risk information, are used to compare different alternatives through fuzzy TOPSIS. The results demonstrates that the proposed method can help systematically analyze fuzzy inputs from contaminant transport modeling, cost implications and stakeholders' preferences, and provide useful ranking information covering a variety of decision-relevant remediation options for decision makers.

1. Introduction

Spill and leakage of petroleum hydrocarbons have resulted in significant environmental concerns in soil and groundwater systems. Removal of such contaminants is often expensive and time-consuming [1]. Over the past years, many remediation techniques (e.g. pump and treat, bioremediation) have been proposed to remove petroleum contaminants from the subsurface [2]. Due to the complexity of the remediation processes, decision-makers are often faced with difficulties in identifying the most desirable remediation strategy from the pool containing a wide range of options with varied remedial efficiencies and costs [3]. It is thus desired that effective tools for supporting site remediation decisions be advanced [4,5].

In fact, identification of a suitable subsurface remediation technology is a complex process, involving consideration of multiple factors such as environmental impact, social acceptance, and system cost [6,7]. Multi-criteria decision analysis (MCDA) is a potential tool for dealing with such discrete decision-making problems [8,9], where the potential management scenarios are compared and ranked based on a number of pre-defined criteria. Groundwater flow and contaminant transport modeling is a critical component in supporting remediation design [10–13]. MCDA is also advantageous in linking simulation to the decision-making framework for obtaining quantitative information related to cost and risk [9]. The conventional MCDA approach typically expresses all inputs as deterministic, however, in a real world groundwater remediation system, imprecise and vague information may exist [13–19]. It is thus desired that a systematic assessment approach for combining inputs from contaminant concentrations obtained by simulation model, health-risk guidelines, system costs analysis and stakeholder views be advanced to accomplish a sound analysis of available remediation options under uncertainty.

Previously, many inexact MCDA techniques were developed for groundwater remediation. Bau and Mayer [20] developed a stochastic data-worth framework to select the optimal design of groundwater remediation operation that could minimize the cost and comply with cleanup goals under parameter uncertainty. In this method, a stochastic inverse flow and transport (FT) model was applied to integrate data towards the estimation of the geostatistical parameters. Singh and Minsker [21] proposed a robust multi-objective optimization method on a field-scale groundwater remediation design. Latin Hypercube sampling, a noisy multi-objective genetic algorithm were used within the optimization framework. Qin et al. [22] advanced a simulation-based stochastic MCDA method to choose remediation scenarios at a

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doi:10.1016/j.jhazmat.2012.02.027

petroleum-contaminated site in western Canada, where Monte Carlo simulation and deterministic MCDA were combined to analyze the final ranking outputs. However, the method would be restricted if the uncertainties could not be addressed by stochastic distributions. Many studies in various fields have focused on applying fuzzy set theory to MCDA applications, in the sense that the imprecise and vague information regarding our knowledge of the state of a system or of human preferences in making trade-off decisions could better be described by fuzzy sets [23–25]. Guan and Aral [11,15] integrated fuzzy simulation into an optimization model for the optimal design of pump-and-treat systems under uncertainty. However, the authors considered only uncertainty in the simulation parameter. Chu and Chang [13] developed a multi-objective dynamic groundwater remediation by integrating fuzzy inference system (ANFIS) with constrained differential dynamic programming model to acquire time-varying pumping rates. The authors conducted the ANFIS procedure on the base of fuzzy if-then rules and fuzzification interface. Kerachian et al. [26] developed a fuzzy game theory approach combined with groundwater quantity and quality simulation models and the optimization model for groundwater resources management. The fuzzy set theory was utilized to define the utility functions of decision makers. In fact, different experts/stakeholders may have different preferences, which may lead to significant variations of the rules or values. Li et al. [3] advanced a fuzzy MCDA approach to help screen remedial alternatives for a petroleum-contaminated site in western Canada, where the approach was capable of dealing with uncertainty in the impact scores expressed as linguistic judgments (e.g. such as 'high risk', 'high cost') and experts' opinions.

In the real-world applications, it has been widely recognized that the decision-making process for site remediation is associated with uncertainties from multiple sources, including (i) measurement and/or estimation errors related to hydrogeological and physicochemical parameters (e.g. dispersivity and porosity) [27]; (ii) preferences of stakeholders with respect to the prioritization of criteria for a decision making process [8]; (iii) descriptions of available decision alternatives based on quantitative or qualitative data that are relying on expert opinions or experiential knowledge [28]. The fuzzy MCDA procedures must be able to address these uncertainties, along with other subjective uncertainties from either ranking criteria or qualitative description of information, for a more comprehensive consideration of uncertainties in site-remediation decisions.

Thus, this study aims to develop a simulation-based fuzzy MCDA (SFMCDA) method for supporting selection of optimal remedial technologies for benzene-contaminated sites. The uncertainties associated with both subsurface conditions and human judgments are tackled as fuzzy sets. A hypothetical benzene-contaminated site is used as a case study to demonstrate the applicability of the proposed method. The paper is organized as follows: (Section 2) development of the SFMCDA method; (Section 3) case study, results analysis and discussions; (Section 4) conclusion.

2. Methodology

SFMCDA consists of two major components: (1) a fuzzy process simulation and a (2) fuzzy multi-criteria decision analysis. The general framework is shown in Fig. 1. The fuzzy process simulation is used to predict contaminant fate and transport under various temporal/spatial scales and remediation scenarios. The obtained contaminant concentrations and the related cost implications are presented as fuzzy sets, which will serve as uncertain inputs for MCDA evaluation. The fuzzy technique ordered preference by similarity to the ideal solution (i.e. fuzzy TOPSIS) method then is applied to rank various alternatives. The detailed procedures are described in the following sections.

2.1. Numerical simulation of contaminant transport

In this study, the remedial options processes are simulated by BIOPLUME III. It is a two-dimensional finite difference model for simulating the natural attenuation of organic contaminants in groundwater due to the processes of advection, dispersion and biodegradation [29]. BIOPLUME III has been applied previously in many studies [25,30,31]. The general equations are [29]:

$$\frac{\partial Hb}{\partial t} = \frac{1}{R_h}\left[\frac{\partial}{\partial x_i}\left(bD_{ij}\frac{\partial H}{\partial x_j}\right) - \frac{\partial (bHV_i)}{\partial x_i}\right] - \frac{H'W}{n} \tag{1a}$$

$$\frac{\partial Pb}{\partial t} = \left[\frac{\partial}{\partial x_i}\left(bD_{ij}\frac{\partial P}{\partial x_j}\right) - \frac{\partial (bPV_i)}{\partial x_i}\right] - \frac{P'W}{n} \tag{1b}$$

$$R_h = 1 + \frac{\rho_b}{n}K_h \tag{1c}$$

where H is the concentration of hydrocarbon [M/L^3]; H' is the concentration of hydrocarbon in source or sink fluid [M/L^3]; n is the effective porosity; b is the saturated thickness [L]; W is the volume flux per unit area [L/T]; V_i is the seepage velocity in the direction of x [L/T]; R_h is the retardation factor for hydrocarbon; D_{ij} is the coefficient of hydrodynamic dispersion [L^2/T]; x_i and x_j are Cartesian coordinates; t is time [T]; ρ_b is the soil bulk density [M/L^3]; K_h is the distribution coefficient [L^3/M]; P is the concentration of oxygen [M/L^3]; P' is the concentration of oxygen in source or sink fluid [M/L^3];

It assumes the aerobic biodegradation process using oxygen as electron acceptors can be simulated as an instantaneous reaction. The biodegradation of contaminants using aerobic electron acceptor is simulated using the principle of superposition with the general equations as follows [32]:

$$\Delta H_{SO} = \frac{P}{F_O}; \quad P = 0 \quad \text{if} \quad H > \frac{P}{F_O} \tag{2a}$$

$$\Delta P_{OS} = HF_O; \quad H = 0 \quad \text{if} \quad P > HF_O \tag{2b}$$

where ΔH_{SO} is the loss in the contaminant concentration due to biodegradation using oxygen; ΔP_{OS} is the concentration loss in the electron acceptor; and F_O is the stoichiometric ratio for oxygen.

2.2. Fuzzy simulation

Fuzzy sets are used for addressing uncertainties derived from fuzziness or vagueness of input parameters in subsurface modeling. These inputs can be received in terms of linguistic judgments, which can then be converted to the form of fuzzy sets [33]. The general notation of fuzzy sets can be presented as follows [34]:

$$A(x) = \{(x, \mu_A(x)), x \in X, \mu_A(x) \in [0, 1]\} \tag{3}$$

where $X = \{x\}$ is a universe set of elements, $A(x)$ is a fuzzy set of X, and $\mu_A(x)$ is the degree of membership for x in A. $\mu_A(x)$ is a number in the range 0–1, with 1 representing full membership and 0 representing non-membership. The closer $\mu_A(x)$ is to 1, the more likely it is that an element x belongs to A. Inversely, the closer $\mu_A(x)$ is to 0, the less likely it is that x belongs to A. The α-cut level (as a useful concept in fuzzy set theory) is defined as the set of elements that belong to fuzzy set A, described as $A_\alpha = \{x|\mu_A(x) \geq \alpha\}$. The support of the fuzzy set A is defined by the classical set as $supp(A) = \{x|\mu_A(x) > 0\}$, and the convexity condition ensures that the support is in an interval [35].

In this study, the prediction of pollutant concentrations is developed based on fuzzy simulation, and the primary procedures of a fuzzy simulation include: (1) divide the membership domain of fuzzy parameters $F_1, F_2, F_3, \ldots$, and F_N into a series of equally spaced

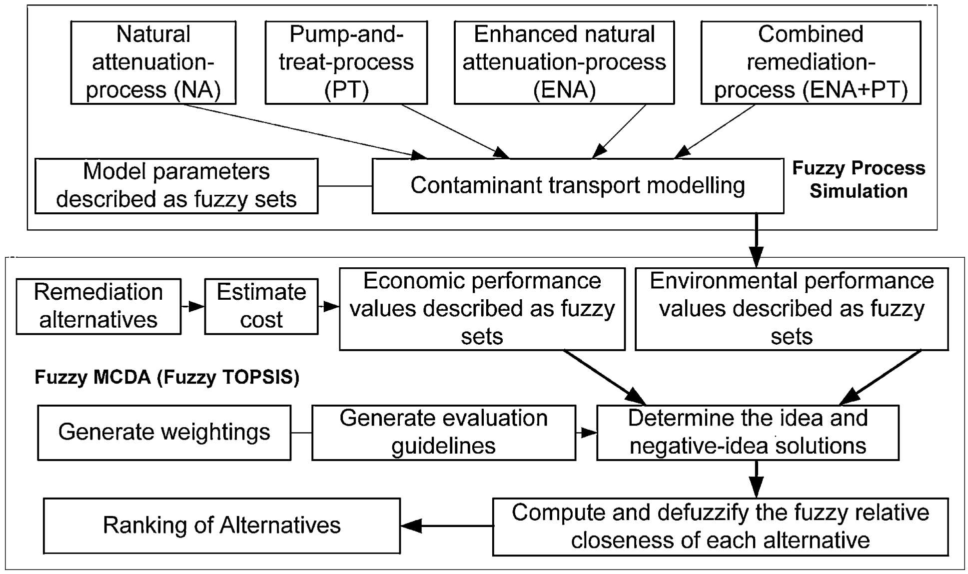

Fig. 1. General framework for SFMCDA.

α-cut levels, the lower and upper bounds of each fuzzy parameters are obtained at each α-cut; (2) select one α-cut level and transfer fuzzy parameters into various permutations by fuzzy transformation techniques (i.e. combine the upper and lower points for the selected α-cut into 2^N distinct permutations [36]); (3) use these permutation as inputs for simulation models and generate 2^N of outputs, (4) form the lower and upper limits of different α-cut levels of the final simulation outputs, (5) repeat the above mentioned steps for all α-cut levels. The fuzzy sets of the predicted item are approximated based on the obtained lower and upper bounds of the simulation outputs under various α-cut levels. For more detailed descriptions of fuzzy simulation, the readers are referred to Prasad and Mathur [25].

2.3. Fuzzy TOPSIS

The decision process for selecting an appropriate alternative is usually faced with uncertainties that may be associated with human judgment regarding relative weights, inadequate information, and evaluation criteria values. In this study, we propose to use the fuzzy TOPSIS method to tackle such uncertain information. Essentially, the corresponding decision matrix elements and the relative weights will be presented as fuzzy sets. The related distribution information (i.e. membership functions) may be obtained from either fuzzy simulation or public survey.

The first step of a fuzzy TOPSIS is to normalize the fuzzy decision matrix $\overline{D_{ij}}$ if necessary and then obtain the ideal and negative-ideal solutions by the following equations [37]:

$$\overline{D_{ij}} = (a_{ij}, b_{ij}, d_{ij}), \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, l) \tag{4a}$$

$$D_j^I = \max_i d_{ij} \tag{4b}$$

$$D_j^{NI} = \min_i a_{ij} \tag{4c}$$

$$\mathbf{I} = \left\{D_1^I, D_2^I, \ldots, D_l^I\right\} \tag{4d}$$

$$\mathbf{NI} = \left\{D_1^{NI}, D_2^{NI}, \ldots, D_l^{NI}\right\} \tag{4e}$$

where a_{ij} and d_{ij} are the lower and upper bound of $\overline{D_{ij}}$, respectively; b_{ij} is the core of $\overline{D_{ij}}$; i is the index of alternatives; m is the total number of alternatives; j is the index of evaluation criteria; l is the total number of evaluation criteria; **I** and **NI** are the ideal solution and negative ideal solution, respectively.

Secondly, the fuzzy relative closeness of each alternative is computed by solving the following non-linear programming model at each alpha-cut level [37]:

$$(RC_i)_\alpha^L = Min \frac{\sqrt{\sum_{j=1}^{l}\left[w_j((D_{ij})_\alpha^L - D_j^{NI})\right]^2}}{\sqrt{\sum_{j=1}^{l}\left[w_j((D_{ij})_\alpha^L - D_j^{NI})\right]^2} + \sqrt{\sum_{j=1}^{l}\left[w_j((D_{ij})_\alpha^L - D_j^{I})\right]^2}} \tag{5a}$$

where

$$(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U, \quad j = 1, 2, \ldots, l \tag{5b}$$

$$(RC_i)_\alpha^U = Max \frac{\sqrt{\sum_{j=1}^{l}\left[w_j((D_{ij})_\alpha^U - D_j^{NI})\right]^2}}{\sqrt{\sum_{j=1}^{l}\left[w_j((Dij)_\alpha^U - D_j^{NI})\right]^2} + \sqrt{\sum_{j=1}^{l}\left[w_j((D_{ij})_\alpha^U - D_j^{I})\right]^2}} \tag{5c}$$

where

$$(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U, \quad j = 1, 2, \ldots, l \tag{5d}$$

where $\overline{D_{ij}}$, $\overline{w_j}$ and $\overline{RC_i}$ are the fuzzy decision matrix, fuzzy weight and fuzzy relative closeness, respectively; $(D_{ij})_\alpha$, $(w_j)_\alpha$ and $(RC_i)_\alpha$ are the elements of $\overline{D_{ij}}$, $\overline{w_j}$ and $\overline{RC_i}$ under the α-cut level of α; $(D_{ij})_\alpha^L$ and $(D_{ij})_\alpha^U$ are the lower and upper bounds of $(D_{ij})_\alpha$; $(w_j)_\alpha^L$ and $(w_j)_\alpha^U$ are the lower and upper bounds of $(w_j)_\alpha$; $(RC_i)_\alpha^L$ and $(RC_i)_\alpha^U$ are the lower and upper bounds of $(RC_i)_\alpha$.

Thirdly, the fuzzy relative closeness is defuzzified by the following equation [37]:

$$(RC_i)_{ALC}^* = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{(RC_i)_{\alpha k}^L + (RC_i)_{\alpha k}^U}{2}\right), \quad i = 1, 2 \ldots, m \tag{6}$$

where $(RC_i)_{ALC}^*$ is the relative closeness represented by averaging level cuts as suggested by Fortemps and Roubens [38]; $\alpha_1, \ldots, \alpha_N$ are different alpha levels satisfying $0 \le \alpha_1 < \ldots < \alpha_N \le 1$; k is the index of α-cut level; N is the total number of α-cuts.

Finally, alternatives are ranked in terms of their defuzzified relative closenesses. The alternative with the highest ratio is deemed the best option.

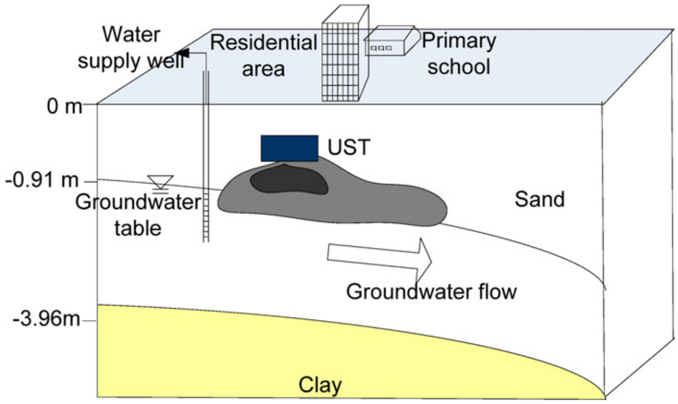

Fig. 2. Conceptual map of the contaminated site.

Table 1
Remediation alternatives considered.

Alternative ID	Description
NA	Natural attenuation
ENA1	Enhanced natural attenuation with only one injection well (0.396 L/s) at the location (253, 458)
ENA2	Enhanced natural attenuation with two injection wells (0.396 L/s) at locations (253, 458) and (253, 397)
PT1	Pump and treat with only one extraction well (0.566 L/s) at location (253, 458)
PT2	Pump and treat with two extraction wells (0.566 L/s) at locations (253, 458) and (253, 397)
ENA + PT	One extraction well-pump-and-treat (0.566 L/s) combined with one injection well-enhanced natural attenuation (0.396 L/s) at locations (253, 458) and (253, 397), respectively

2.4. Simulation-based fuzzy-MCDA method

Integration of the contaminant transport modeling, fuzzy simulation and fuzzy TOPSIS into a general framework lead to the formulation of a simulation-based fuzzy-MCDA (SFMCDA) method. The detailed operation process of an SFMCDA can be summarized as follows:

Step (1): Identify m alternatives (i.e. $a1$, $a2$,. . ., am), and l evaluation criteria (i.e. $c1$, $c2$,. . ., cl) for an MCDA problem, and obtain fuzzy weightings for the evaluation criteria.
Step (2): Select an α-cut level for the fuzzy parameters of the simulation model; use fuzzy simulation to calculate the interval values for contaminant concentration under various scenarios of alternatives.
Step (3): Generate the performance matrix and weightings, determine the ideal solution and the negative ideal solution by Eqs. (4a)–(4e).
Step (4): Compute the fuzzy relative closeness of each alternative by solving the NLP models by Eqs. (5a)–(5d).
Step (5): Repeat steps 2–4 for the other α-cut levels, and the overall ratings of alternatives can be obtained by Eq. (6).
Step (6): Rank alternatives in terms of their defuzzified relative closenesses.

3. Case study

3.1. Background and system configuration

A hypothetical petroleum-contaminated site was adopted as a case study to demonstrate the capability of SFMCDA for determining the most desirable remediation alternative. Fig. 2 shows a conceptual diagram of the study system. The contaminant plume was assumed to be produced by a leaking underground storage tank (UST) that was supposed to be removed after contamination has been detected. The concentration of the representative organic pollutant (i.e. benzene) was supposed to be highly exceeding SERM (Saskatchewan Environment and Resource Management) groundwater guidelines. The reason for choosing benzene was due to its well-known toxicity where direct exposure may cause acute nonlymphocytic (myelogenous) leukemia (ANLL) and a variety of other blood-related disorders in humans [39,40]. The receptors include: (i) a primary school, about 156 m to the downstream of the contamination source; (ii) a municipal drinking water supply well, about 91 m to the upstream of the plume center; (iii) a residential area, about 158 m at the southwest of the plume center and (iv) the contamination source center (i.e. the starting location of the contamination). All of the receptors are considered at risk (the details of the site overview are given in Section S1, Supplementary material). Thus, this site may pose significant threats to the surrounding communities and the environment; urgent remediation measures are needed for cleaning up the contaminated groundwater system. As there are many possible methods to deal with this, the decision makers need to know which remediation alternative is the most cost-effective in terms of risk and cost. The proposed methodology will be used for providing decision support for identifying the desired remediation option for the study site.

The remediation technologies, well locations and its pumping rates are mostly referred to Prasad and Mathur [25] where a trial and correction procedure is used for identifying optimal operating conditions. Six remediation scenarios were designed for the contaminated site (in Table 1). Fig. 3 shows the conceptual design for the remediation wells. Each remediation option operates for 2 years. The pumping rates of the extraction wells and injection wells were kept constant at 0.566 and 0.396 L/s, respectively. The injection wells supply O_2 dissolved in the injected water at a concentration of 0.008 g/L.

Six criteria were used for the evaluation, including both environmental and economical factors. The criteria weights were obtained through public survey, expert consultation and weights as described in Li et al. [3]. As shown in Table 2, they are expressed as triangular fuzzy sets. In defining membership functions, if the weight of installation cost is estimated to be within an interval of [0.08, 0.12], it may be reasonable to describe this criterion with a fuzzy set of “about” 0.1 using triangular membership functions. The other weights are defined similarly. Environmental performance was determined based on the dissolved concentrations of benzene in the groundwater beneath the locations of the primary school, residential area, supply well and the center of the contamination source. According to the SERM-based risk assessment method [41], the membership functions of the fuzzy risk levels can

Table 2
Fuzzy weights.

ID	Fuzzy values
Risk at the contamination source center	Support = (0.16, 0.2), core = 0.18
Risk at the residential area	Support = (0.1, 0.14), core = 0.12
Risk at the supply well	Support = (0.21, 0.27), core = 0.24
Risk at the primary school	Support = (0.14, 0.18), core = 0.16
Installation cost	Support = (0.08, 0.12), core = 0.1
Operation and maintenance cost	Support = (0.17, 0.23), core = 0.2
Risk at the contamination source center[a]	Support = (0.17, 0.23), core = 0.2
Risk at the residential area[a]	Support = (0.12, 0.18), core = 0.14
Risk at the supply well[a]	Support = (0.23, 0.29), core = 0.26
Risk at the primary school[a]	Support = (0.12, 0.16), core = 0.14
Installation cost[a]	Support = (0.06, 0.1), core = 0.08
Operation and maintenance cost[a]	Support = (0.16, 0.2), core = 0.18

[a] The values are the new setting weights.

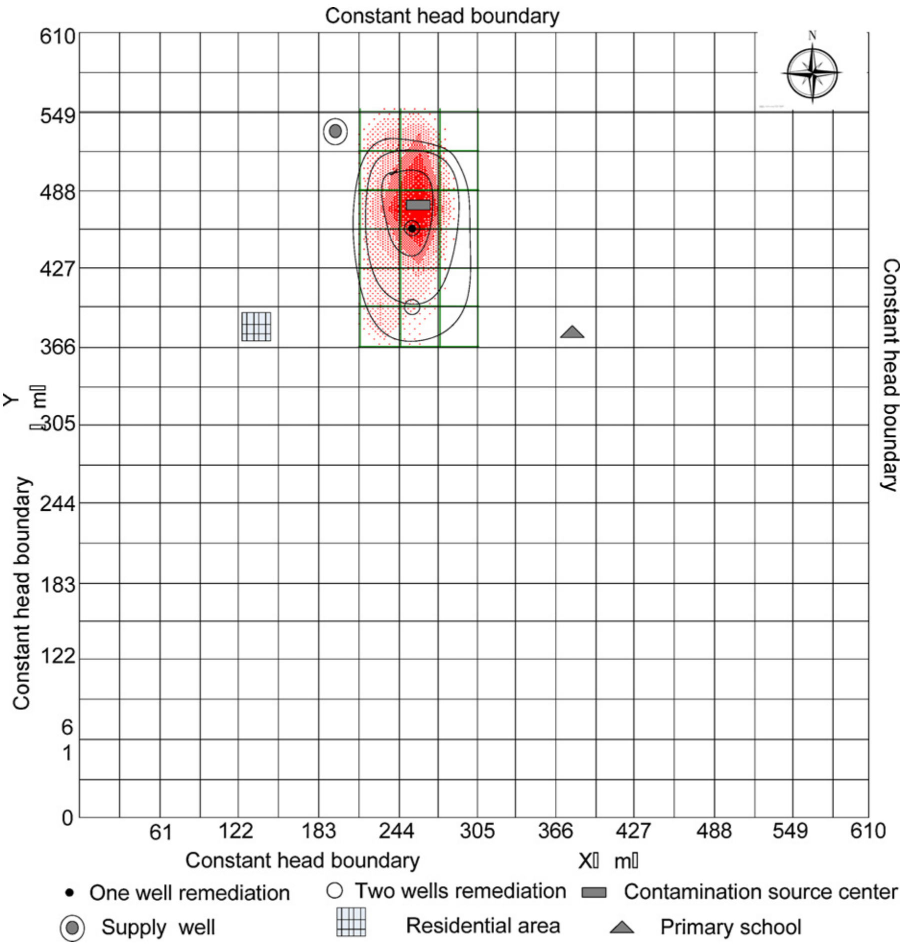

Fig. 3. Numerical domain of the study system.

be established by comparing the simulated benzene concentration with the SERM guideline. The contaminated groundwater in the subsurface can thus be categorized into five risk levels: "Clean", "Practically not risky", "Slightly risky", "Risky", and "Highly risky" (see Table S2, Supplementary material). The membership functions of these fuzzy events are shown in Fig. 4A. In order to construct the fuzzy decision matrix, an evaluation mechanism must be established for converting all the triangular fuzzy membership functions into quantitative values (i.e. scoring). We chose a scale from1 to 9 to express them, as shown in Fig. 4A. For example, the benzene concentrations at these receptors may fall within the interval [0.001, 0.25] mg/L; the rating may be defined as 9 when the concentration is less than 0.001 mg/L, 1 when the concentration is higher than 0.25 mg/L, and 2–8 when the concentration are within 0.001 and 0.25 mg/L. Accordingly, the higher score means the receptor would suffer from a lower risk level.

The economical factors include both installation and operation costs. The cost coefficients are also based on a literature survey and expert consultation (in Table 3). The costs for different remedial technologies mainly include installation, operation, analysis and labor (i.e. the total cost is the sum of these components). Except for the installation cost, the other items may increase with the increment of operation years. It presumes that the analytical services for system monitoring will be conducted four times each year, and the cost is about 0.5 to 0.8×10^3 \$ per event according to AFCEE [42]. It also assumes that the performance labor cost would vary for different alternatives, and the annual costs are also referred to AFCEE [43]. The operation cost is estimated based on a constant injection or pumping (cost per L/s yr), according to Prasad and Mathur [25]. Similar to the identification of risk levels, the membership functions of the related fuzzy remediation cost levels were established as follows: "low cost level"; "low-to-medium cost level"; "medium cost level"; "medium-to-high cost level"; and "high cost level" (see Tables S3 and S4, Supplementary material). The membership functions of these fuzzy events are shown in Fig. 4B and C. We also need to convert all triangular fuzzy membership functions into scores using the scale from 1 to 9. The higher the score, the less costly the remediation alternative is.

3.2. Result analysis

Hydrological parameters, such as the porosity (ϕ) and aquifer dispersion coefficient (D), can vary significantly and exhibit high spatial variability even within the same site, leading to uncertainties in the subsurface modeling results [27]. In a real case, the parameters can be obtained by field measurements (i.e. use groups of pumping tests or slug tests in different regions), literature survey, or expert consultation [28]. For example, based on the experts' knowledge of the concerned aquifer and also his experience on other aquifers (i.e. longitudinal dispersivity affecting contaminant transport at a certain scale in an aquifer), a triangular fuzzy membership function of a hydrogeological parameter can be defined by specifying the most credible, the lowest and the highest possible values. In this study, the effective porosity of the sand media normally varies from 0.2 to 0.4 [43]. So, the possibility distribution of this parameter is defined as a fuzzy set with a core of 0.3 and a support of (0.2, 0.4). According to Rifai et al. [29] and Shieh and Peralta [30], the longitudinal dispersivity is also assumed fuzzy and

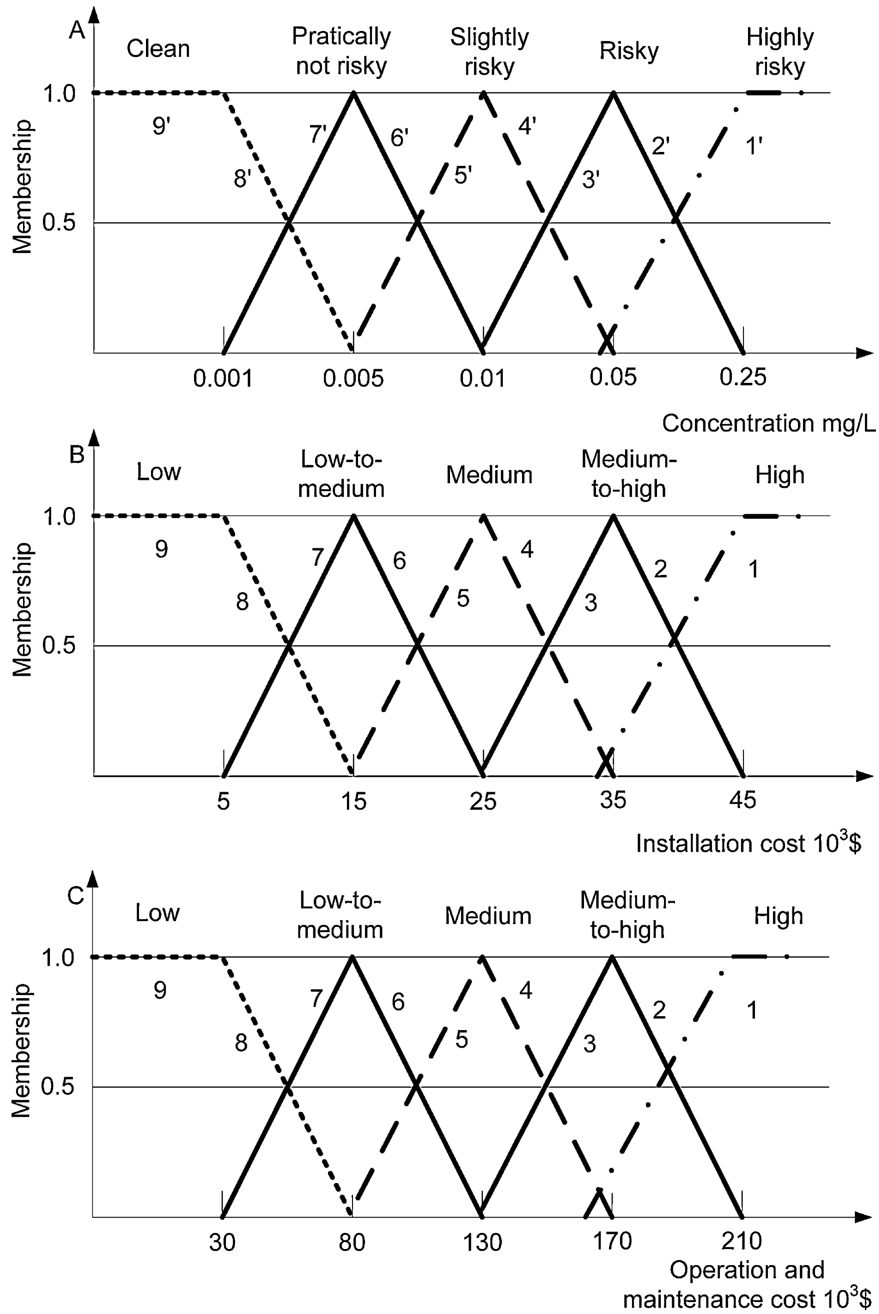

Fig. 4. Membership functions of scores related to (A) risk levels, (B) installation cost levels and (C) operation and maintenance cost levels.

described by a core of 15 m and a support of (11, 19) m. Transverse dispersivity is dependent with longitudinal dispersivity by a multiplicative factor of 0.1. The hydraulic conductivity of the sand media falls within the range from 10^{-5} to 10^{-3} m/s [44]. Based on sensitivity analysis (shown in Table 4), the concentration values of the maximum plume concentration obtained by BIOPLUME III model are found to be less affected by hydraulic conductivity compared with porosity. Therefore, the uncertainty of conductivity is not accounted for in this study. The parameters used in the hypothetical simulation system are given in Table 5.

3.2.1. Fuzzy simulation results

The remediation period is set to 2 years for the various remediation alternatives. Through fuzzy simulation, the distributions of the benzene concentration at the study site under various scenarios could be obtained. In this study, one simulation run on a 3 GB RAM and 1.86 GHz Duo-Core PC took about 30 s. As the fuzzy vertex method required many rounds of simulation, the total simulation time was about 1 h. Fig. 5 presents the most likely distributions for the plume contamination (i.e. when the membership degree is 1) for the six remediation scenarios.

In general, the results in Fig. 5 show that the concerned remediation actions could reduce benzene concentrations to various degrees. For the same technology, a two-well implementation plan would perform better than a single-well one. For example, in terms of pump-and-treat operations, the highest benzene concentration obtained from one-well operations would be 2.332 mg/L; it would decrease to 0.288 mg/L when two wells are in operation. In addition, it appears that bioremediation is cheaper than pump-and-treat. For example, the base costs of ENA1 and ENA2 are 115.1 and 125.3×10^3 \$, respectively, and those of PT1 and PT2 are 173.6 and 197.5×10^3 \$, respectively. Thus, the bioremediation-based options

Table 3
Cost function coefficients.

Type of cost (10^3 $)	NA	ENA1	ENA2	PT1	PT2	ENA + PT
An automatic mixing system[a]	–	20–25	20–25	–	–	20–25
A slow-release substrate system[a]	–	3–10	3–10	–	–	3–10
Pumping system	–	–	–	10–15	10–15	–
Injection and monitoring well installation costs (per well)[a]	1.5–2.2	1.5–2.2	1.5–2.2	1.5–2.2	1.5–2.2	1.5–2.2
Analytical services for system monitoring (per event)[a]	0.5–0.8	0.5–0.8	0.5–0.8	0.5–0.8	0.5–0.8	0.5–0.8
Injection (oxygen) not including labor (per L/s year)[b]	–	4.755	4.755	–	–	4.755
Pumping operation not including labor (per L/s year)[b]	–	–	–	15.85	15.85	15.85
Performance labor cost (per year)[b]	5.6–8.4	42.5–63.2	44.9–67.3	63.2–86.8	65.6–90.4	65.6–90.4
Total installation cost[c]	[6.5, 7, 9.6]	[31, 38.9, 46.8]	[31.5, 39.8, 49]	[18, 22.4, 26.8]	[18.5, 23.7, 29]	[37.5, 45.8, 54]
Operation and maintenance cost (two year)[c]	[16.8, 19.6, 22.4]	[94.4, 115.1, 135.8]	[102.9, 125.3, 147.7]	[150, 173.6, 197.2]	[172.7, 197.5, 222.3]	[158.5, 183.3, 208.1]

[a] The values are referred to AFCEE [42].
[b] Prasad and Mathur [25].
[c] The fuzzy sets are defined as [p, q, r] where p and r are the lower and upper bounds of a triangular fuzzy set and q is the most-likely value; the related data are adapted from AFCEE [42] and Prasad and Mathur [25].

Table 4
Sensitivity of model results to changes in hydrogeologic parameters.

Variable	Change in parameter (100%)	Change in max. plume concentration (mg/L)
Longitudinal dispersivity	10	0.00578
	5	0.00289
Effective porosity	10	0.00279
	5	0.00145
Hydraulic conductivity	10	0.00023
	5	0.00013
Storage coefficient	10	0.00012
	5	0.00005

would lead to higher benzene removal efficiencies at the contamination source center than the pump-and-treat-based ones. From Fig. 5, the maximum concentrations after remediation would be 10.374, 0.006, 0.001, 0.601, 0.108, and 0.034 mg/L for alternatives NA, ENA1, ENA2, PT1, PT2, and ENA + PT, respectively.

From Fig. 5, the plume areas are about 36,000, 26,100, 58,050, and 25,200 m^2 for alternatives ENA1, PT1, ENA2, and PT2, respectively. The pump-and-treat-based options show relatively better control on the overall plume area. The NA option does not seem to result in a large plume area; this is because the solute transport process under natural attenuation is not influenced by pumping actions. The difference of the plume areas among various remediation alternatives may lead to varied benzene concentrations at a specific receptor location. For example, the benzene concentrations in the residential area would be 0.453, 0.914, 0.753, 0.152, 0.028, and 0.116 mg/L from remediation options NA, ENA1, ENA2, PT1, PT2, and ENA + PT, respectively. It is therefore difficult to determine which remediation alternative performs better by using a single standard. The predicted results for the benzene concentrations under the various conditions will be used for further comparisons.

Table 5
Parameters used in the simulation model.

Input parameter	Values
Grid size	20 × 20
Cell size	30.5 × 30.5 m
Hydraulic conductivity	1.99×10^{-4} m/s
Anisotropic factor	1.0
Aquifer thickness	3.05 m
Hydraulic gradient	0.005
Longitudinal dispersivity	Support = (11, 19), core = 15 m
Transverse dispersivity	Support = (1.1, 1.9), core = 1.5 m
Effective porosity	Support = (0.2, 0.4), core = 0.3
Retardation factor	1.0
Recharge	3.9×10^{-10} m^3/s
Background concentration of oxygen	1 mg/L
Concentration of oxygen in injected water	0.008 g/L
Storage coefficient	0.2
Boundary conditions	Constant head

Fig. 6 shows the benzene concentrations for the two locations, the residential area and the supply well, under various remediation scenarios. Since the benzene concentration in the supply well is less than 0.001 mg/L in scenario ENA + PT, it is not presented in the respective figure. The results demonstrate that the predicted benzene concentrations would present as fuzzy sets. The uncertainty degree of the results varies with the changes of fuzzy membership degree (FMD). At a lower FMD, the intervals of the benzene concentrations are wider, implying a higher vagueness in the predicted benzene concentrations; when FMD increases, the results would become more deterministic.

From Fig. 6, it can also be seen that the fuzzy simulation could provide quantitative information of the benzene contamination under uncertainty. However, the vagueness in the predicted outputs makes it arduous to conduct a direct comparison among the various remediation alternatives. According to Fig. 6A, in the residential area, remediation scenario PT2 would have the best performance as the benzene concentration is the lowest (i.e. ranging from 0.006 to 0.087 mg/L, with the average value being 0.024 mg/L). Scenario ENA1 performs the worst as the benzene concentration falls within the interval of [0.326, 0.754] mg/L. It is difficult to compare scenarios NA, ENA2, PT1 and ENA + PAT, as their membership functions overlap with each other. From Fig. 6B, in the supply well, scenario ENA + PT achieves zero concentration; PT2 performs the second best as the benzene concentration ranges from 0.004 to 0.097 mg/L, with the average value being 0.04 mg/L. Scenario NA has the worst performance as the benzene concentration would reach up to 3.15 to 3.394 mg/L. Scenarios ENA1, ENA2 and PT1 are mingled together and hard to differentiate.

3.2.2. *Fuzzy performance matrix*

Since the six proposed evaluation criteria are assessed using the same scoring scale, a normalization process won't be necessary. Based on the fuzzy simulation results, along with the risk and cost analyses, we generated the fuzzy performance matrix, given in Table 6. Their values were described as interval numbers for a variety of membership degrees (i.e. α levels). The performance matrix indicated that the enhanced natural attenuation and

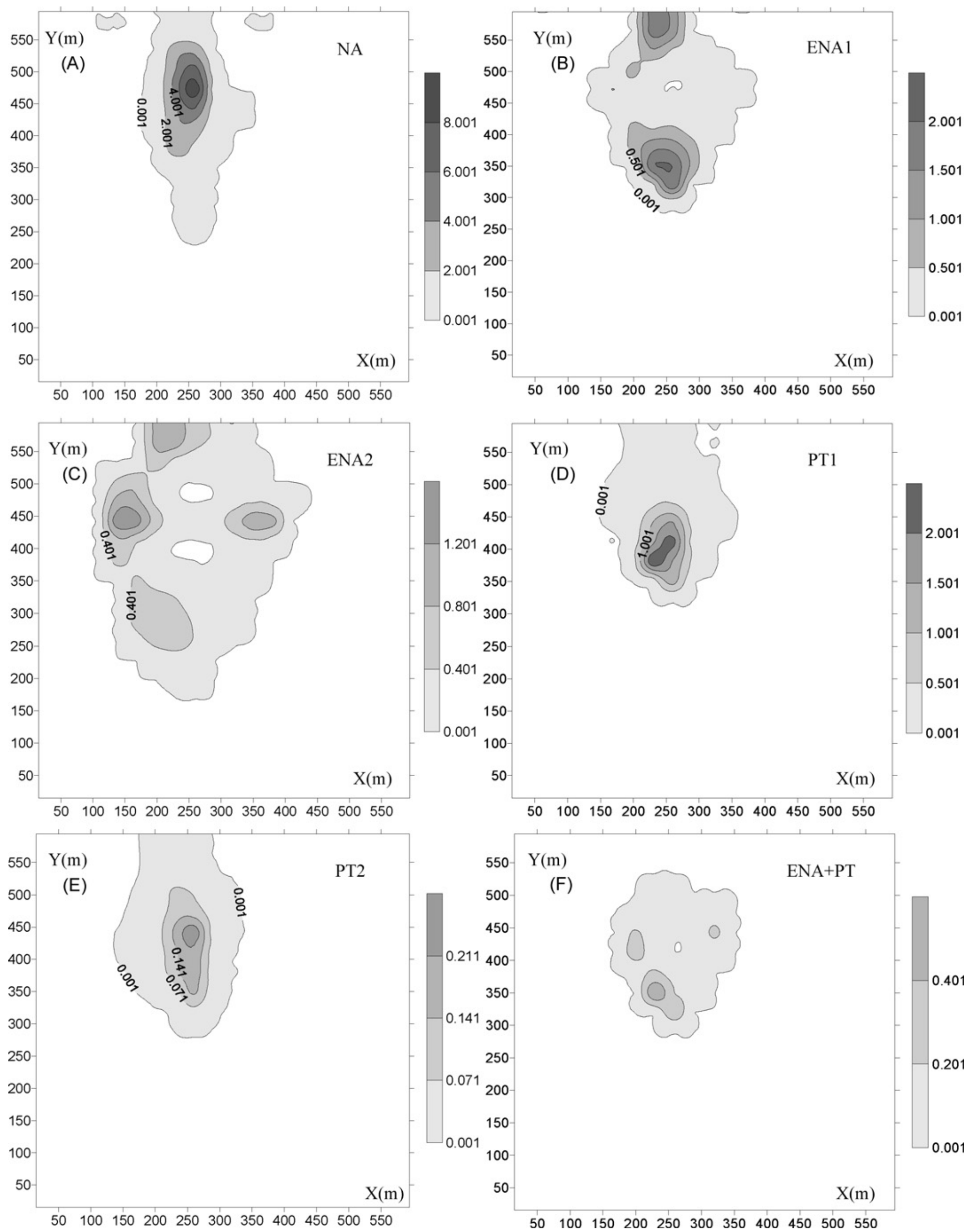

Fig. 5. Mean distributions of benzene concentrations at the study site for the six scenarios.

pump-and-treat remediation options, to a varied extent, could reduce the risk of contamination at the different receptors. For example, the $c2$ scores for scenarios NA and ENA1 are both 1 at the membership degree of 1 (compare also Fig. 4), indicating a "Highly risky" condition; for scenario ENA2, the $c2$ score is (1, 3) at the membership degree of 0.5, implying a "Risky" to "Highly risky" condition. In addition from Table 6, it is found that a single remediation alternative may have notably different mitigation effects for the different receptors. For example, ENA2 may bring a higher reduction of contamination risk at the source center (i.e. the $c1$ scores are in the range of 6–9) than the other remediation alternatives; PT2 may have a better performance for the school area ($c4$).

Moreover, the costs associated with different remediation scenarios also have large variations ($c5$ and $c6$ in Table 6). The scenario NA is the least costly, followed by ENA1; scenario ENA + PT is the most expensive. Since the above-mentioned data are characterized by uncertainties and contradictions, further tradeoff analysis is therefore needed for supporting remediation decisions.

3.2.3. Inexact ranking results

The proposed fuzzy TOPSIS method is then used for investigating the impact of uncertainties and multi-criteria performances on rankings. Fig. 7 shows the ranking distributions before defuzzification (i.e. a process to evaluate a fuzzy set by a crisp value). The results of the relative closeness (RC) are also presented as possibilistic distributions, where most of the curves deviate significantly under different fuzzy membership degrees. It is also indicated that, a number of curves are overlapping with each other and can hardly be differentiated. For example, at the fuzzy membership degree of 0.75, the lower bounds of scores for scenarios NA, ENA1,

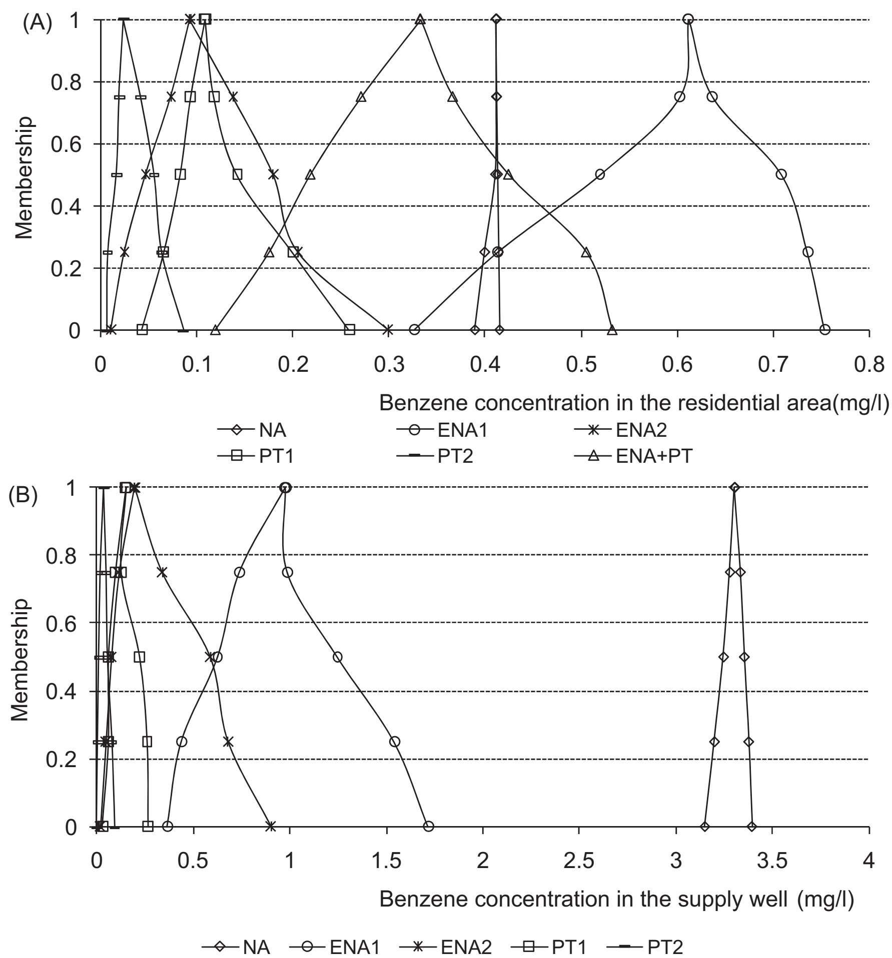

Fig. 6. Membership functions of benzene concentrations in (A) the residential area and (B) the supply well for different remediation scenarios.

ENA2, PT1, PT2 and ENA + PT are 0.385, 0.251, 0.356, 0.195, 0.243 and 0.434 respectively, and the upper bounds are 0.426, 0.353, 0.425, 0.233, 0.365 and 0.506, respectively. The relative closeness value is computed as ratio of NIS/(IS + NIS), where NIS and IS are overall distance of each alternative from the negative ideal solution and ideal solution, respectively. The alternative with the highest ratio is far away from negative ideal solution and close to ideal solution, which is deemed as the best option. Therefore, scenarios ENA1 and PT2 are likely ranked in the 4th or 5th position. Generally, the inexact ranking results can hardly be used directly for decision making. A further defuzzification effort is needed.

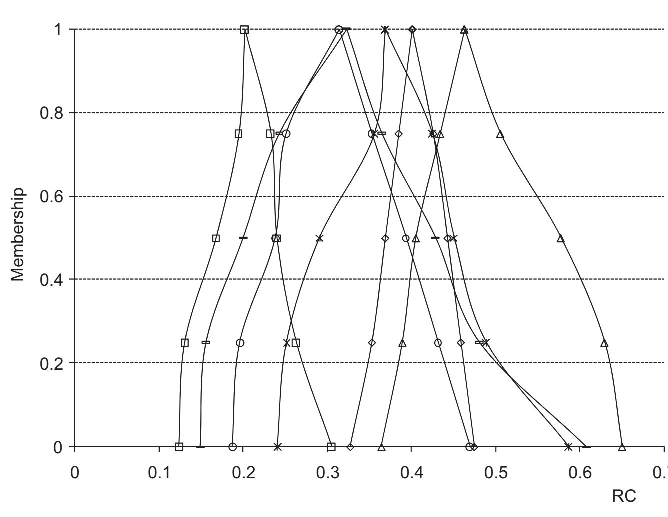

Fig. 7. Membership functions of the ratings at the study site associated with the six scenarios.

By computing the relative closeness of the averaging level cuts by Eq. (6), the overall ratings for all the alternatives (in the order: EN, ENA1, ENA2, PT1, PT2 and ENA + PT) are 0.4093, 0.3149, 0.383, 0.2063, 0.3277, and 0.4883, respectively. Therefore, the final ranking result would be: ENA + PT > NA > ENA2 > PT2 > ENA1 > PT1. Obviously, the system tends to find the remediation strategy with a lower risk of environmental impact and a lower remediation cost, although all of the designed remediation alternatives may not be efficient enough as the score values are far lower than 1. Scenario ENA + PT is the most expensive alternative, but it is deemed the best option for the study site remediation. Scenario NA is the 2nd best option followed by scenario ENA2; this is because natural attenuation is the cheapest option, though it hardly reduces the receptors' risk (other options also hardly reduce the receptors' risk to acceptable levels, due to the limited remediation time); and enhanced natural attenuation is more cost-effective compared with the pump-and-treat operation using the same well settings. Hence, it is reasonable that ENA1 would outrank PT1, but be inferior than PT2 due to its lower remediation efficiency.

The proposed SFMCDA methodology assessed six criteria, which were described by a set of linguistic variables, to rank six remediation options under uncertainty. For comparison, if no uncertainty

Table 6
Results of the fuzzy performance matrix.

Remediation scenarios	Alpha levels	*c*1	*c*2	*c*3	*c*4	*c*5	*c*6
NA	0	1	1	1	(2, 4)[a]	8	9
	0.25	1	1	1	(3, 4)	8	9
	0.5	1	1	1	(3, 4)	8	9
	0.75	1	1	1	(3, 4)	8	9
	1	1	1	1	3	8	9
ENA1	0	(4, 9)	1	1	1	(1, 3)	(4, 6)
	0.25	(4, 8)	1	1	1	(1, 2)	(4, 6)
	0.5	(4, 7)	1	1	1	(1, 2)	(5, 6)
	0.75	(4, 7)	1	1	1	2	5
	1	6	1	1	1	2	5
ENA2	0	(6, 9)	(1, 4)	(1, 4)	(1, 4)	(1, 3)	(4, 6)
	0.25	(6, 9)	(1, 4)	(1, 2)	(1, 2)	(1, 2)	(4, 5)
	0.5	(7, 9)	(1, 3)	(1, 2)	(1, 2)	(1, 2)	(4, 5)
	0.75	(8, 9)	2	(1, 2)	(1, 1)	2	5
	1	8	2	1	1	2	5
PT1	0	1	(1, 3)	(1, 3)	4	(4, 6)	(1, 3)
	0.25	1	(1, 2)	(1, 2)	4	(4, 6)	(1, 3)
	0.5	1	2	(1, 2)	4	5	(2, 3)
	0.75	1	2	2	4	5	(2, 3)
	1	1	2	2	4	5	2
PT2	0	(1, 4)	(2, 6)	(2, 7)	(4, 9)	(4, 6)	(1, 2)
	0.25	(1, 3)	(2, 5)	(2, 5)	(4, 8)	(4,5)	(1, 2)
	0.5	(1, 3)	(2, 4)	(2, 4)	(5, 8)	5	(1, 2)
	0.75	(1, 2)	(3, 4)	(2, 4)	(6, 7)	5	1
	1	2	4	3	7	5	1
ENA + PT	0	(1, 9)	(1, 2)	9	(2, 3)	(1, 2)	(1, 3)
	0.25	(2, 9)	1	9	(2, 3)	(1, 2)	(1, 3)
	0.5	(2, 9)	1	9	2	1	(1, 2)
	0.75	(2, 5)	1	9	2	1	2
	1	3	1	9	2	1	2

[a] *Note:* (a, b) means an interval value.

is considered (assume all fuzzy sets are set using deterministic values at their most likely value), the relative closenesses of the six alternatives become 0.401, 0.314, 0.369, 0.202, 0.323, and 0.463, respectively. Although these values are lower than the defuzzified ones, the deterministic approach leads to the same ranking as the fuzzy one using the most likely condition. However, it produces only a crisp (i.e. precise) point estimate for the score of each alternative. From Fig. 7, we can see that the deterministic values are contained within the results of the SFMCDA. SFMCDA could produce a fuzzy estimate rather than a crisp point estimate or an exaggerated fuzzy estimate (i.e. the results may coincide with the results obtained without considering uncertainty) [36]. In this study, triangular fuzzy membership functions were used to reflect parameter uncertainty due to information imprecision. Since fuzzy simulation considers all possible combinations of parameter values, and the width of the support base of the membership function is an important factor that affects the results [11]. It is possible that the simulation outputs might vary significantly if different shapes of fuzzy possibility distributions (e.g. trapezoidal or polygonal) are used. This may lead to different ranking results.

3.2.4. Discussions

The application of SFMCDA was demonstrated by a hypothetical benzene-contamination case study, which was much simpler in magnitude than a possible real-world problem. This was to draw a clear picture of the problem-solving procedures and highlight the effectiveness of the proposed methodology. In real-world applications, a number of issues may be encountered in applying the proposed methodology due to increased complexities: (i) the contaminant transport process is more complicated (i.e. due to increased heterogeneity and anisotropy of aquifer media) which could bring time-consuming computations in fuzzy simulation and extensive efforts in model calibration and verification; (ii) the characterization of the uncertainties in the groundwater remediation system may need more careful site survey, literature review or expert consultation efforts; (iii) the remediation techniques, operation time, and cost analysis may be site specific; this brings difficulties in scenario design and identification of suitable evaluation criteria and weightings.

At present, the available BIOPLUME III software cannot do an automatic run for a loop simulation. We actually did this manually, by inputting the data many times when running the fuzzy simulation. Since the test example is not very large (one simulation requires about 30 s of CPU time), we managed to obtain the simulation results in a reasonable time. For a complex site (i.e. more grid cells, complex boundary and initial conditions, etc.), it may not feasible to rely on manual input. It will be more preferable to use other software packages (such as UTCHEM or BIOF&T) which are more programmable for automatic running. Since this paper aimed to focus on the development of a novel framework for evaluating the trade-offs between risk and cost, and finding the best remediation alternatives while hedging against parameter uncertainties, we chose BIOPLUME III for easy configuration. The validity of such a model for simulating enhanced natural attenuation, pump-and-treat, and natural attenuation processes was well demonstrated by Prasad and Mathur [25]. The same physiology shall apply to other models and remediation processes.

In real-world applications, identification of the fuzzy distribution of a hydrogeological parameter needs careful site investigations. Strictly speaking, if a site is highly heterogeneous, every grid of the numerical domain should have an individual fuzzy membership function of the hydrogeological parameter. However, the data is difficult to obtain due to cost limitations. However, with some simplifications, a heterogeneous domain can be divided into a number of regions, where each region is assumed to be homogeneous. This could be determined based on the geological survey

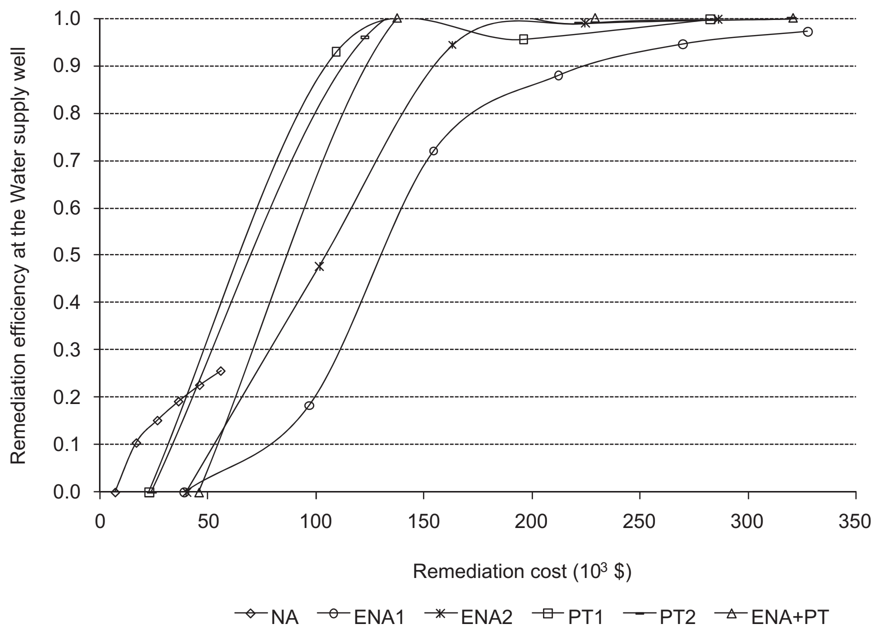

Fig. 8. Remediation costs vs. remediation efficiency at the supply well for different remedial alternatives involving 1–5 years of pumping under the most likely condition.

results. Then for each region, a pumping test campaign can be conducted to get a set of deterministic values for the hydrogeological parameter. The fuzzy membership function can then be generated based on the surveyed data. Eventually, we will have a number of fuzzy sets for the hydrogeological parameter. The greater the number of the regions to be divided, the more the pumping test campaigns is needed. If the entire site is considered homogeneous, a single pumping test campaign would be acceptable.

In the remediation decision analysis process, the uncertainties can be related to parameter uncertain in natural porous media [45], risk assessment [46], alternative selection [3]. Fuzzy set theory provides an efficient mechanism for carrying out appropriate reasoning processes when available information is uncertain, incomplete, imprecise, or vague [15]. The involvement of experts has been identified as a critical aspect of the decision-making process [47]. In fact, the subjectivity may certainly exist in experts interviews. However, on one side, the weights value may not be given randomly, which needs experts and stakeholders to make trade-offs to finalize the weights. To a certain extent, given weight is a relative objective process. On the other side, different experts may have different preferences on each evaluation criteria; it is thus we made the weight of each criterion an uncertain value. In this paper, our study focused on the application of fuzzy simulation and fuzzy TOPSIS decision analysis to the evaluation and ranking of remediation alternatives instead of ‘decision by racking their brains’. Almost of the aforementioned uncertainties associated with the remediation decision analysis process were addressed. The proposed method can reduce the subjectivity as much as possible.

Fig. 8 shows the remediation efficiency versus remediation cost at the water supply well for 1–5 years pumping for the six remediation alternatives. It is found that the tradeoff curve follows an exponent trend (i.e. the remediation cost increases exponentially with the increase of the pumping duration). Scenario ENA + PT is found to be the most efficient, as almost 100% treatment efficiency could be obtained after only 1-year operation. Furthermore, at the same level of remediation cost (i.e. 223×10^3 \$), scenarios ENA + PT shows the highest efficiency (100%), followed by PT2 (98%) and PT1 (92%). Fig. 8 also presents the results for treatment years vs. remediation costs under the most likely value. The installation costs (i.e. the remediation cost at the starting treatment year) for each remediation alternative are ca. 7.0, 38.9, 39.8, 22.4, 23.7, and 45.8×10^3 \$, respectively. It can be observed that the costs for the different remediation alternatives increase with the number of operation years at stable increments of 9.8, 57.69, 61.57, 86.78, 98.75, and 91.66×10^3 \$ per year; this is incurred by operation, analysis and labor costs. Scenario PT2 has the highest increment, as the pump-and-treat operation is costly. It can be obtained that the costs associated with PT2 may surpass that of ENA + PT after 4 years of operation. Thus, from a long-term management point of view, a time-series cost analysis could be added to the SFMCDA procedures for addressing such effects.

The overall ratings of alternatives for this study case indicated that the designed remediation alternatives may not be efficient enough. Even the best choice ENA + PT, with a score value of 0.4883 was far lower than 1. In real world applications, there are many remediation techniques and their operation conditions. A prescreening or pre-analysis effort is necessary in order to reduce the number of alternatives [6]. For example, at a specified site, if a single remedial technology is to be considered, the most cost-efficient configuration of well numbers, well locations and pumping rates in applying such a technology could be identified first using an optimization model; then this technology with optimized operating parameters could be considered as a potential alternative for further ranking. It is thus suggested to integrate both decision analysis and optimization into a general framework for better decision making.

In many practical applications, different experts/stakeholders may have different preferences on evaluation criteria, which may lead to significant variations of the weighting levels even for the same criteria. Thus, it should be appreciated that if the weights of the evaluation criteria change, the ranking results may be different. For example, if the experts consider “less importance” for the cost and risk at the primary school area, and “high importance” for the risk at the locations of source zone, residential area and supply well, the weights of the six criteria may change to a new set of values (as shown in Table 2). The scores for alternatives NA, ENA1, ENA2, PT1, PT2 and ENA + PT would become 0.3589, 0.3156, 0.3937, 0.1831, 0.3136 and 0.5212, respectively. Then, the ranking scheme would change to: ENA + PT > ENA2 > NA > ENA1 > PT2 > PT1. Scenario ENA + PT still ranks at the top due to its superior performances at the contamination source center and the supply well. The ranking for scenarios ENA2 and NA has changed due to the lowered weights of cost criteria. Scenarios with pump-and-treat operation rank behind due to their poor performance at the source zone. This indicates that the ranking results are sensitive to the weights of evaluation criteria. In real-world applications, it is highly suggested that the weights be carefully selected by the related experts and stakeholders.

4. Conclusions

In this study, the focus is on the formulation and computational aspects of the SFMCDA method. The following facts have been found:

(1) Simulation models are important means to help analyze contaminant fate and transport under different remediation alternatives. Compared with the FMCDA method proposed by Li et al. [3], the proposed SFMCDA method could evaluate the environmental performance by transport modeling under a variety of remediating scenarios; the uncertainty associated with the simulation system could be tackled effectively by coupling the simulator and fuzzy vertex analysis that is less computationally intensive.
(2) The weights for the decision-making process are important factors that would influence the ranking results. According to Bonano et al. [47], the remediation alternatives were relied on stakeholders' inputs which were described as deterministic values. Normally, different experts or stakeholders may have different preferences on each evaluation criterion, which may lead to significant variations of the weights. It is thus important to consider the weighting level of each criterion an uncertain variable, and enable the selection of remediation alternatives in an uncertain environment.
(3) The ranking information obtained by SFMCDA takes uncertainty into consideration and is more reliable than those by conventional MCDA methods. Fuzzy TOPSIS decision analysis could produce a fuzzy estimate rather than a crisp-point estimate or an exaggerated interval estimate, where subjectivity has been reduced as much as possible.
(4) Generally, the proposed SFMCDA method has the following advantages and innovations: (i) it systematically accounts for inputs from pollution impact, cost analysis and stakeholders' judgment; (ii) it is capable of addressing multiple-source uncertainties associated with simulation parameters, prioritization of criteria and description of alternatives; (iii) it could help mitigate subjectivity of human judgment through the application of the fuzzy TOPSIS inference operation; (iv) it is also applicable for other environmental systems. SFMCDA also has much room for improvement. For example, the stochastic uncertainty and fuzzy uncertainty may occur in the same system, leading to difficulties of applying the proposed method; a coupled fuzzy stochastic simulation strategy may have to be used; it could also be combined with an optimization model to tackle continuous variable problems.

Acknowledgements

This research was supported by the Major Project Program of the Natural Sciences Foundation (51190095), the Beijing Municipal Program of Technology Transfer and Industrial Application, and the Program for Innovative Research Team in University (IRT1127). We deeply appreciate the anonymous reviewers' insightful comments and suggestions, which have helped much in improving the manuscript.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jhazmat.2012.02.027.

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