Dynamic Programming Approach to Optimization of Site Remediation

W. Eric Showalter, Ph.D., P.E.[1]; and Daniel W. Halpin, Ph.D.[2]

Abstract: Environmental restoration is a matter of national concern. Decades of abuse by industry, agriculture, and the military have caused devastating contamination of the earth, air, and water. The Department of Energy alone will spend hundreds of billions of dollars on containment and restoration. It is imperative that restoration costs are minimized. Every dollar spent on restoration is a dollar that will not go toward research, a dollar that will not go to upgrade our nation's infrastructure. The work presented here uses cost as a decision variable in restoration projects. Contaminated sites frequently vary from one point to another in type and level of contamination. In addition, a single piece of property may contain several distinct contaminated areas, each of which has characteristics unlike any of the other areas. Thus one should look at optimizing the selection of remediation technologies to address the variation. A methodology has been developed that will optimize the selection of remediation technologies based on cost. This methodology uses geostatistics and dynamic programming to break a site into discrete cells and then select the optimal sequence of remediation technologies.

DOI: 10.1061/(ASCE)0733-9364(2008)134:10(820)

CE Database subject headings: Computer programming; Construction management; Cost estimates; Optimization; Environmental issues; Restoration.

Introduction

Environmental contamination has reached crisis levels in the United States and in many other parts of the world. The legacy of the Cold War is estimated to cost hundreds of billions of dollars to clean up (U.S. Congress 1991). Soil remediation planning sometimes pays little regard to the distribution of contaminants on the site. If variation of contamination in the site is considered, then we must select the best set of remediation technologies to use. Further, it is difficult to use cost as a selection parameter for remediation technologies. To address these shortcomings a methodology has been developed that looks at a contaminated site as a series of discrete blocks of contaminated soil followed by optimization of the technology selection. Dynamic programming is used as the optimization method, and cost is the criteria to be minimized. This paper details the development of the methodology, and illustrates its application to a hypothetical site. The model, SORTS (Soil Remediation Technology Selection), allows the decision maker to run sensitivity studies and to determine whether the level of uncertainty in the cost estimates is significant to the decision-making process.

Treatment of Remedial Investigation Data

Statistical methods used in engineering include regression, hypothesis testing, and correlation. However, in classical correlation, two different attributes are usually considered. In remediation and other areas where spatial data are important, it is important to investigate correlation between values of a single attribute measured at different points in space. Geostatistics is a specialized branch of statistics developed for estimation of ore reserves that considers spatial distribution information. It can be used to divide a site that has been randomly sampled into any number of equally sized blocks. For each block, a central tendency (mean) and a variance can be calculated. The variance of a block depends on the variation between the independent samples and the distance between sampling points.

This paper focuses on selection of technologies for remediation. Literature reviews and communications with industry personnel turned up no statistically based method of optimizing technology selection for remediation and accounting for spatial variation of contamination across a site when planning remediation projects.

Waste disposal pits and trenches can have considerable variation in type and level of contamination from one area to another. Considering this and the fact that many remediation technologies are quite specialized in their application, attention should be given to the spatial variation in contamination. The method proposed here could also be applied when there are several distinct areas with differing characteristics.

The remedial investigation phase extensively characterizes the site. Application of geostatistics to this characterization data will allow the site to be divided into a number of discrete sectors or cells. Once the site is divided into sectors, optimization algorithms can be applied.

In order to develop an illustration of the concepts developed in this research, a hypothetical site has been developed, based on data from the DoE. Next, a set of candidate technologies was selected based on EPA documents (USEPA 1988, 1990, 1991a,b). The technologies were chosen such that each contaminant could be addressed by at least one technology. Further, each technology

[1]Lecturer, Dept. of Civil Engineering, Univ. of Missouri–Rolla, Rolla MO 65409.

[2]Professor Emeritis, Dept. of Civil Engineering, Purdue Univ., West Lafayette, IN.

Note. Discussion open until March 1, 2009. Separate discussions must be submitted for individual papers. The manuscript for this paper was submitted for review and possible publication on June 8, 1998; approved on November 17, 2005. This paper is part of the ***Journal of Construction Engineering and Management***, Vol. 134, No. 10, October 1, 2008. ©ASCE, ISSN 0733-9364/2008/10-820–827/$25.00.

in the set is capable of treating one or more of the target contaminants in the site. Finally one technology, in situ vitrification, could potentially be applied to the entire site. The chosen technologies are: in situ vitrification (ISV), soil vapor extraction (SVE), rotary kiln incineration, biodegradation, soil washing, stabilization/solidification, and long-term monitored storage.

A detailed estimate of the costs was developed for each of the seven technologies listed earlier. The estimates can be found in Showalter et al. (1992) and Showalter (1994).

Solution Algorithm

Dynamic programming was chosen over other possible optimization methods. A general background on dynamic programming is presented to develop the specific equations required. A small example is solved using the method to illustrate key points.

Dynamic Programming

Dynamic programming (DP) was developed by Richard Bellman at the RAND Corporation in the 1950s. DP is designed to handle multistage decision processes, overcoming the shortcomings associated with linear programming, calculus of variations, and other approaches to solving these problems. Most important, DP was created from the beginning to be computationally feasible. Although iterative methods such as DP may not be as elegant as mathematical formulations, they can be much faster to formulate and solve, and results may be easier to understand.

The primary use of DP in the field of civil engineering has been for water resources management. It can handle nonlinear constraints, and optimize stochastic models. There are many examples in the literature of planning optimal reservoir control, where there are stochastic inflows, multiple objectives, and nonlinear constraints.

Principles of Dynamic Programming

The most important principle of DP is the principle of optimality, stated as follows: *Principle of Optimality*. "*An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision*" (Bellman 1962).

White (1969) restates this principle as "an optimal policy has the property that all its contractions are optimal." Thus if the optimal path from point 1 to point N contains point j, then the part of the path from 1 to j is also optimal. This allows piecewise optimization and iterative methodologies to be implemented.

Advantages and Limitations of Dynamic Programming

One major advantage of dynamic programming is that it allows the transformation of a single n-dimensional problem into n one-dimensional problems. This greatly reduces the number of equations to solve. The above-presented principle allows this transformation.

A second advantage over other methods is that if DP finds a minimum or maximum it will be a global one. Other methods of finding optima can become stuck in relative (local) optima. For example, the first derivative of a function being equal to zero is a *condition* of the optimum, not proof.

DP can also handle nonlinear and discontinuous functions. Requiring integer solutions or allowing negative decision variables can also be formulated in a DP optimization. Integer variables can even make DP more efficient.

The major limitation of DP is that if the dimensionality of the state space becomes too large, the number of calculations becomes large also, and may exceed the limits of computation. This is known as "the curse of dimensionality."

Finally, DP is an approach to optimization. It is not a solution method or algorithm. Dynamic programming is a way of looking at optimization problems, and, as such, solutions may be more or less difficult to formulate in DP than in other methods.

Functional Equations of Dynamic Programming

If we consider a set of points $[P_i]$, $i=1$ to N, and an associated cost matrix $[c_{ij}]$, where c_{ij}=cost of moving from state (point) i to state j (using i to represent P_i from now on), then we can seek the least cost path from 1 to N. The least cost from any point i to the end is denoted by $f(i)$.

If we move from point i to point j, the cost is c_{ij}, and our objective is to then move optimally from j to the end point. Recalling that the optimal cost from j to the end is $f(j)$, the cost from i to j then optimally to the end is

$$c_{ij} + f(j) \tag{1}$$

The functional equation is therefore

$$f(i) = \min(c_{ij} + f(j)) \tag{2}$$

This is the forward equation, used to decide where to move to in the next step from whatever point i is now occupied. It can also be written in the backward form as

$$f(i) = \min(f(j) + c_{ji}). \tag{3}$$

Here we are deciding which point to move *from* to get to the required step i.

A powerful feature of DP is that when a network is solved for optimal control (also referred to as the optimal trajectory), it also gives the optimal control at every state in the process. This is known as "invariant imbedding." As the optimal control at every stage and state is known, if there is deviation from the optimal trajectory, the optimal control for the remaining stages is already known.

Let us introduce slightly different terminology. S will refer to the entire set of candidate technologies, ISV, SVE, in situ bioremediation, and soil washing. The particular technology being considered at a particular stage will be referred to as j, and J will refer to the technologies (if any) already mobilized. The function will now be $f_{ij}(J)$, meaning the optimal cost of using Technology j at Stage i given that the set of Technologies J has been already mobilized. As this formulation is solved from the end of the project to the beginning it is not known at any point in the solution which technologies have been previously mobilized. The equation is

$$f_{ij}(J) = c_{ij} + \min(f_{i-1}(J \cup j)) + \begin{cases} md_j & \text{if } j \text{ not mobilized} \\ 0 & \text{if } j \text{ mobilized} \end{cases} \tag{4}$$

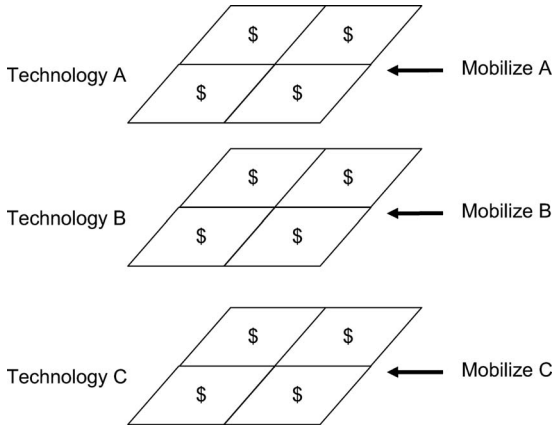

Fig. 1. Methodology model

Model Development

Remobilizing is a potential cost that is not included in this technique. If a technology is idle for a period, there may be some cost incurred to start using it again, and this cost would have to be added to the model. However, the fact that a technology is used in nonadjacent areas does necessarily mean those areas are not treated sequentially. Here the solution form will be developed in a descriptive form with an example, leading to a mathematical formulation.

A contaminated site has been divided into a series of discrete cells, which must be traversed at a minimal cost. The problem can be visualized as a three-dimensional stack of checkerboards. The squares on the bottom board correspond to the cost matrix to remediate the cells of the site with some Technology A. The squares on the second board correspond to the cost matrix to remediate the *same site* with Technology B and so on. See Fig. 1 for a depiction of three technologies in four sectors. The checkerboards each represent the same site, the difference is the chosen technology. It is possible to move from square to square on any one board, or between any pair of checkerboards. There is a cost to move from board to board. Changing boards is analogous to changing remediation technologies and incurring the mobilization and demobilization costs of that new technology.

Consider a scenario with m candidate technologies, denoted t_j, $j=1,\ldots,m$, and a site divided into n sectors, s_i, $i=1,\ldots,n$. There is also a cost matrix md_j, $j=1,\ldots,m$, that is the cost of bringing a technology to the site, and includes mobilization, demobilization, treatability studies, and other one-time costs (hereafter all these costs will be referred to as mobilization). Matrix c_{ij}=cost of using Technology t_j in Sector s_i excluding the costs of mobilization.

For example, assume a simple scenario with three technologies and four sectors. The cost information is given in Table 1. Thus Technology A costs \$400 to bring to the site. To remediate Sector 3 with Technology B would cost \$200, if B is already at the site.

Table 1. Example Cost Data

		c_{ij}			
Technology	Mobilization	1	2	3	4
A	\$400	\$700	\$400	\$300	\$300
B	\$250	\$500	\$350	\$200	\$100
C	\$450	\$150	\$200	\$300	\$400

If a technology were not applicable to a particular sector, the cost can be entered as a number so high that it never enters the optimal solution.

Each sector of the site will be a stage in the solution. A stage is a decision point; in this case the decision is whether to continue with the current technology on the site or to change to a different one. At each stage there are several distinct states that are possible, at least one for each combination of technologies.

The next problem to address has to do with mobilization costs. If a large site is divided into many sectors, it is possible that the optimal trajectory would be to switch back and forth among technologies. If the solution method does not explicitly allow for this, this would cause them to incur the mobilization more than once. We need a method that either allows nonsequential solution and goes through all sectors or keeps track of which technologies have been mobilized.

The solution pursued here is to solve the problem sequentially, from the last cell to the first, and remember which technologies have been mobilized. This is accomplished by allowing more states at each stage of the solution as described in the following.

We define $f^*_{(i)}$ as the cost of the optimal policy at Stage i. Beginning at the last cell to be remediated we will work toward the best starting policy. f^*_0 is defined as \$0, as it represents the end of the model.

In order to account for all the possibilities that a technology may or may not have been previously mobilized, additional states are introduced. At f_1 we could choose to use any of technologies. For each technology we either have or have not used it previously. For three technologies there are eight combinations, calculated in the following as a series of combinations:

$$ {}_3C_0 + {}_3C_1 + {}_3C_2 + {}_3C_3 = 1 + 3 + 3 + 1 = 8 \tag{5} $$

In fact for any number of technologies m there are 2^m combinations. Now there are at least eight states possible at each stage in our example.

If we are in Stage 1, searching for the best policy in Cell 4, we must calculate each possible state. For example, if A is used in Cell 4, we may have arrived there by using A, or combinations AB, AC, or ABC, so the mobilization cost has been incurred and the cost is only for the remediation, \$300. If we have used only B or C, or BC (or none) then the cost would be \$300 plus the \$400 mobilization cost of A for a total of \$700. Eight possible states for each of the three technologies brings the total number of states at each stage in the example to 24. For any number of technologies m the number of states at each stage is given by

$$ \text{states per stage} = m \times 2^m \tag{6} $$

The top of Table 2 shows the results for Stage 1 (Sector 4) or f_1. The calculation is in the following:

$$ f_1 = c_{ij} + \begin{cases} md_j, & j \text{ not mobilized} \\ 0, & j \text{ mobilized} \end{cases} \tag{7} $$

Next we move to Stage 2 and perform similar calculations, and then add the minimum of the appropriate column from Stage 1. The particular technology being considered at this stage is referred to as j, and J will refer to the technologies (if any) already mobilized. The function will now be $f_{ij}(J)$, meaning the optimal cost of using Technology j at Stage i given that the set of Technologies J has been already mobilized. It is worth recalling that as this formulation is solved from the last sector to the first it is not known at this point which technologies have been previously mobilized. Eq. (8) is given as

Table 2. Example Calculations

	Previously mobilized							
F_1	A	B	C	AB	AC	BC	ABC	None
A	300	700	700	300	300	700	300	700
B	350	100	350	100	350	100	100	350
C	850	850	400	850	400	400	400	850
F_2								
A	600	800	1,000	400	600	800	400	1,000
B	550	300	550	300	550	300	300	550
C	1,050	850	650	850	600	400	400	1,100
F_3								
A	950	1,100	1,350	700	950	1,100	700	1,350
B	900	650	900	650	900	650	650	900
C	1,200	950	750	950	750	500	500	1,200
F_4								
A	1,600	1,750	1,850	1,350	1,450	1,600	1,200	2,000
B	1,400	1,150	1,250	1,150	1,250	1,000	1,000	1,400
C	1,350	1,100	900	1,100	900	650	650	1,350

$$f_{ij}(J) = c_{ij} + \min(f_{i-1}(J \cup j)) + \begin{cases} md_j & \text{if } j \text{ not mobilized} \\ 0 & \text{if } j \text{ mobilized} \end{cases} \tag{8}$$

The results of this calculation for f_2 are also in Table 2. For example, to use Technology A, if only A has been used previously, we take the cost c_{A3} (300) and then find the minimum of the column in the upper part of the table (f_1) corresponding to $J = A \cup A$ (=A). The minimum of (300, 350, 850) is 300, so $f_{2A}(A)$ equals \$300+\$300=\$600. To use B having only used C previously would require mobilizing B (250), using B (200), then finding the minimum of the column in f_1 corresponding to $J = B \cup C$ (=BC), which is the minimum of (700, 100, 400) equals 100. Therefore $f_{2B}(C)$ equals \$250+\$200+\$100=\$550.

The final calculations for this example are f_4 shown in the lower part of Table 2. The minimum cost must be found in the "None" column, because we are now at the beginning of the project with no technologies mobilized. The minimum is equal to \$1,350. The other columns are not required; they are included for consistency.

To find the sequence that corresponds to the minimum cost, it is necessary to trace back through the calculations. The optimum cost (f_4^*) in the None column is in the C row, meaning that the optimum policy begins with Technology C. Subtracting the mobilization (\$450) and Sector 1 remediation costs (\$150) for C from \$1,350 gives us \$750, the optimum cost for f_3^*. Under f_3 we look in Column C (which is the only technology on site at this point) and find \$750. This corresponds to Row C again, meaning that the second sector should also be treated by Technology C. Subtracting the remediation cost of Sector 2 using C (\$200) gives \$550, which is f_2^*.

We again go to the C column under f_3 (still the only technology mobilized) and find that \$550 occurs in the B row. To follow the optimum trajectory we use Technology B in Sector 3. Subtracting the mobilization (\$250) and Sector 3 remediation costs (\$200) for B gives the optimum cost for f_1^*, \$100. This is found by looking in the BC column under f_1, as we now have both B and C mobilized. One hundred dollars is in Row B, making B the technology to use in Sector 4. The B remediation cost is \$100, taking us to \$0, the end (f_0). Therefore the optimal trajectory or policy is C-C-B-B, at a cost of \$1,350.

This example took 96 calculations to find the optimal policy. It could also have been solved by complete enumeration. Each sector could use any one of the three technologies, so the number of combinations is three raised to the fourth power, or 81. However, as the size of the problem increases, dynamic programming becomes much more efficient.

Consider a scenario with six technologies and 12 sectors. Using Eq. (6) and multiplying by 12 sectors we get 4,608. For complete enumeration there are 12 sectors, each of which could be remediated with any of six technologies. Complete enumeration requires 6^{12} calculations, about 2.18 billion. This is a ratio of 1:472,000, representing a huge savings in computation time.

Another advantage of DP over some other types of optimization is that DP becomes more efficient when constraints are added. This can be used to our advantage in the problem considered here.

As the detail of the problem grows, as happens when the site is divided into more sectors, the number of equations to be solved increases. This is a linear increase. In the case of six technologies, each sector (stage) added will require $6 \times 2^6 = 384$ calculations. This may become a problem eventually, but we can increase the level of detail by four and expect to quadruple the number of equations and roughly quadruple the computing time.

The problem occurs when more technologies are entered into the solution set. From Eq. (6), the number of equations to calculate at each stage is a function of 2 raised to the number of technologies, times the number of technologies. This means that the solution equations more than double for each additional technology. Six technologies take 384 equations per stage, seven technologies require 896, and 12 require 49,152 calculations at every stage.

We can mitigate this problem by adding a constraint. It does not seem reasonable that all of the technologies will be mobilized to the site. The cost of mobilizing, running treatability studies, decontaminating equipment, etc., would make this unlikely. Therefore, we can constrain the solution space to some subset of the technologies under consideration.

In the case of 12 technologies, if we limit the number of allowed technologies in the solution to three, the solution space in decreased considerably. The number of equations is found by calculating the combinations of 12 taken zero, one, two, and three at

a time as shown in Eq. (8). This represents an order of magnitude reduction in the solution space required to solve the equations

$$12 \times ({}_{12}C_0 + {}_{12}C_1 + {}_{12}C_2 + {}_{12}C_3) = 12 \times (1 + 12 + 66 + 220) = 3{,}588 \quad (9)$$

Returning to the example, it is worth noting another point. If we had developed an algorithm which simply chose the least expensive next step we would have reached a suboptimal solution. The first choice, among A, B, and C, would have resulted in the selection of C as the least expensive. From there we would proceed to C-C as the second choice. The third choice would be C-C-C, and finally we move to C-C-C-B at $1,450, a cost greater than that on the optimal path, C-C-B-B at $1,350.

The reason that the result is not optimal is because at the third stage it is not known what will happen in the fourth stage. If it were known that B would be mobilized anyway, then the choice would be to use B in the third stage (C-C-B), and proceed with B in the fourth stage. As this is unknown, the mobilization cost of B spoils the overall optimum by allowing the solution to be distracted to a local optima. The DP algorithm avoided this pitfall.

Implementation and Illustration of the Model

Section Introduction

To illustrate the use and results of the SORTS model an application of the model to a simulated remediation site was performed. This section was developed in conjunction with the model development to aid in eliminating problems that might be encountered in an application.

Site Description

The site data used for this illustration are based on information from a site known as the acid pit. The acid pit is located at Idaho National Engineering Laboratory, and is part of the radioactive waste management complex (RWMC). The RWMC covers an area of 144 acres, and has been used for waste disposal since 1952. The acid pit is about 90 feet wide by 180 feet long, by 15 to 21 feet deep (Lugar and Rice 1992). The pit received a variety of organic, inorganic, and radioactive wastes. Accurate records are limited as to the composition and quantities of wastes. Clearly this type of site demands careful analysis and planning prior to any remedial action.

For illustration purposes, a simplified site was developed. This hypothetical site has a variety of contaminants, each of which poses a different challenge to remediate. The illustration site is 25 m wide by 150 m long, and a uniform 5 m deep. It has been divided into 24 equal sized sectors, each 12.5 m^2 and 5 m deep, for a sector volume of 781.25 m^3. At a density of 2.0 g/cm^3, each sector contains over 1.56×10^6 kg of soil, or about 1,722 t. The site is contaminated with organic, metal, and radioactive pollutants. TCE, lead, cadmium, and radium are the contaminants of interest.

The distribution of contaminants across the site is such that not all of the sectors contain all of the contaminants. Each sector is contaminated by at least TCE, and some also contain lead, cadmium, or radium, or a mixture as shown in Fig. 2. Geostatistics were used to determine a mean value for each contaminant in each sector.

Cell 12: TCE, Lead	Cell 24: TCE, Cadmium, Radium
Cell 11: TCE	Cell 23: TCE, Lead, Cadmium
Cell 10: TCE	Cell 22: TCE, Lead, Cadmium
Cell 9: TCE, Lead, Cadmium	Cell 21: TCE, Lead, Cadmium
Cell 8: TCE, Lead, Cadmium	Cell 20: TCE, Lead, Cadmium
Cell 7: TCE	Cell 19: TCE, Lead, Cadmium
Cell 6: TCE	Cell 18: TCE
Cell 5: TCE	Cell 17: TCE
Cell 4: TCE	Cell 16: TCE
Cell 3: TCE	Cell 15: TCE
Cell 2: TCE	Cell 14: TCE
Cell 1: TCE	Cell 13: TCE

Fig. 2. Contamination by block

Technology Cost Estimates

Six technologies were chosen for the illustration. The technologies are: in situ vitrification, incineration, soil vapor extraction, stabilization/solidification, bioremediation, and soil washing. Cost estimates were developed for each of the candidate technologies. The costs vary with the contamination level, and are reported in detail in Showalter (1994).

Model and Implementation

The flowchart in Fig. 3 shows the methodology of the SORTS model. Remediation projects begin with a phase of data gathering. These data are the first element in the model presented here.

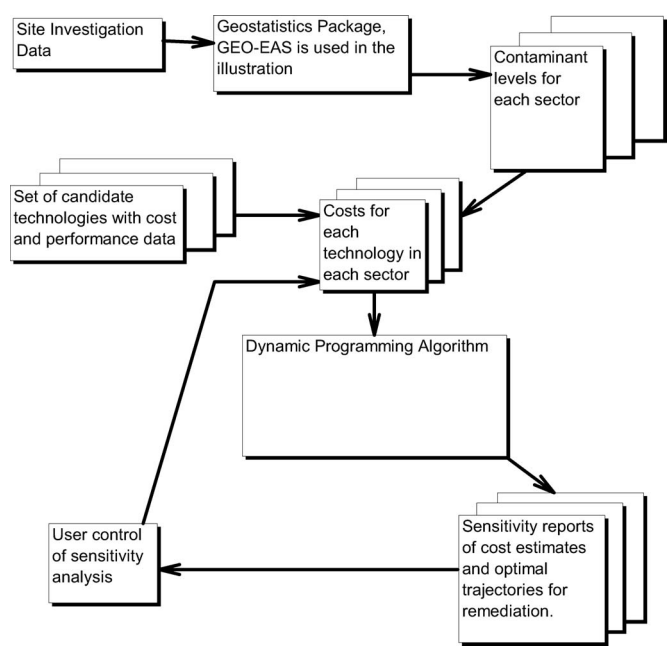

Fig. 3. SORTS methodology flow sheet

Table 3. Mobilization Cost

Technology	Mobilization cost
In situ vitrification	$484,269
Incineration	$402,360
Soil vapor extraction	$103,325
Solidification/stabilization	$110,000
Bioremediation	$299,325
Soil washing	$145,000

Once the site data are available, geostatistical analysis is used to divide the site into sectors. In each sector, a mean value for each contaminant is calculated. The site in the illustration has been divided into 24 sectors.

A set of candidate technologies must be determined. The set should include all technologies that are applicable to the contaminants at hand. Cost and performance data for each technology must be available.

The contaminant levels and the cost functions are then combined to determine the cost to remediate each cell with each technology. Nonfeasible options such as bioremediation of heavy metals can be assigned arbitrarily high values ($\$1 \times 10^{10}$) so that they never enter the solution.

The cost data are then entered into a dynamic programming algorithm. The DP algorithm involves calculating from the final sector to the first sector one step at a time. A second pass is used to trace the optimal path (trajectory) for remediation.

Once the optimal sequence of technologies has been determined, the decision maker can vary parameters to see the influence on the optimal trajectory. This sensitivity analysis will help to point out potential problems and assist in determining areas where more information is required. If it is believed that the cost estimates are accurate to within +20 to −30%, then the costs of technologies that are in the solution can be increased by 20%, and the costs of technologies not in the solution can be decreased by 30% to see if the previously excluded technologies will then enter the optimal solution. Analyses can be performed until the decision maker is confident in a particular sequence of technologies.

The optimization is done in a spreadsheet. Contaminant levels are entered in one page. Each of the candidate technologies is on a page detailing its costs and applying those costs to the contaminant levels to come up with a cost for each sector.

The cost information is then passed to a page that performs the dynamic programming calculations to find the optimal trajectory in terms of cost. The optimal cost and trajectory are finally passed on to a page that is used to view the optimal trajectory and to perform parameter studies. The mobilization and operating costs of the various technologies can be adjusted up or down individually. For example, the mobilization cost of a technology could be reduced to 75% of the estimate, whereas its operating costs are decreased to 90% of the original estimate. This allows the decision maker to quickly adjust the costs up or down without changing the original estimate.

Results

With the costs set at 100% of their estimated value, the cost of mobilization of each technology is listed in Table 3. The cost to remediate each cell is shown in Table 4. Cells that have (NA) as a cost cannot be remediated by that particular technology. Where this is the case, a very large cost ($100 million) is used in the optimization.

Only one of the technologies, in situ vitrification, is capable of handling all of the contaminants. The cost to do the entire site by ISV would be $10.6 million. The dynamic programming algorithm will find the optimal cost, which will not exceed the ISV cost.

In order to solve this problem efficiently, the number of technologies in the solution has been constrained to four of the six total. If the optimal solution requires four technologies, then the problem can be checked using five technologies to see if there is an improvement. Recalling Eq. (6), the number of equations to solve by dynamic programming when 24 sectors are used is

$$24 \times \{6 \times ({}_6C_0 + {}_6C_1 + {}_6C_2 + {}_6C_3 + {}_6C_4)\}$$
$$= 24 \times 6 \times (1 + 6 + 15 + 20 + 15) = 8{,}208$$

The complete enumeration of the possibilities would require 6^{24} calculations, about 4.7 quintillion (4.7×10^{18}). At 1 billion calculations/s, complete enumeration would require 150 years to solve. The dynamic programming algorithm can be solved on a personal computer in seconds.

With the costs of the technologies at 100% of their estimated value, the optimal sequence and the minimum cost are as shown in Table 5. Note that the constraint of four technologies has not affected the solution, which uses three technologies.

The first parameter changed in the sensitivity analysis is to change the mobilization costs. This may change the optimum path by making it less expensive to bring a new technology to the site. However, even if the mobilization costs are changed to zero the optimal trajectory (sequence of technologies) is unchanged, at a cost of $2,263,165.

The next step is to vary the operating costs and test the results. To do this, the costs for technologies already in the optimal path are increased, and the costs for technologies not in the optimal are decreased. Increasing costs of excluded technologies or decreasing costs of included technologies would not affect the optimal mix of technologies, however the total cost would decrease.

In an actual application, the relative accuracy of the estimates might be known. If incineration had been used recently on a similar site, the estimate might be expected to be within 10%. A new technology might only be within 50% of the estimate. A straight +20% to −30% range has been applied to the technologies in this illustration. Table 6 shows the results of increasing the operating costs of previously included technologies and decreasing the operating costs of the previously excluded technologies. The result of changing the costs is that D, solidification/stabilization, has now entered the optimal solution, replacing soil washing. The decision maker should look at the estimates for both solidification and soil washing to determine the accuracy.

Further sensitivity studies were run. Each of the technologies included in the original solution (in situ vitrification, bioremediation, and soil washing) had their costs increased one at a time, holding the other technologies costs constant at 100%, until that technology was no longer economical. Then each of the technologies that was not included in the original solution (incineration, soil vapor extraction, and solidification/stabilization) had their costs decreased one at a time, holding the other technologies costs constant at 100%, until that technology became economical.

The results of this sensitivity analysis show that some technologies are clear winners in terms of cost, and that even fairly large errors in estimation of their costs will not effect whether they are the best choice. In the case of other technologies the

Table 4. Cost of Remediation by Sector

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
ISV	$420,564	$420,564	$420,564	$414,316	$414,316	$414,316
Incineration	$338,366	$338,366	$338,366	$338,366	$338,366	$338,366
SVE	$230,689	$230,689	$230,689	$230,689	$230,689	$230,689
S/S	$198,030	$198,030	$198,030	$198,030	$198,030	$198,030
Bioremediation	$41,377	$41,377	$41,377	$41,377	$41,377	$41,377
Soil wash	$148,523	$148,523	$148,523	$148,523	$148,523	$148,523
	Cell 7	Cell 8	Cell 9	Cell 10	Cell 11	Cell 12
ISV	$414,316	$414,316	$420,564	$433,060	$433,060	$433,060
Incineration	$338,366	(NA)	(NA)	$338,366	$338,366	(NA)
SVE	$230,689	(NA)	(NA)	$230,689	$230,689	(NA)
S/S	$198,030	$198,030	$198,030	$198,030	$198,030	$198,030
Bioremediation	$41,377	(NA)	(NA)	$41,377	$41,377	(NA)
Soil wash	$148,523	$148,523	$148,523	$148,523	$148,523	$148,523
	Cell 13	Cell 14	Cell 15	Cell 16	Cell 17	Cell 18
ISV	$433,060	$433,060	$420,564	$420,564	$414,316	$414,316
Incineration	$338,366	$338,366	$338,366	$338,366	$338,366	$338,366
SVE	$230,689	$230,689	$230,689	$230,689	$230,689	$230,689
S/S	$198,030	$198,030	$198,030	$198,030	$198,030	$198,030
Bioremediation	$41,377	$41,377	$41,377	$41,377	$41,377	$41,377
Soil wash	$148,523	$148,523	$148,523	$148,523	$148,523	$148,523
	Cell 19	Cell 20	Cell 21	Cell 22	Cell 23	Cell 24
ISV	$414,316	$414,316	$420,564	$420,564	$420,564	$454,331
Incineration	(NA)	(NA)	(NA)	(NA)	(NA)	$1,554,299
SVE	(NA)	(NA)	(NA)	(NA)	(NA)	(NA)
S/S	$198,030	$198,030	$198,030	$198,030	$198,030	(NA)
Bioremediation	(NA)	(NA)	(NA)	(NA)	(NA)	(NA)
Soil wash	$148,523	$148,523	$148,523	$148,523	$148,523	(NA)

choice is not so clear, and more accurate estimates may be required to make the best decision.

Bioremediation is one of the choices that the decision maker can be confident in. Even increasing the costs to 200% of the original estimate did not cause bioremediation to leave the optimal solution. Only when soil vapor extraction was decreased to 30% of its estimate and bioremediation was increased to 150% of its estimate did SVE become more attractive than bioremediation. Cost estimates should be accurate within a smaller range than this.

Table 5. Optimal Control Trajectory

Cell 12: Soil washing	Cell 24: In situ vitrification
Cell 11: Bioremediation	Cell 23: Soil washing
Cell 10: Bioremediation	Cell 22: Soil washing
Cell 9: Soil washing	Cell 21: Soil washing
Cell 8: Soil washing	Cell 20: Soil washing
Cell 7: Soil washing	Cell 19: Soil washing
Cell 6: Bioremediation	Cell 18: Bioremediation
Cell 5: Bioremediation	Cell 17: Bioremediation
Cell 4: Bioremediation	Cell 16: Bioremediation
Cell 3: Bioremediation	Cell 15: Bioremediation
Cell 2: Bioremediation	Cell 14: Bioremediation
Cell 1: Bioremediation	Cell 13: Bioremediation

Note: Minimum cost: $3,191,759.

In situ vitrification of the radioactive wastes was also a clear choice. Incineration coupled with long-term storage must be reduced to about 40% of its original estimated cost before it becomes competitive with in situ vitrification.

As previously discussed, the choice between soil washing and solidification is not as clear. If soil washing is increased to 130% of its original estimated cost or if solidification is decreased to 75% of its original estimate, then solidification becomes viable. There may be need for further cost studies of these two technologies prior to making a decision.

Conclusions and Recommendations

A model has been developed that can aid in selection of cost effective technologies for environmental remediation. SORTS analyzes the site investigation data, then estimates the cost and selects an optimal sequence of technologies for remediation. Sensitivity analysis allows the decision maker to analyze "what-if" scenarios.

Discussions with industry experts and a search of the literature did not find cost-based optimization approaches to selecting technologies for environmental remediation projects. The SORTS model is one way to give structure to the cost estimating component of selecting a viable remediation sequence. The magnitude of the cost of environmental remediation projects ($400 billion for the DOE alone) dictates that cost should be given strong consid-

Table 6. Sensitivity Analysis

	A:ISV	B:Incineration	C:SVE	D:S/S	E:Bioremediation	F:Wash
Mobilize (%)	100	100	100	100	100	100
Operate (%)	120	70	70	70	120	120

1;E	2;E	3;E	4;E	5;E	6;E	7;E	8;D	9;D	10;E	11;E	12;D
13;E	14;E	15;E	16;E	17;E	18;E	19;D	20;D	21;D	22;D	23;D	24;A

Note: Total remediation cost: $2,263,165.

eration. Even if public pressures are the primary factor in selecting the remediation method, SORTS can help to show the cost of appeasing the public.

It has been shown that if the waste site has significant variation in the contaminants from place to place, it may be advantageous to break the site into discrete cells. The remediation of each cell can then be considered separately.

Sensitivity analysis of the costs can be used to better understand the estimate for remediation. Costs that require better definition can be identified. The illustration showed that some technologies may be clearly more economical than the others considered. Other choices are more sensitive to errors and uncertainties in their estimation.

The SORTS model should be considered when the site is fairly large and the contaminants vary in concentration and composition across the site. Possible sites fitting this description might include a series of pits, or a waste trench that also has had a large spill in one area.

Recommendations

The lack of cost data is one of the major limitations to the application of this research. It is difficult to make estimates of the remediation cost. Further work is required in the area of environmental remediation cost estimation. Parametric cost estimation relies on historical records, which are rare in this field. A concentrated effort could have some success in creating cost functions. Tools such as the methods described herein can then be used to run sensitivity analysis or simulations to determine if the costs are sufficiently precise to discriminate between technologies.

Geostatistics can determine a mean and standard deviation in contaminant levels for each cell. It is possible to generate multiple equiprobable scenarios using Monte Carlo simulation. By running simulations and optimizing the results, confidence limits for the cost of particular combinations of technologies could be developed. This would help in forecasting more accurate schedules and cost, thereby improving the technology selection process.

The process could be integrated into a geographic information system (GIS) to analyze the site investigation data and select the optimal path through the remediation. The ability to display the contaminant levels graphically would be an added benefit of using a GIS.

The selection of the grid spacing (sector volume) under the geostatistical analysis requires further analysis. For the illustration, spacing was chosen without a detailed analysis of its impact. ISV, for example, operates on a discrete volume of soil in each set up. Grid spacing should consider the operating characteristics of ISV to treat it fairly. For this research it was assumed that an expert could make the decision on grid spacing and weigh the tradeoffs.

SORTS can also be extended to look at the risks involved in remediation. Geostatistics provide a measure of the uncertainty involved in site sampling. Linking uncertainties in the technological capabilities of the remediation methods with the uncertainty in the contamination data will allow analysis of the risk of failure in the remediation project. If the consequences of failure can be translated into a monetary figure, then the optimization would be straightforward. Otherwise a weighting scheme must be developed and methods of multiattribute optimization applied.

Finally, it must be remembered that this method is another tool in the toolbox. It cannot make the decision of which technology is the best suited to remediate the site in question. It can hopefully help to identify good candidates for the remediation, and perhaps help identify areas of cost estimation that need more work.

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