Risk Based Corrective Action Design Using Genetic Algorithms

Gayathri Gopalakrishnan and Barbara Minsker

Civil and Environmental Engineering, University of Illinois, Urbana, Illinois
4146 NCEL, MC-250, 205 N. Mathews Ave., Urbana, IL 61801

Beth Padera
University of Illinois, Urbana, IL (Now at Harza Engineering Company, IL)

ABSTRACT

Considerable resources have been expended in attempting to restore sites with contaminated groundwater. In the past, the cleanup goals were often established without regard to risk, mandating remediation of groundwater to background or non-detection or maximum contaminant limits. These are often difficult or impossible to achieve and have made site restoration prohibitively expensive. In response to these concerns, risk-based corrective action (RBCA) is becoming a method of choice for remediating contaminated groundwater sites. Under RBCA, the risks to human health and the environment due to contamination are evaluated and measures taken only to minimize the risk to acceptable levels.

A major difficulty in RBCA is negotiating an appropriate risk-based limit and a reasonable corrective action approach, particularly given all of the sources of uncertainty in predicting risk. To aid in this process, a new framework for negotiation is being developed that combines an optimization model with simulation models in order to develop risk-based remedial designs that are both cost effective and reliable. The model combines contaminant fate and transport simulation models and health risk assessment procedures with genetic algorithms to simultaneously predict risk and propose cost effective strategies for reducing the risk. To use the model, stakeholders first negotiate the objectives of the remediation, which may include minimizing risk, minimizing cost, and minimizing cleanup time. Then any constraints such as hydraulic head limits or social or economic constraints are considered. In this paper, the steps are demonstrated using a case study.

INTRODUCTION

In the past, clean up goals for contaminated aquifers were established without regard to risk. Remediation of the contaminated groundwater was often mandated to background or non-detection levels or maximum contaminant levels. This practice often resulted in remediation targets that are difficult to achieve and have made site restoration prohibitively costly. However, many sites now allow the use of site-specific risk-based criteria as remediation targets instead of fixed water quality standards. The risk-based criteria are usually determined by negotiating an acceptable risk level with regulators and then calculating a contaminant concentration corresponding to that risk level with conservative assumptions. This paper presents a risk management model that explores the tradeoffs between risk and cost for several candidate designs; the model is applied to a case study developed by *Smalley et al (2000)*. However, this process ignores critical relationships among risk, cost, and remediation design that should be considered in the negotiation process.

CASE STUDY

A case study was developed using data from the Borden site as detailed in *Smalley et al (2000)*. The aquifer configuration is shown in Figure 1. The dimensions of the study are approximately 60m by 20m and the aquifer was modeled using a coarse grid of 16 by 8 elements. The coarse grid was derived from a finer mesh of 128 by 64 elements that were used to generate multiple hydraulic conductivity realizations. The hydraulic conductivity generation technique is detailed in *Smalley et al (2000)*. Multiple parameter sets were defined, with each set consisting of a single sample drawn randomly from the set of generated realizations and from each of nine variable exposure model parameter realizations. For the results shown in this paper, one sample set was selected as the "true" parameter set so that the tradeoffs could be assessed under ideal conditions. The contaminant benzene, with an initial peak concentration of 133 mg/L, was assumed to be present on the site.

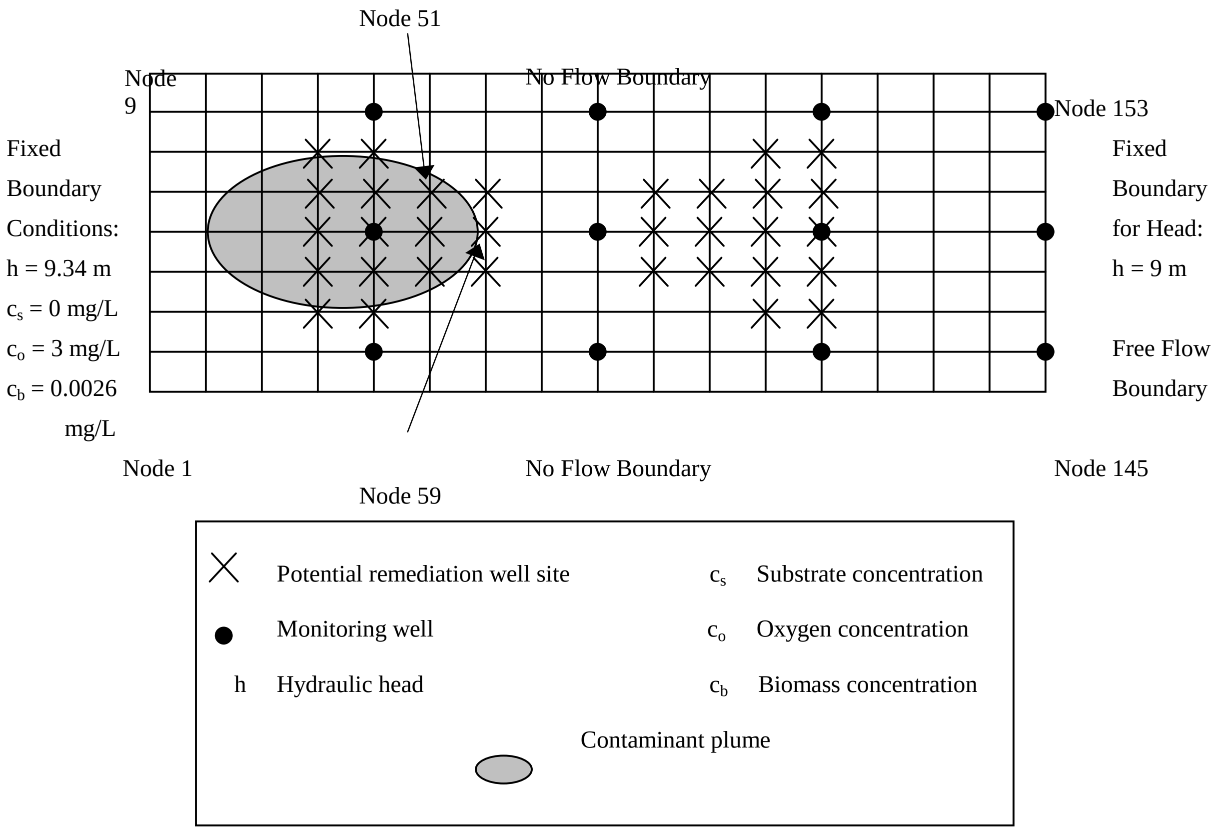

Figure 1. Plan View of the aquifer

RISK MANAGEMENT MODEL

A risk based remediation plan was developed for the case study using a modified form of the risk management model developed in *Smalley et al, 2000*. The management model, which is detailed in *Padera (1999),* combines a genetic algorithm with a fate and transport simulation model and a risk assessment module to identify promising remediation designs.

The fate and transport model called BIO2D is used to predict contaminant concentrations that would be measured in the contaminant source area for each possible design solution, which consists of well locations and pumping rates for extraction and injection wells, assuming aerobic biodegradation of the contaminant.

The risk assessment module uses an analytical model that predicts contaminant concentrations at off-site exposure wells and estimates human health risk associated with the predicted concentrations. For further information on these modelues , see *Smalley et al (2000)*.

In order to identify designs that minimize both risk and cost, a genetic algorithm called the Non-dominated sorted genetic algorithm (NSGA) that uses a multi-objective approach was incorporated into the management model. The objective function and constraints for the problem are shown below

$$Min\ C_{TOT} = C_{REM} + C_{MON} + C_{SYST} \tag{1}$$

The objective function for cost, C_{TOT} consists of three components – $C_{REM,}$ which is the capital and operating costs for the wells; $C_{MON,}$ which is the cost of on-site monitoring; and C_{SYST} which includes additional capital and operating costs for the remediation system. (for details, see *Smalley et al, 2000*.)

The objective function for risk, $Risk_{t,k}^{TOTAL}$, at a time *t* and exposure location *k*, is given as

$$Min\ Risk_{t,k}^{TOTAL} = Risk_{t,k}^{w} + Risk_{t,k}^{shw} + Risk_{t,k}^{nc} \qquad \forall t, \forall k \tag{2}$$

where $Risk_{t,k}^{w}$, $Risk_{t,k}^{shw}$ and $Risk_{t,k}^{nc}$ are the cancer risks due to ingestion of contaminated drinking water, inhalation of volatiles from contaminated water due to showering, and inhalation of volatiles from contaminated water due to other non-consumptive uses respectively.

The optimization algorithm searches for solutions that best meet these objectives subject to the following constraints.

$$u_{\min} \leq \left|u_{i,j}\right| \leq u_{\max} \qquad \forall i \tag{3}$$

$$h_{\min,l} \leq h_{i,j} \leq h_{\max,l} \qquad \forall i \qquad \textit{at each } l \tag{4}$$

where u_{min} and u_{max} represent the minimum and maximum pumping rates for a given remediation well (m^3/day); $h_{i,l}$, $h_{min,l}$, and $h_{max,l}$ are the computed hydraulic head for remediation well i (m), the minimum hydraulic head (m), and the maximum hydraulic head (m) allowed at remediation well location l, respectively.

To evaluate remediation options for the case study, several assumptions were made. At most two remediation wells were assumed to be installed at the locations shown in Figure 1, chosen from one of the following three schemes: (1) an injection well located within the up-gradient well set and an extraction well in the down-gradient well set, (2) an extraction well within the up-gradient well set and an injection well in the down-gradient set or (3) an injection well within both the up-gradient and down-gradient sets of wells. It was assumed that all the extracted water was re-injected, and hence a system of two extraction wells was not possible. Injection wells are used to inject nutrients to stimulate biodegradation of the contaminants and the extraction wells are used only to control flows. Pumping rates were allowed to vary between 0 and 64 m^3/day.

To minimize computation effort, the model is run without considering uncertainty when the cost and risk tradeoffs are evaluated.

BASICS OF THE NSGA ALGORITHM

As mentioned earlier in this paper, the optimization algorithm used in the risk management model is the Non-dominated sorted genetic algorithm or NSGA. Classical approaches for solving multi-objective optimization problems include the weighting method and the constraint method. However, these methods are very time consuming as they require multiple optimizations to identify the tradeoff curve. Identification of the appropriate penalty weights is also a trial and error process that can require numerous model runs. These difficulties are overcome with the use of the NSGA.
NSGAs were first suggested by *Goldberg (1989)* and then presented by *Srinivas and Deb (1995)* for use on multi-objective problem optimization. Research by *Weile, Michielssen and Goldberg (1996)* indicated that the NSGA's performance was significantly better than the other algorithms used in previous work.

A GA searches a decision space using methods that are analogous to Darwinian "natural selection" processes. The optimal solution is found using the basic operators – selection, crossover and mutation. The NSGA differs from the simple GAs in that they direct the algorithm to converge to an optimal set of solutions instead of one optimal solution. They accomplish this by changing the way selection occurs, while the crossover and mutation operators remain the same. The NSGA first identifies the non-dominated individuals in the population and then assigns them to the first non-dominated front. All the individuals in the first front are given the same dummy fitness value to ensure that they have equal reproductive potential and the dummy fitness values are shared to ensure representation along the entire frontier [see *Srinivas and Deb (1995)* for details].Once sharing is complete for the first non-dominated front, the individuals in that front are temporarily ignored while the rest of the population is assigned into fronts and given dummy fitness values that are less than that assigned to the previous front. On completion of the run, it is seen that the NSGA converges to an optimal set of solutions known as the Pareto frontier.

For this particular case study, the NSGA was run with a population size of 100 to generation 90. The probability of crossover was set to 0.5 and that of mutation to 0.01. As suggested by *Srinivas and Deb(1995)* the NSGA parameter σ_{share} was set to 0.1. The NSGA was also designed to ensure that cost and risk would have equal considerations in determining non-dominated solutions.

RESULTS AND DISCUSSION

Figure 2 shows the NSGA results for the case study. A number of remediation designs were identified (represented by the points shown in the figure), each of which entails a different cost and risk. A tiered effect is seen in the results, with the solutions clustered around three cost levels - $48000, $65000, $80000. Each cost level corresponds to a different pumping scenario with the lowest cost being the scenario where no pumping wells are installed and only monitoring costs ensue. These are the “monitored natural attenuation” solutions. The solutions near $65000 represent the solutions where the one well is installed and pumping and solutions near the $80000 represent schemes with two pumping wells.

These results show how the management model can be used to assess the tradeoffs between cost and risk. It is clear that, in this case study, a range of risk levels can be generated with little increase in cost. However, beyond a certain level, the costs increase substantially.

Although the NSGA is more computationally intensive than the classical methods of constraint handling given earlier, it has the advantage of being able to generate multiple solutions on the non-inferior frontier efficiently and easily. The tradeoff information obtained by using the NSGA for the case study is invaluable in allowing all the parties involved in remediation design to better understand and evaluate the tradeoffs involved in remediation.

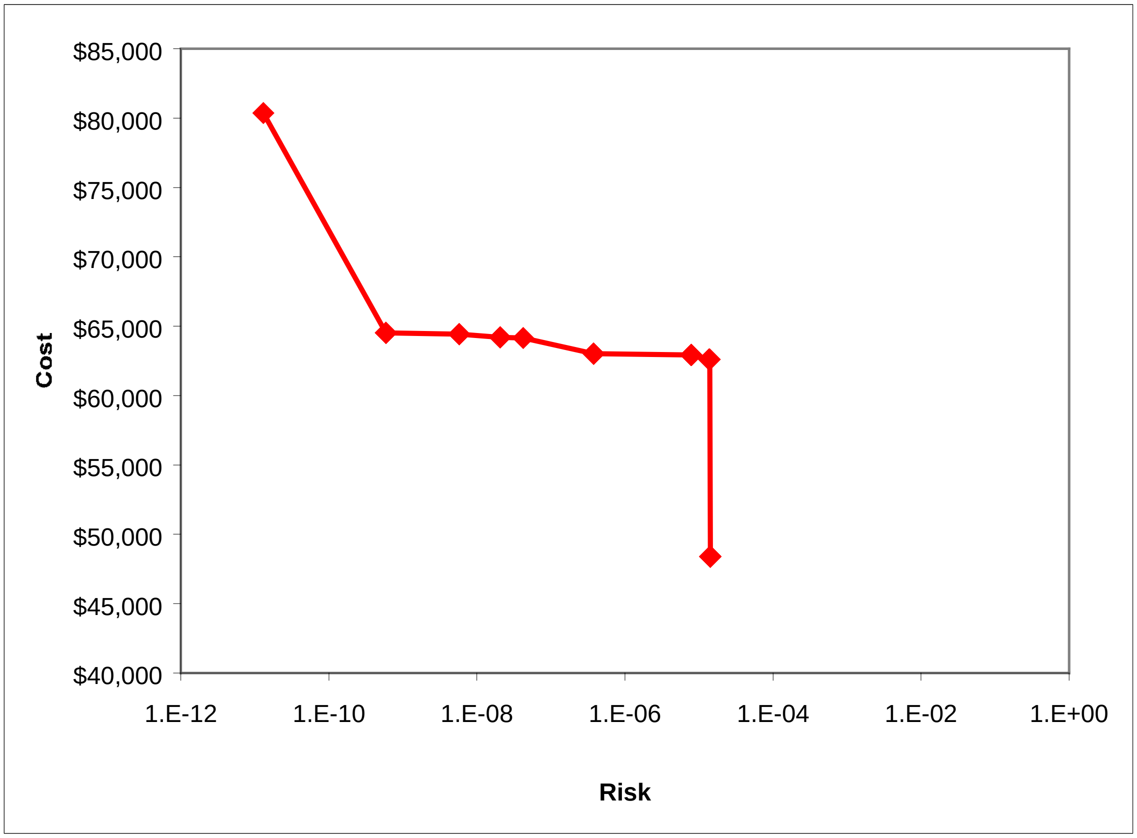

Figure 2: NSGA results, showing cost – risk tradeoffs. Each point represents an optimal remediation design for the target risk and cost shown.

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