Which Groundwater Remediation Objective is Better, a Realistic One or a Simple One?

Xiaolin Ren[1] and **Barbara Minsker**[2], **Associate Member, ASCE**

[1] Department of Civil and Environmental Engineering, 4146 NCEL, MC.250, 205 N. Mathews, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, Tel: (217)333-1657, Email: xren@uiuc.edu

[2] Assoc. Prof., Department of Civil and Environmental Engineering, 3230d NCEL, MC.250, 205 N. Mathews, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, Tel: (217)333-9017, Email: minsker@uiuc.edu

Abstract:

One of the first steps in setting up an optimal groundwater remediation design problem is developing an appropriate objective function, which represents the primary goals of the design. Selecting appropriate objective functions can be challenging. A more realistic objective function, which is a cost function applied to a realistic site without simplification, may yield more accurate results but at the same time it will require more time and effort to develop the appropriate function for a particular application. On the other hand, a simple function will save setup time but may sacrifice the accuracy of the results. This research seeks to identify what situations encountered in remediation design would make the development of a realistic objective function necessary. It also examines tradeoffs among three objectives: total cost, risk, and total cleanup time. A pump-and-treat system is designed for a case study to explore these questions. The model used here is NSGA II (Non-dominated Sorting Genetic Algorithm-II) combined with two numerical models (Modflow and RT3D) and an exposure and risk assessment model. Four different cost functions are applied, ranging from simple to complex. The results show that the realistic cost function generally found better solutions than the simplified ones, especially for shorter-term cleanups. These findings are now being tested for a field-scale application at Umatilla Army Depot in Oregon.

Introduction

One of the first steps in setting up an optimization model for water resources management is developing an appropriate objective function, which represents the primary goals of the design. For groundwater remediation design, the primary focus of this research, several types of objective functions have been used in the literature, which are: 1) cost function without capital cost, e.g. *Gorelick et al* (1984), *Wagner and Gorelick* (1987), *Andricevic and Kitanidis* (1990), *Culver and Shoemaker* (1992), *Sawyer and Lin* (1998), *Yoon and Shoemaker* (1999); 2) cost function with fixed capital cost, e.g. *Marryott et al* (1993), *Culver and Shoemaker* (1997), *Kwanyuan and Fontane* (1998), *Lee and Kitanidis* (1991), *McKinney and Lin* (1996), *Rizzo and Dougherty* (1996), *Culver and Shenk* (1998), *Aly and Peralta* (1999), *Johnson and Roger* (2000); 3) realistic cost function, including fixed and variable capital costs and operational costs, e.g. *Huang and Mayer* (1997), *Smalley and Minsker* (2000). Most groundwater remediation optimization efforts have considered only a single objective, but a few have considered two objectives, such as: *Cieniawski et al* (1995), *Coello* (1999), *Van Veldhuizen et al* (2000) and *Reed* (2001).

Previous work has usually focused on the problems after the optimization models had been setup, such as the algorithm selection, uncertainty analysis etc. This paper focuses on the setup of optimization model, namely the choice of objective functions. What are the tradeoffs in cost, human health risk, and remediation time? How does the choice of cost function affect the optimal solutions found? A detailed, realistic cost function was implemented on a case study and compared with simpler cost functions that have been used in the past. In the first section of this paper, the case study that was used to test the cost function is introduced, and then the methodology is described in the second section. In the last two sections, the results are presented.

Background of the Case Study

The case study examined here involves a multi-objective groundwater remediation design to find cost-effective optimal pumping strategies for treating a contaminated aquifer using pump-and-treat. The case study is based on a hypothetical confined, heterogeneous and isotropic aquifer, 480m by 240m by 20m, which has been studied by *Smalley et al* (2000). The target contaminant is BTEX. The initial plume is shown in Figure 1.

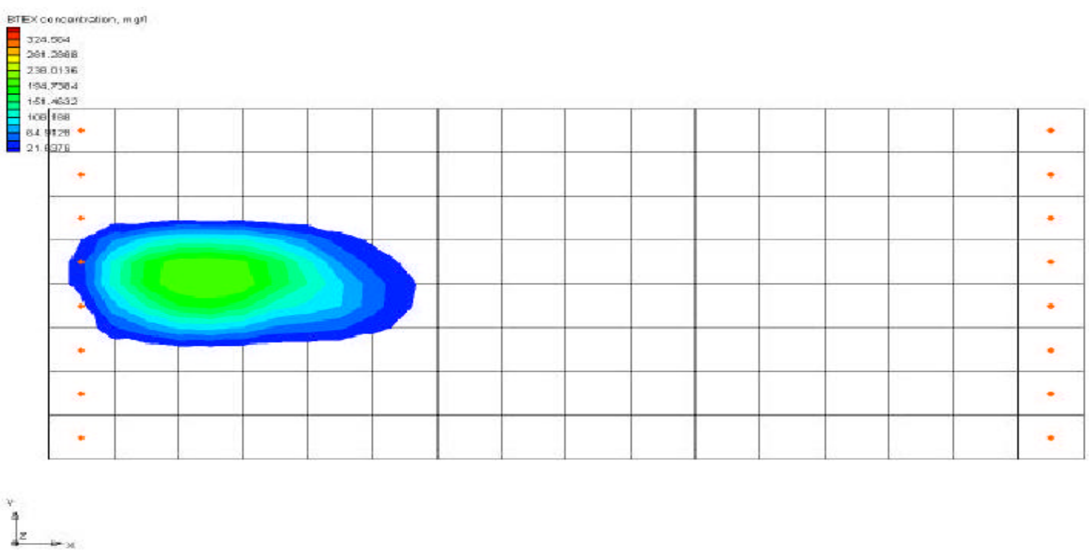


Figure 1 Initial BTEX plume (adapted from *Babbar et al* (2002))

The flow of the groundwater in the aquifer is assumed to be steady state and the direction of flow is from left to right in Figure 1. The average hydraulic conductivity is 2256 m/year. The porosity of the field was assumed to be 0.3 and the soil bulk density of the aquifer was 2000 kg/m^3. The longitudinal dispersivity was assumed to be 15 m with a ratio of transverse to longitudinal dispersivity of 0.2 and a ratio of vertical to longitudinal dispersivity of 1.0. The left and right boundaries of the domain in Figure 1 are constant head boundaries with a mean hydraulic gradient of 0.00146. The upper and lower boundaries are no flow boundaries. The reaction constant for a linear sorption reaction is 0.000062 m^3/ kg.

For the remediation model (Figure 2), fifteen monitoring wells were used to monitor the concentrations of the contaminant in the aquifer for the whole remediation period. Five above-ground treatment technologies (air stripper low profile tray stack, air stripper packed tower, modular carbon adsorbers-duel bed, modular carbon adsorbers-permanent and modular carbon adsorbers-disposable) were selected for inclusion in the model based on a previous analysis (*Vieux*(1999)). The model chooses the most cost-effective technology for any selected pumping rate, using the ranges shown in Table 1. Three remediation wells were allowed for extraction/injection at the 58 candidate locations shown in Figure 2. The maximum pumping capacity of each well was assumed to be 250 m^3/day. For more detailed information, please see *Babbar et al* (2002).

Table 1: Cost-effective pumping rate ranges for aboveground treatment technologies

Technology	Effective pumping rates (gpm)	Effective pumping rates (m^3/day)
Air stripper low profile tray stack	0 ~ 750	0 ~ 4088
Air stripper packed tower	10 ~ 2250	55 ~ 12264
Modular carbon adsorbers-duel bed	0 ~ 2000	0 ~ 10901
Modular carbon adsorbers-permanent	0 ~ 200	0 ~ 1090
Modular carbon adsorbers-disposable	0 ~ 200	0 ~ 1090

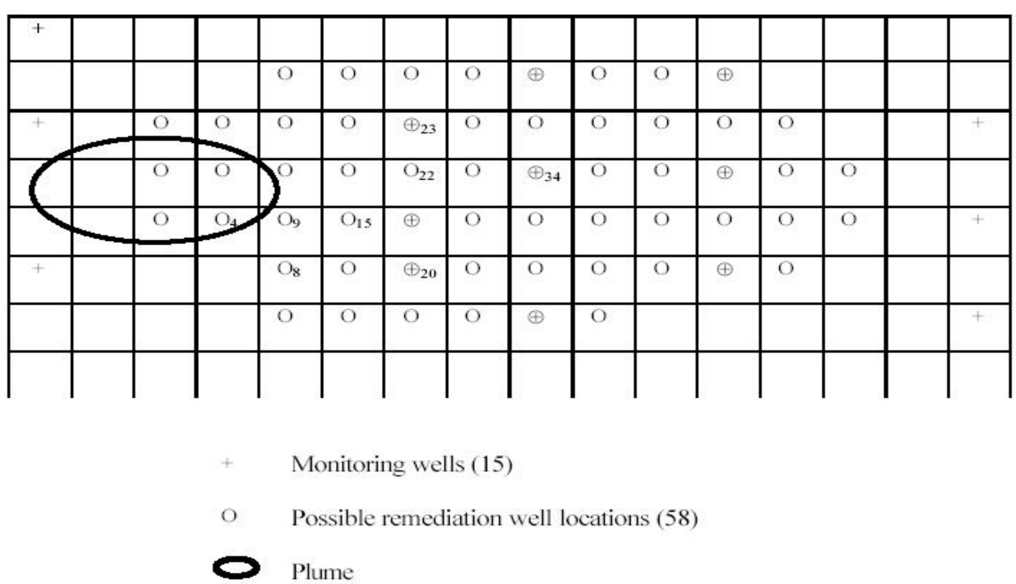


Figure 2 Plan view of the case study aquifer (adapted from *Babbar et al* (2002))

Methodology

The case study was used to investigate the importance of objective function selection in a multi-objective groundwater remediation design model. The model is composed of several components: NSGA II (Non-dominated Sorting Genetic Algorithm-II), an optimization model, two numerical models (Modflow and RT3D) and an exposure and risk assessment model.

Optimization Model

The optimization model is composed of three objective functions and several constraints. The objective functions represent the main goals of the model: minimize the cost of the pump-and-treat design, minimize the maximum human health risk, and minimize total clean-up time. The objectives are shown mathematically below:

Min $C_{TOT} = C_{REM} + C_{MON} + C_{SYST}$

Min (Max $risk_{t,k}^{TOTAL} = risk_{t,k}^{w} + risk_{t,k}^{shw} + risk_{t,k}^{nc}, \forall t, \forall k$)

Min t_{total}

C_{TOT} : Total cost

C_{REM} : Capital and operation costs for remediation wells

C_{MON} : Costs for site monitoring

C_{SYST} : Capital and operation costs for remediation system

$risk_{t,k}^{TOTAL}$: Total individual lifetime health risk at time t and exposure location k

$risk_{t,k}^{w}$: Risk of ingestion of contaminated drinking water

$risk_{t,k}^{shw}$: Risk of inhalation of due to showering

$risk_{t,k}^{nc}$: Risk of inhalation of volatiles from contaminated water due to other non-consumptive use

t_{total} : The total clean-up time

For detailed functions of C_{REM}, C_{MON} and $risk_{t,k}^{TOTAL}$, please refer to *Smalley et al (2000).*

The detailed equation for remediation cost is (based on *Vieux*(1999))

$$C_{SYS} = C_{j,k}^{cap} X_i + C^{cap,POTW} X_i + (C_{j,k}^{op} (\sum^{NW} |Q_i|) + C^{ana} g + C^{op,POTW} (\sum^{NW} |Q_i|)) * (P \mid A, i, n)$$

$C_{j,k}^{cap}$: Capital cost for technology j of contaminant class k associated with total pumping rate

$C_{j,k}^{op}$: Annual O&M cost for technology j of contaminant class k per year

$C^{cap,POTW}$: Capital cost for disposing of treated groundwater to POTW (publicly-owned treatment works) associated with total pumping rate

$C^{op,POTW}$: Annual O&M cost of disposing treated groundwater to POTW per year

C^{ana} : Cost of collecting, testing and analyzing groundwater and off-gas sample for technology j of class k per test

NW : Number of remediation wells

g : Number of tests per year

Q_i : Pumping rate of remediation well i

$(P \mid A, i, n)$: Financial factor for converting a series of O&M costs to a present value

X_i : A indicator variables of well installation, $X_i = 1$ if well i is installed, otherwise, $X_i = 0$

All the data for the remediation cost were obtained from RACER (Remedial Action Cost Engineering and Requirement), a parametric modeling system. The capital cost can be obtained directly from RACER for a particular site and pumping rate. To get the annual O&M cost (including treatment and discharge costs), the variable O&M costs over a 15-year remediation period were annualized and plot for different flow rates. The O&M costs showed a linear relationship within different flow ranges, which were used to create detailed functions for each flow range and technology.

All of the objectives are subject to the following constraints:

1) The pumping rates (or injection rates) of the wells, Q_i, should be within the well capacities [$Q_{\min,i}$, $Q_{\max,i}$] for any remediation well *i*.

$$Q_{\min,i} \le |Q_i| \le Q_{\max,i}, \forall i$$

2) The hydraulic head, $h_{i,l}$, for remediation well *i* should be within the allowed head range [$h_{\min,l}$, $h_{\max,l}$] at any well location *l*.

$$h_{\min,l} \le h_{i,l} \le h_{\max,l}, \forall i, \forall l$$

Numerical Model and Risk Assessment Model

Groundwater Modeling System (GMS) modules MODFLOW (*McDonald et al*, 1988) and RT3D (*Clement et al*, 1998) were used in this case study to create and run the numerical model. Modflow was used to predict the groundwater flow, while RT3D was used to predict fate and transport of the contaminant in the source area shown in Figures 1 and 2.

The concentrations of the contaminant within the source zone from the two numerical models were then used to predict human health risks at an exposure point 200 m downgradient of the right boundary of Figure 2 using a risk assessment model. Please refer to *Smalley et al* (2000) for more information on the risk assessment model.

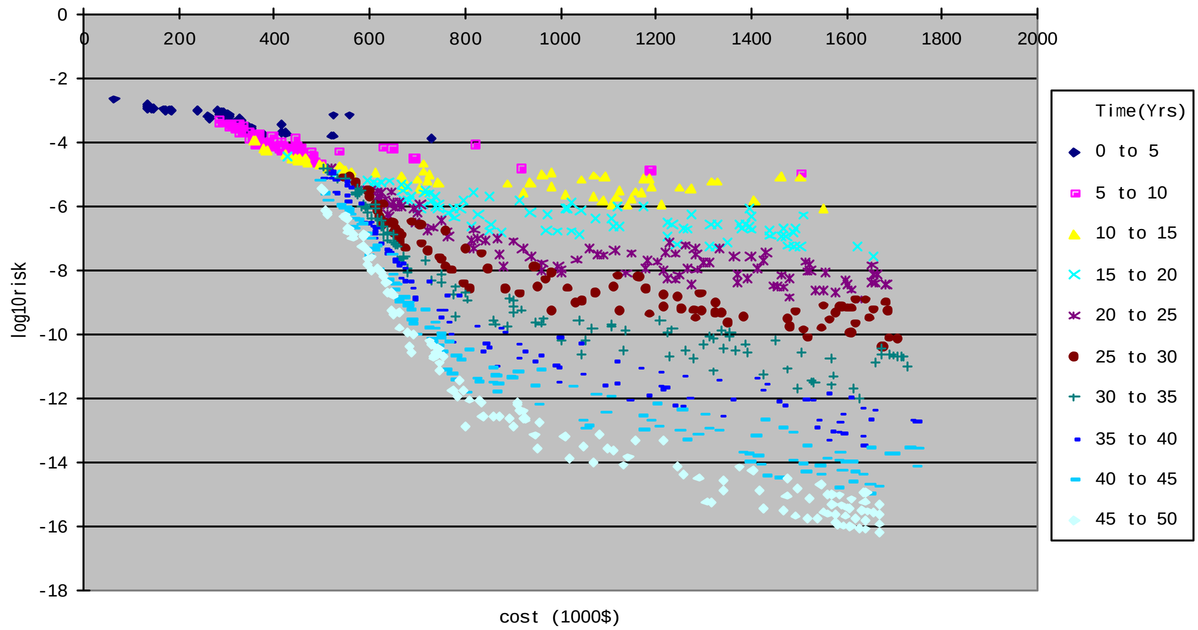
NSGA II (Non-dominated Sorting Genetic Algorithm-II)

This multiobjective optimization problem was solved using NSGA II (Non-dominated Sorting Genetic Algorithm-II) (*Deb et al.* (2000)). NSGA II was used in this problem because it has been shown to perform as well as or better than other second generation Multiobjective genetic algorithms on difficult, high order problems (see *Deb et al.* 2001). For detailed information on how NSGA II works, please refer to *Deb et al.* (2000).

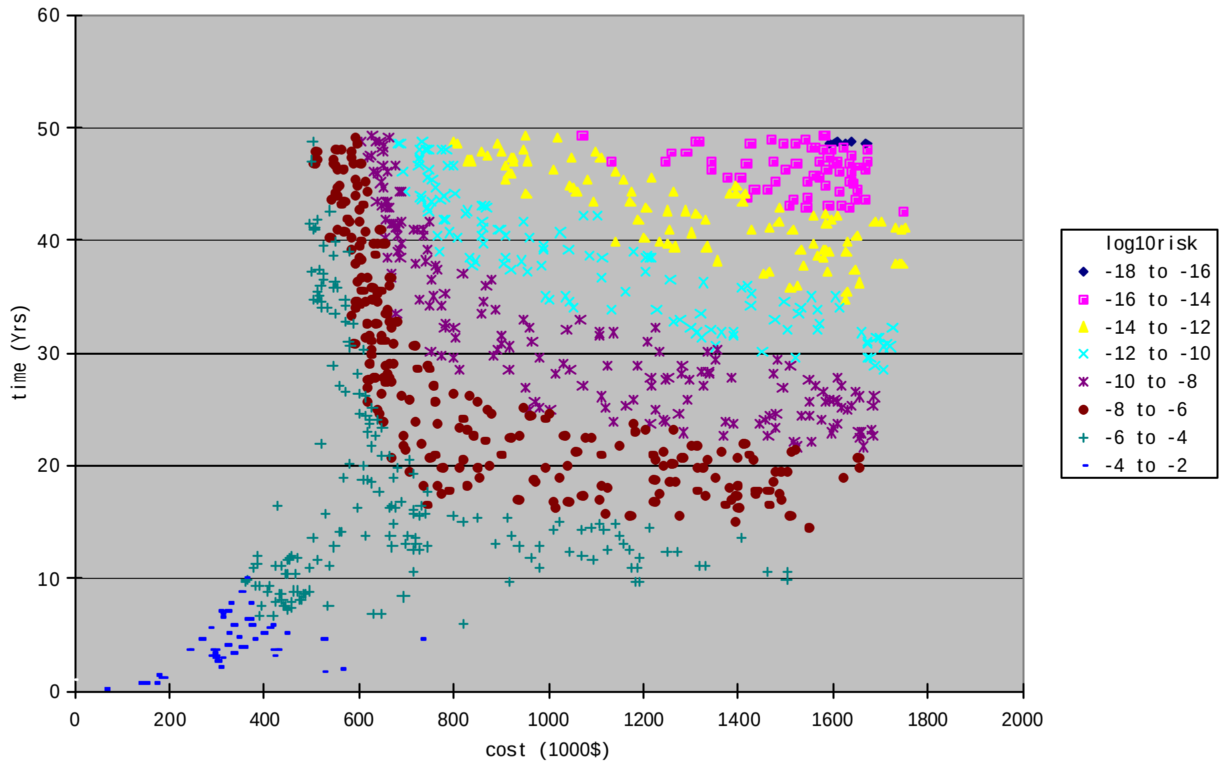
Tradeoffs Among Objectives

There are many ways to illustrate the non-dominated solutions of high order problems (problems with more than two objectives), such as scatter-plot matrix method, value path method, bar chart method, etc. (Please refer to *Deb* (2001) for detailed information.) In this paper, we propose a new approach to express the tradeoffs among three objectives that allows easy visualization of all of the relationships among the objectives to improve decision making.

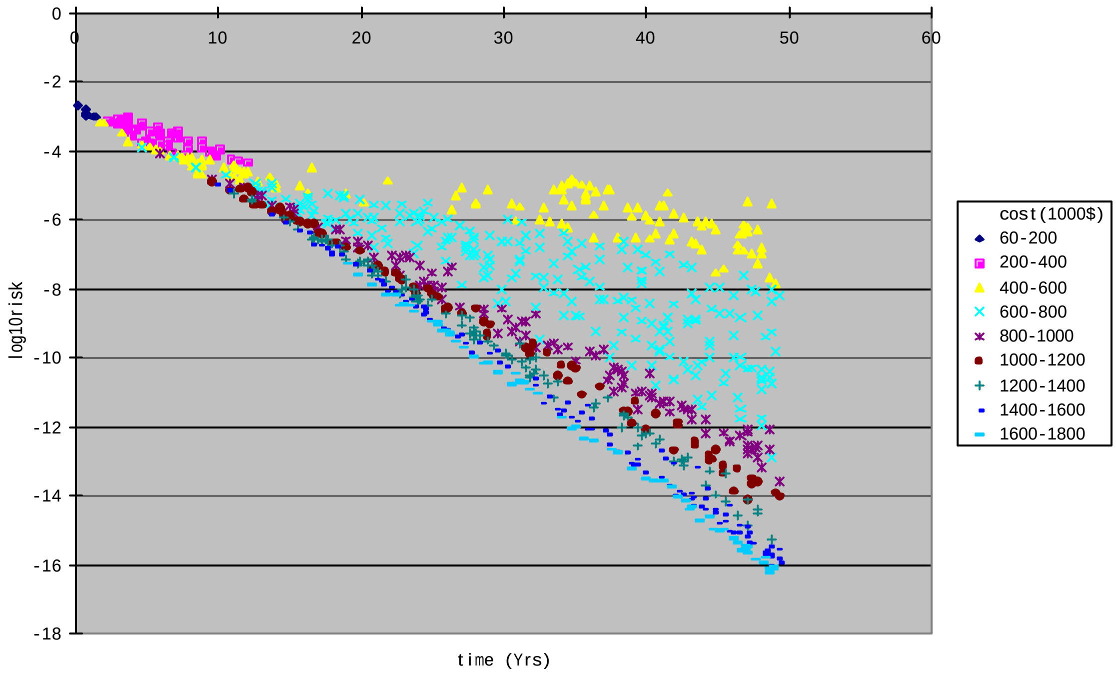
Figure 3 shows the tradeoffs between two objectives based on different ranges for the third objective. Figure 3(a) shows the tradeoffs between cost and log risk for different ranges of time, while 3(b) shows the tradeoffs between cost and time based on different ranges of log risk and 3(c) shows time and log risk tradeoffs for different cost ranges. This visualization approach is very straightforward for elucidating the relationships among the objectives. The effects of possible bounds on different objectives can be easily seen and candidate solutions that meet the bounds identified. For example, if the project is constrained by time, Figure 3 (a) can be used to find the tradeoff between cost and risk for different ranges of cleanup time. Or if a target risk is to be set, Figure 3 (b) can be used to identify tradeoffs in cost and cleanup time. Generally, Figure 3(b) shows that if the required risk level is high (higher than 10^{-4}), a short term remediation (less than 10 years) is preferred. For a low risk level (especially lower than 10^{-10}), a long term remediation is shown to be more cost effective. The non-dominated solutions for risk level less than 10^{-4} are almost all gathered in the area where cleanup time less than 10 years, while almost all the non-dominated solutions for risk level greater than 10^{-10} are gathered in the area where time is larger than 30 years.



(a) Tradeoffs between cost and log risk for different ranges of cleanup time



(b) Tradeoffs between cost and cleanup time for different ranges of log risk



(c) Tradeoffs between time and log risk for different ranges of cost

Figure 3 Tradeoffs among objectives

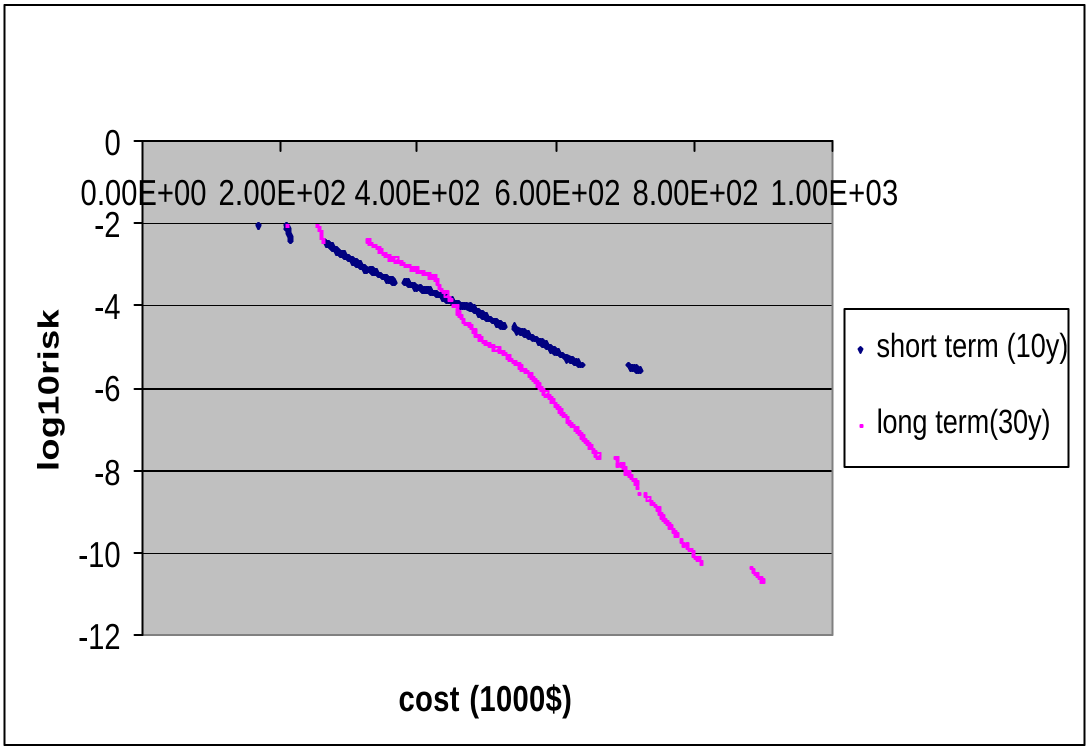
Complexity of Cost Objective Function

A realistic objective function, such as the one proposed above, may yield more accurate results but at the same time it will require more time and effort to develop the appropriate function for a particular application. On the other hand, a simple function will save setup time but may sacrifice the accuracy of the results. In this section, four different cost functions from complex to simple were applied to the case study described previously. The study was performed for two objectives (cost and risk) with two different clean-up times to simplify the analysis.

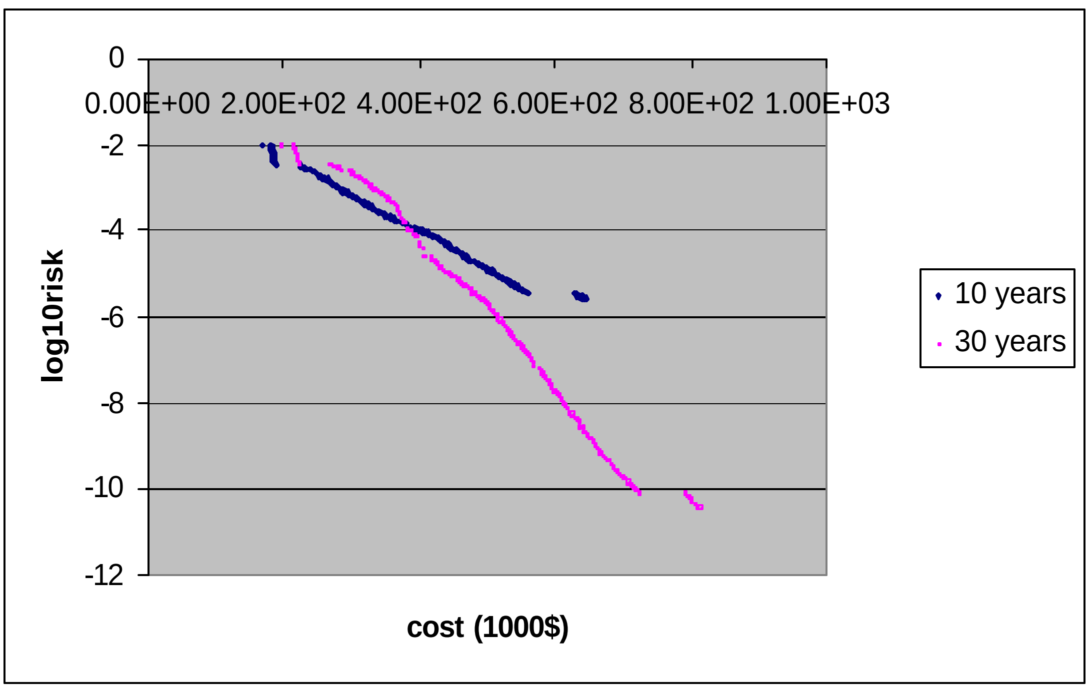
The four different functions used in this study were:

1. Realistic: Fixed capital cost + variable capital cost + O&M cost (given previously)
2. Fixed Capital + O&M cost
3. O&M cost
4. Total pumping rates

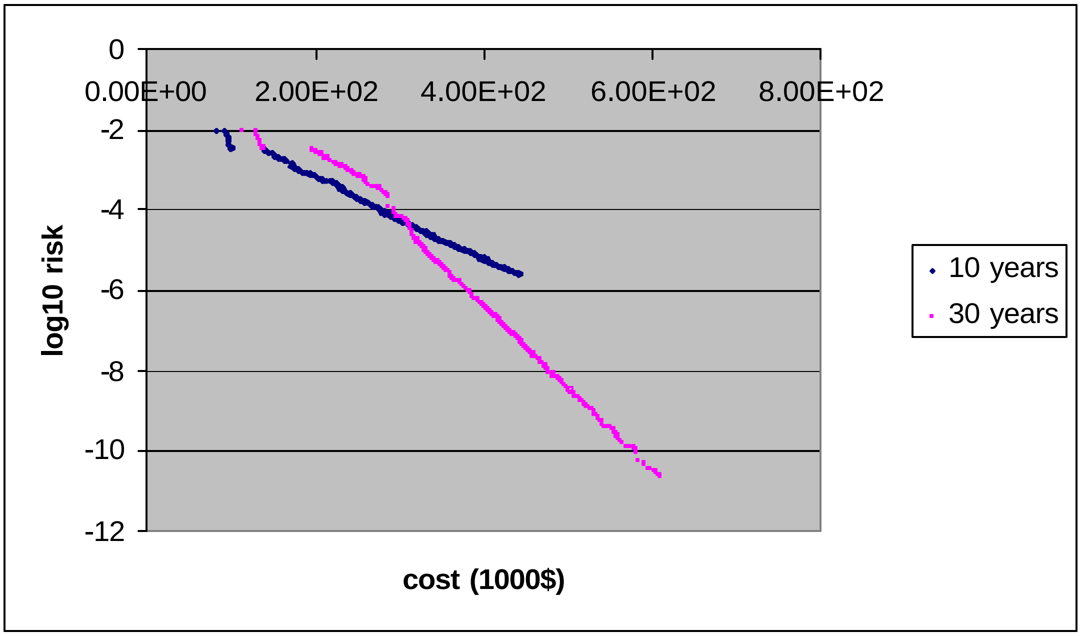
Figure 4 compares the optimal tradeoffs for different clean-up times. The first three cost functions show that for a high risk level, a short term remediation is more cost effective, as was the case for three objectives. But the results of total pumping rates did not show that. This suggests that for this case, total pumping rates as an objective may not be a good choice.



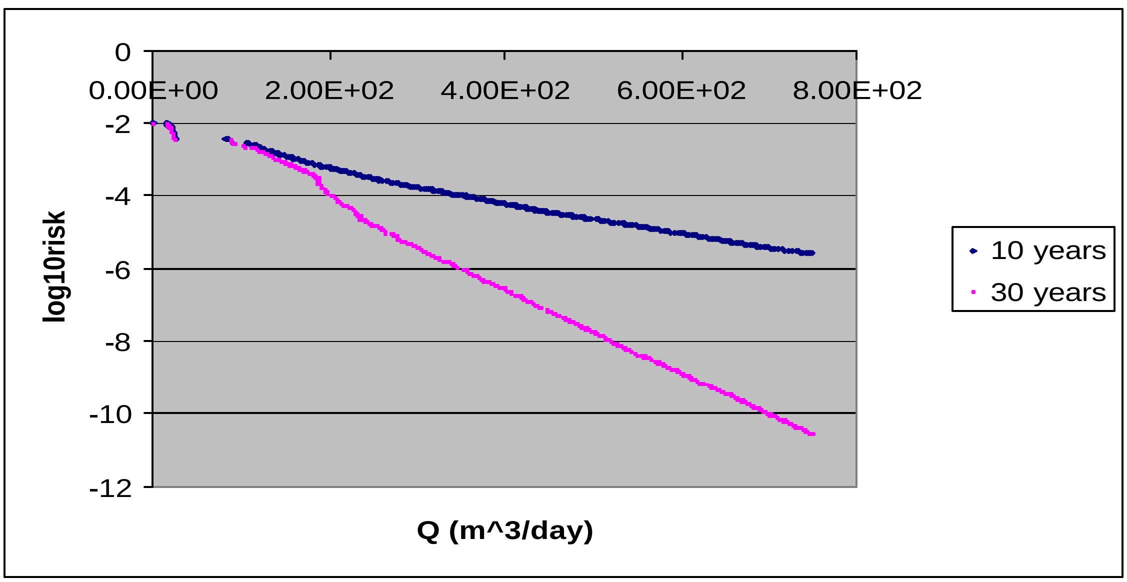
(a) Tradeoffs between cost and risk for two different remediation times for the realistic cost function



(b) Tradeoffs between cost and risk for two different remediation times for linear capital + O&M cost function



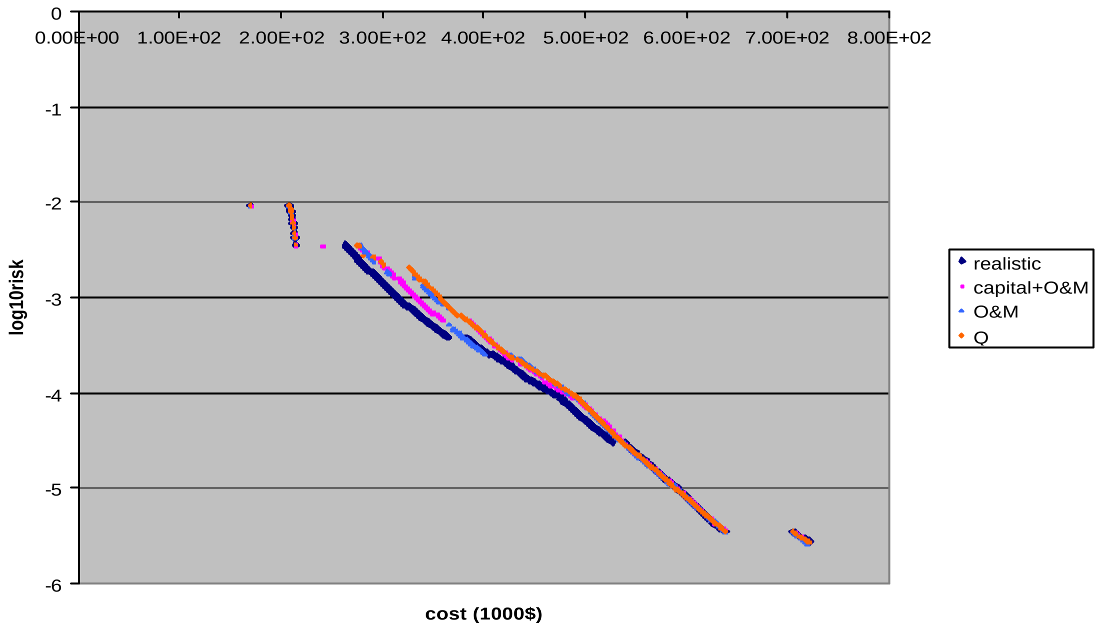
(c) Tradeoffs between cost and risk for two different remediation times when O&M cost function was used



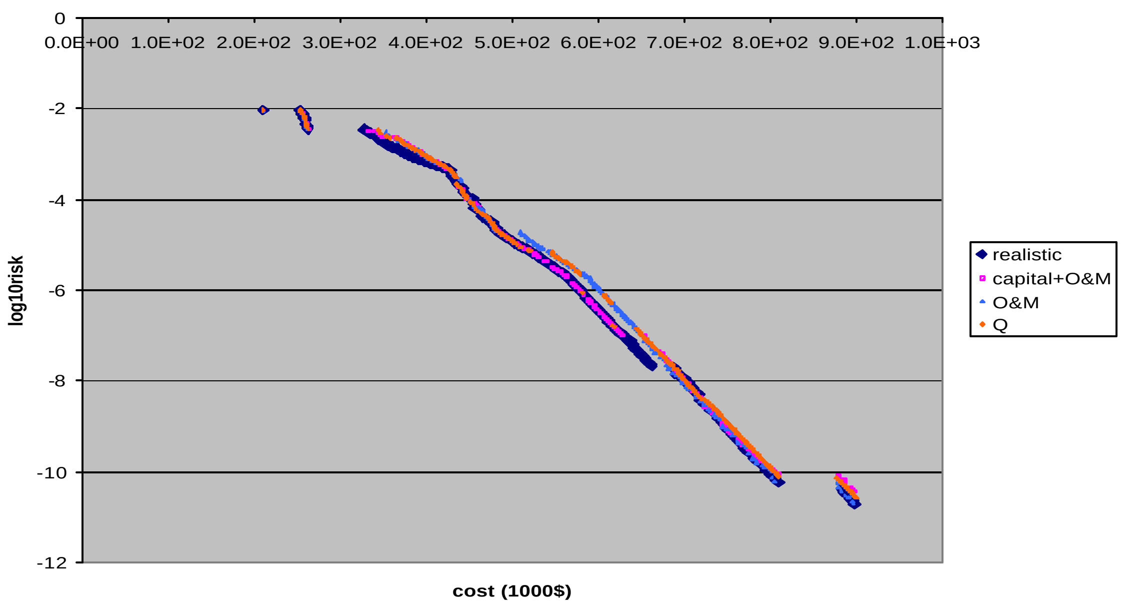
(d) Tradeoffs of cost and risk for two different remediation times for the total pumping rates function

Figure 4 Tradeoffs between cost and risk for each cost function with two clean-up times.

Next, we examine the effects of choosing a simpler cost function if the real cost function is more complex (as represented by the realistic cost function). To ensure comparison, the optimal designs identified with each of the four cost functions were re-evaluated with the realistic function. Figure 5 shows the resulting Pareto fronts.



(a) Short term case (10 years)



(b) Long term case (30 years)

Figure 5 Comparison of Pareto fronts from four cost functions, evaluated using the realistic cost function

Results for both short and long cleanup durations indicate that the realistic cost function performed better than the other functions. The differences are greater for the short-term cleanup where capital costs would represent a larger fraction of the total present worth cost. For example, for a risk level of 10^{-3}, the solution found using the total pumping rate objective function would be 13% more expensive than one found with the full realistic cost function.

When the solutions of the other functions were re-evaluated by the realistic function, some of the solutions were no longer optimal and are dominated by other solutions that used to be on the same front. More solutions were dominated for the short term cleanup than the long term cleanup. Fixed capital cost + O&M cost function gave better solutions than the O&M cost function, but not consistently better. For some risk levels (from $10^{-3.59}$ to $10^{-3.28}$), O&M cost actually gave better solutions than capital + O&M cost. Further study is needed to identify whether this finding is random or a true phenomenon. The function of total pumping rates performed the worst for short-term cleanups, but was almost the same as O&M cost for a long term project. However, the total pumping rate function did not identify as many solutions on the Pareto front as the other functions did.

Conclusion

In this paper, we have presented a new approach to illustrate the tradeoffs among three objectives that allows easy visualization of all of the relationships among the objectives. This approach demonstrated that for a high risk level, short-term remediation is most cost effective, but low risk criteria longer-term remediation is most cost-effective. We have then compared the performance of four different cost functions. Our findings show that the realistic cost function found better solutions than the simplified ones, especially for shorter-term cleanups. Total pumping rates performed the worst for both cleanup durations studied. For a long-term remediation project, the function of fixed capital cost + O&M cost performed almost as well as the realistic one for the entire range of risks and the O&M cost could also be used at some risk levels. However, for a short-term project, the realistic function appears to be more important, with as much as 16% improvement in the solutions found. These findings are now being tested for a field-scale application at Umatilla Army Depot in Oregon.

Acknowledgement

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