Why Optimize Long Term Groundwater Monitoring Design?
A Multiobjective Case Study of Hill Air Force Base

Patrick M. Reed*, Barbara S. Minsker*, and Albert J. Valocchi*

*3230 Newmark Civil Engineering Laboratory, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N. Mathews Ave., Urbana, IL, 61801, PH (217) 333-6967; FAX (217) 333-6968; email: preed@uiuc.edu, minsker@uiuc.edu, valocchi@uiuc.edu

Abstract

Mathematical tools from the field of optimization have significant potential for reducing long-term monitoring costs and aiding site managers in making informed decisions on sampling strategies for sites undergoing long-term monitoring. A case study is presented that demonstrates the use of a Nondominated Sorted Genetic Algorithm (NSGA) for monitoring design at Hill Air Force Base (AFB). The method combines fate-and-transport simulation (although it can also be used only with historical data), plume interpolation, and adaptive search to identify the tradeoff between monitoring costs and mass estimation error. The method efficiently provides decision makers a direct representation of the tradeoff between monitoring objectives such as cost and error. Additionally, the most and least significant monitoring wells in a preexisting monitoring network are identified.

Introduction

The National Research Council (NRC) (1997) estimates that between 300,000 and 400,000 contaminated sites within the United States will require a potential remedial cost of up to a trillion dollars. The tremendous magnitude of these costs has motivated a shift in the environmental industry toward risk-based approaches to remedial design, which require significant long-term monitoring (LTM). Long-term monitoring at many sites can require decades of expensive sampling at tens or even hundreds of existing monitoring wells, resulting in hundreds of thousands or millions of dollars for sampling and data management per year.

Developing efficient and effective LTM sampling plans can be difficult when numerous options exist. At any given monitoring period, the number of possible sampling plans is 2^n, where n is the product of the number of wells and the number of possible constituents to be measured. A site with 10 wells where up to 3 constituents can be measured (n = 30) requires the decision maker to identify a sampling plan among the more than one billion that exist while also trying to balance the cost and other performance objectives for each sampling scheme. This study extends the single objective approach of Reed et al. (2000a) to search large sampling decision spaces while also directly quantifying the tradeoff between cost and global mass estimation error for sites undergoing long-term monitoring.

Monitoring Application

The application used to demonstrate NSGA performance in this paper seeks to quantify the optimal balance between long-term monitoring costs and the accuracy of estimates of the mass of dissolved BTEX predicted to be present at Hill AFB site. Concentrations in future monitoring periods are predicted using Modflow and RT3D. Ordinary kriging is then used to interpolate the total (i.e. global) mass of contaminant in the plume using predicted measurements at all sampled wells. The aquifer is unconfined with a saturated thickness of less than 0.9 meters and a modeled area of approximately 810,000 square meters. A two-dimensional domain was assumed to be adequate in our study and in previous studies (Wiedemeier et al. 1995 & Lu et al. 1999) because of the aquifer's negligible thickness relative to its areal extent. The numerical grid has 6708 cells used to calculate groundwater flow and contaminant transport.

The goal of the optimization is to identify subsets of wells that achieve the best tradeoff between the global contaminant mass estimation error and sampling costs. Each sampling plan (or population member) is represented by a binary string (or chromosome). Within each of these chromosomes a value of 1 in the i^{th} digit represents sampling from the i^{th} well at the site.

The Basics of the Nondominated Sorted Genetic Algorithm

The goal of multiobjective optimization is to find the Pareto optimal frontier (tradeoff curve), which consists of the non-dominated solutions. One solution is dominated by another when it performs worse in both objectives. The NSGA (*Srinivas and Deb*, 1995) quantifies the Pareto frontier by searching for sampling designs that are not dominated by any other plans in terms of both cost and mass estimation error. The NSGA operates in much the same manner as the simple genetic algorithm. Sampling designs are encoded into binary strings, where if the i^{th} value equals 1 then the i^{th} monitoring location is sampled. A population of sampling designs undergoes selection, crossover, and mutation in successive generations as optimal solutions are evolved in a process analogous to Darwinian natural selection. The primary difference between the simple GA and NSGA lies in how the NSGA assigns fitness values to individual designs.

Fitness assignment in the NSGA requires two steps: (1) classification to a non-domination front and (2) sharing (or niching). Unlike the simple GA, the NSGA must evolve a set of non-dominated solutions. Classification of the individual sampling designs into non-domination fronts is the means by which the NSGA evolves a set of solutions representing the optimal tradeoff between cost and uncertainty. Each plan is evaluated in terms of its cost and mass estimation error. After all of the plans in a population have been evaluated, they are sorted into fronts using each of their objective function values. Initially, the subset of sampling designs that are not dominated by any other designs are placed in the first front. These designs are then removed from the population and a second subset of non-dominated designs are identified and classified to a second front. The process continues until every member of the population has been classified into a front. Members of each of the fronts are then assigned a single “dummy” fitness such that all of the members in the first front will always have a higher fitness than all other fronts. The use of a single dummy fitness for the non-dominated front ensures that all of its members will have the highest probability of passing their traits to successive generations.

The second step in the fitness assignment consists of penalizing sampling plans that are similar to one another in a process termed niching. This step ensures that solutions are found across the entire Pareto front (*Goldberg*, 1989; *Srinivas and Deb*, 1995). Penalties are assessed using a sharing function recommended in *Srinivas and Deb* (1995). Each individual’s dummy fitness is reduced by an amount dependent on the number of nearby individuals. Note that the NSGA requires that the lowest dummy fitness in a front be larger than those belonging to succeeding fronts, again ensuring that non-dominated sampling designs have the highest probability of passing their traits to successive generations. For further details on the competent design of the NSGA for search and optimization see Reed et al. (2001).

Results

Figure 1 shows the cost versus accuracy tradeoff curve evolved by the NSGA for the Hill AFB test case. The figure shows that the number of wells sampled ranged between 11 and 18 of the original 30 well network. The relative mass estimation errors ranged between 0.03 and 0.8 percent. The tradeoff curve shows significant potential cost savings while maintaining mass estimates nearly as accurate as sampling all wells. The 11, 14, 16, and 18 wells solutions highlighted in figure 1 are further analyzed below.

Figure 2 shows the 18 well solution overlaid on the two dimensional representation of the BTEX plume at Hill AFB. To aid analysis of the selected sampling schemes the plume was separated into Zones A thru C as shown below. This sampling scheme has a cost of $6300 and relative estimation error of 0.03 percent, representing a 40 percent cost savings relative to sampling all available locations. The highest density of samples is in Zone A where 9 have been selected for sampling. In Zone B only 4 of the available 9 sampling points are sampled, but in Zone C 5 of the 6 available monitoring points are sampled. The figure shows that samples near the boundaries and the leading edge of the plume generally have the most influence on mass estimation accuracy.

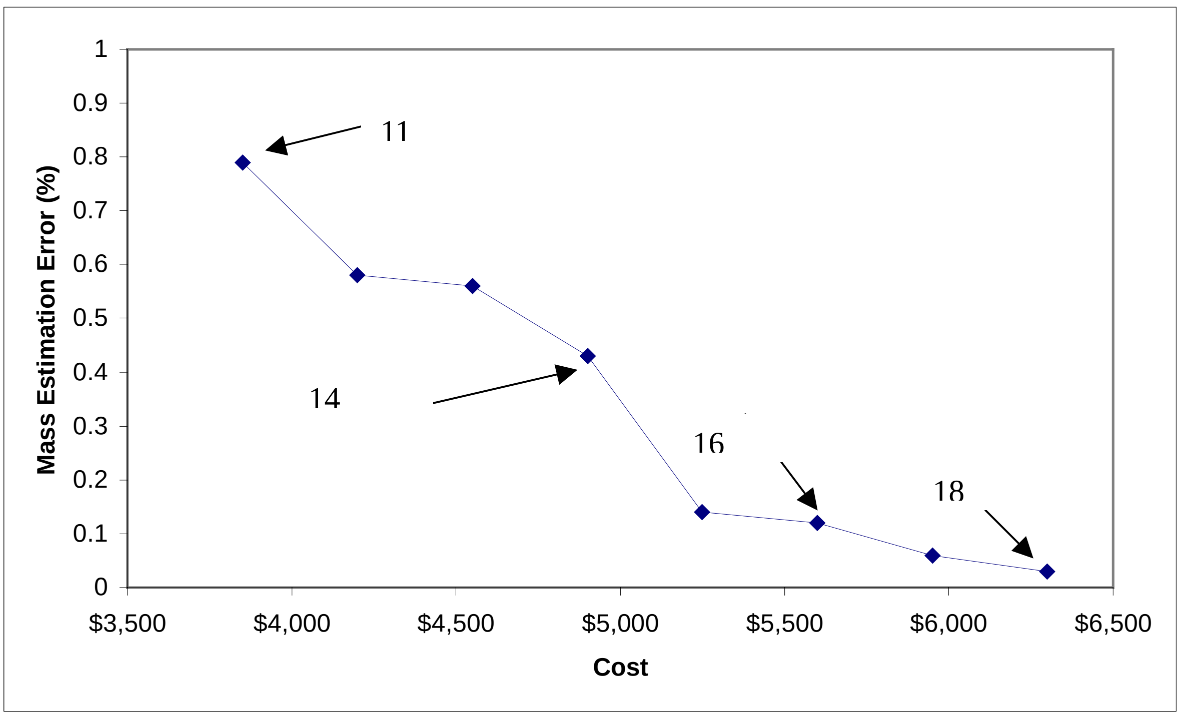

Figure 1. Cost versus accuracy tradeoff curve.

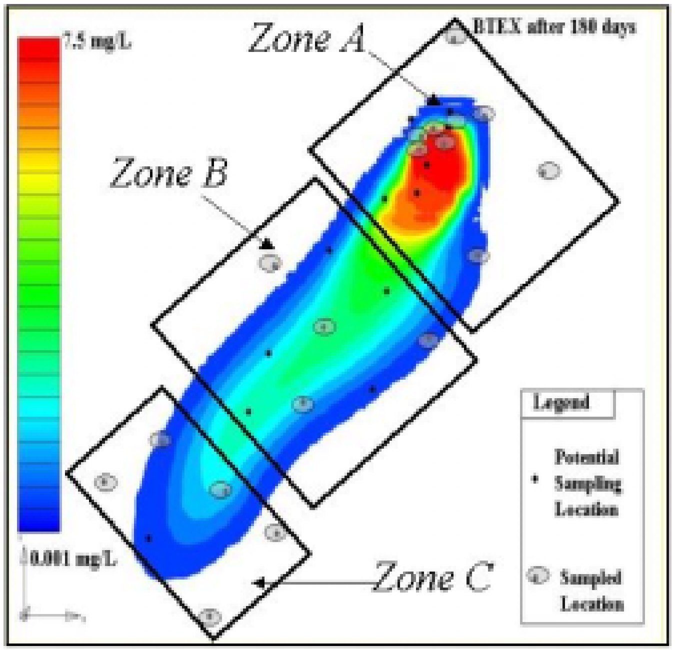

Figure 2. Schematic of the 18 well solution.

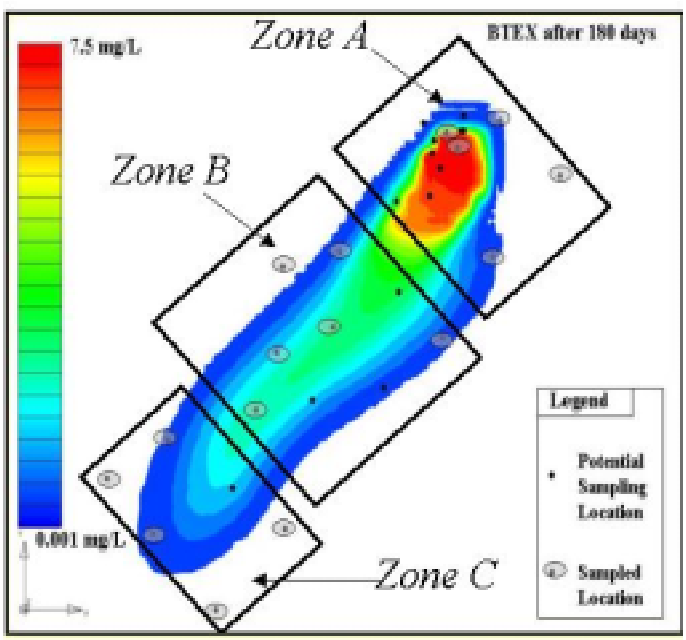

Figure 3. Schematic of the 16 well solution.

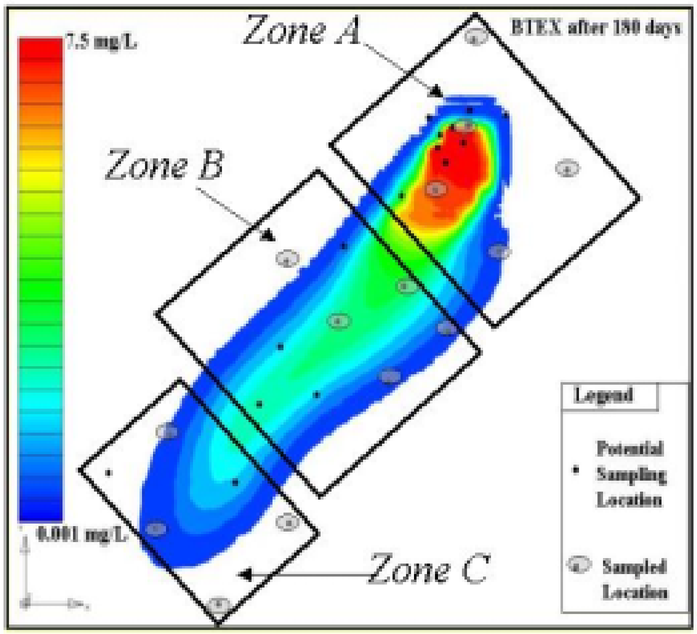

Figure 4. Schematic of the 14 well solution.

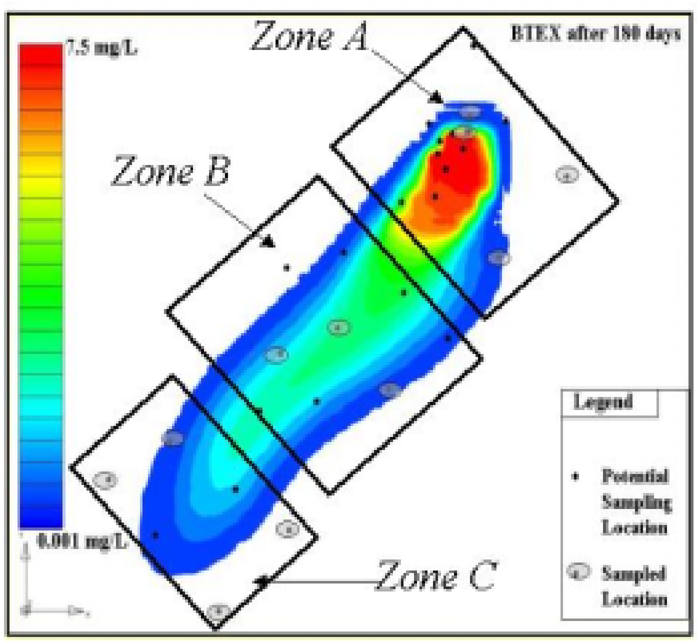

Figure 5. Schematic of the 11 well solution.

Figure 3 shows the 16 well solution. The 16 well solution has a cost of $5600 for sampling BTEX with a relative mass estimation error equal to 0.12 percent. This sampling scheme represents a 47 percent cost savings relative to sampling all of the available monitoring wells and shows a redistribution of the selected sampling points relative to the 18 well solution. Zone A has the greatest level of redundancy as evidenced by sampling only 5 points, 4 fewer than shown in figure 2. Again, note that 5 of 6 available points are sampled in the leading edge of the plume in Zone C showing a reduced degree of spatial redundancy.

Figure 4 further shows that the highest degree of spatial redundancy occurs in the interior monitoring points of the plume. Note that only 4 of the 14 samples in figure 4 are taken in the interior of the plume, further substantiating the importance of samples taken along the boundary of the plume in accurate mass estimates. Sampling 14 wells has a cost of $4900 and represents a cost savings of 53 percent.

Figure 5 shows the least cost solution found in this study with 11 wells. This solution had a cost of $3850 and a mass estimation error of 0.79 percent. The solution shows a potential cost savings over 60 percent relative to sampling all available monitoring points while maintaining accurate global mass estimates. Analysis of the sampling in Zones A through C shows that Zones A and B have the highest degree of redundancy. In Zone A, only 4 of the 14 available sampling points are required for an accurate mass estimate. Likewise, only 3 of the 9 available monitoring points in Zone B are sampled.

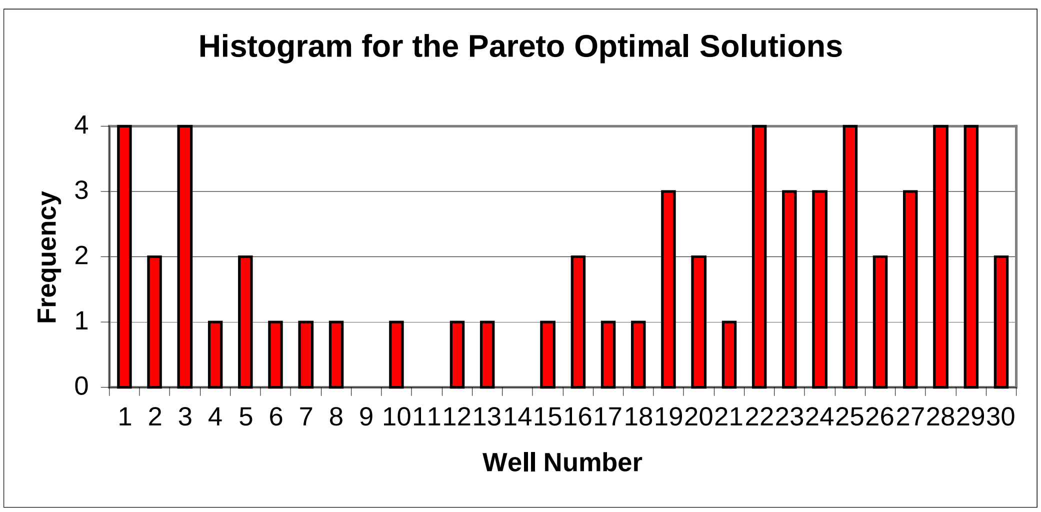

Figure 6. Sampling histogram

Figure 6 shows a histogram analysis of the solutions presented above, where the frequency of sampling each well location is used to discern the relative importance of each sampling location. The histogram plot shows that 6 of the 30 monitoring points were sampled in all four of the illustrated sampling schemes. Additionally, the plot shows that sampling locations 9 and 11 were not sampled by any of the solutions. This type of analysis aids the site manager in identifying the most (and least) important sampling locations. The NSGA was able to find low cost, accurate solutions while also allowing for the direct analysis of the inherent tradeoff between these two objectives.

Conclusions

In developing long-term monitoring plans, regulators and stakeholders must negotiate monitoring objectives and decision parameters while accounting for technical, social, or regulatory constraints. Identifying sampling plans to achieve objectives and satisfy constraints can be a difficult and time-consuming process at sites with many wells or many constituents to measure. Multiobjective optimization efficiently identifies the best sampling plans, enabling decision makers to assess the tradeoffs among a variety of performance objectives for a long-term monitoring network. Management modeling allows new optimal designs to be easily identified as objectives and constraints are revised to satisfy all parties involved in selecting a sampling scheme for a network undergoing long-term monitoring. The example application at Hill AFB demonstrates how potential data redundancies can be exploited to reduce costs with a minimal increase in global mass estimation errors. The analysis shown provides decision makers a direct means of ascertaining which monitoring locations are the most important in attaining low cost, accurate mass estimates. The NSGA is not limited in the number of objectives it can consider and the management model could be adapted to any other quantifiable monitoring objectives, such as local mass errors, estimation variance, etc. The methods presented can be used either with historical data or with future monitoring data predicted from fate-and-transport models, as shown in this study.

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