MULTI-OBJECTIVE OPTIMIZATION OF RISK-BASED IN-SITU BIOREMEDIATION DESIGN

BY

BETH ELLEN PADERA

B.S., University of Notre Dame, 1996

SPECIAL PROJECT

**Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Environmental Engineering in Civil Engineering
in the Graduate College of the
University of Illinois at Urbana-Champaign, 1999**

Urbana, Illinois

Abstract

Risk-based corrective action (RBCA) is becoming a popular method for generating cost effective corrective action decisions that protect both human health and the environment at chemical release sites. The RBCA process accounts for the principles of toxicology, exposure assessment and fate and transport in its three-tiered approach to risk assessment. The RBCA approach has already been incorporated into an optimization and risk management model to enable enhanced remediation design and decision making. This model links a numerical fate and transport model with an exposure and risk assessment model to calculate the probable movement of the contamination plume and the human health risks associated with this migration. A genetic algorithm then searches for the least-cost injection and extraction well locations and pumping rates to reduce the risk to a specified level. Presented in this paper is an improved multi-objective approach that can simultaneously examine all risk and cost levels. The approach uses a Non-dominated Sorted Genetic Algorithm (NSGA), which can search the entire multi-objective non-inferior frontier in both cost and risk decision space. The NSGA arranges all solutions into fronts, which are pareto-optimal with respect to both cost and risk. Adding the NSGA to the model allows the algorithm to search simultaneously for multiple objectives and therefore determine the tradeoffs between cost and risk. This information will be beneficial for improved design selection and analysis. It was found that the NSGA method was able to generate the cost-risk tradeoff curve in at least one-tenth of the time that it would take a simple GA using the weighting or constraint methods, which are more traditional multi-objective optimization techniques. Application of the model to a case study demonstrates the importance of well installation costs in determining cost-risk tradeoffs for in situ bioremediation.

1. Introduction

Increasingly, risk-based corrective action (RBCA) is becoming an accepted approach to contaminant remediation. Under RBCA, the level of assessment and remediation required at a site is determined by the ecological and human health risks associated with contaminants present at the site. Once the level of risk at a site is estimated, RBCA designs for reducing risk to an acceptable level must be identified. Recently, Smalley and Minsker (1999) applied a noisy genetic algorithm to a risk-based in situ bioremediation design scenario that was optimized for a low-cost and low-human health risk solution. Their approach treated RBCA design as a single-objective optimization problem in which the objective was to minimize cost while meeting a human health risk constraint. This paper explores a multi-objective approach to this problem wherein both cost and risk are objectives to be minimized. The conversion to a multi-objective approach is accomplished using a Non-dominated Sorted Genetic Algorithm (NSGA). The entire cost-risk tradeoff curve is created under this multi-objective approach; this information

will better inform the decision-maker and will ultimately lead to improved design selection. A comparison of the NSGA method to earlier methods for multi-objective optimization is also presented in Section 2.3.2.2.

2. Methodology

The multi-objective risk-based in situ bioremediation design model is composed of a numerical model, an exposure and risk assessment model, and an optimization model. Figure 1 gives an overview of how the various components fit together to function as the groundwater management model.

2.1 Numerical Model

The numerical groundwater flow and contaminant fate and transport model is used to evaluate possible design solutions, which consist of well locations and pumping rates for injection and extraction wells. The model was developed by Taylor (1993) and is called Bio2D. This model is a two-dimensional, depth-averaged finite-element flow, transport and biodegradation model. Assuming a confined aquifer, it calculates the hydraulic heads and the contaminant, oxygen, and microbial biomass concentrations that would occur on-site under a particular design solution (i.e. pumping rates and well locations). Smalley and Minsker (1999) and Minsker and Shoemaker (1998) outline the model's numerical formulation and detail the governing equations underlying the Bio2D fate and transport model.

2.2 Exposure and Risk Assessment Model

The exposure and risk assessment model includes a human health risk calculation component and an analytical model for predicting concentrations of contaminant at off-site exposure wells. The analytical model starts with the concentrations calculated by the numerical model at the onsite monitoring wells and then simulates the advection, dispersion, adsorption and degradation of the contaminant into the future using an equation from Domenico and Schwartz (1990). This component of the model predicts the contamination concentrations in the off site exposure wells over longer periods of time than would be possible using a computationally intensive numerical model. These predicted contamination levels are then used to estimate

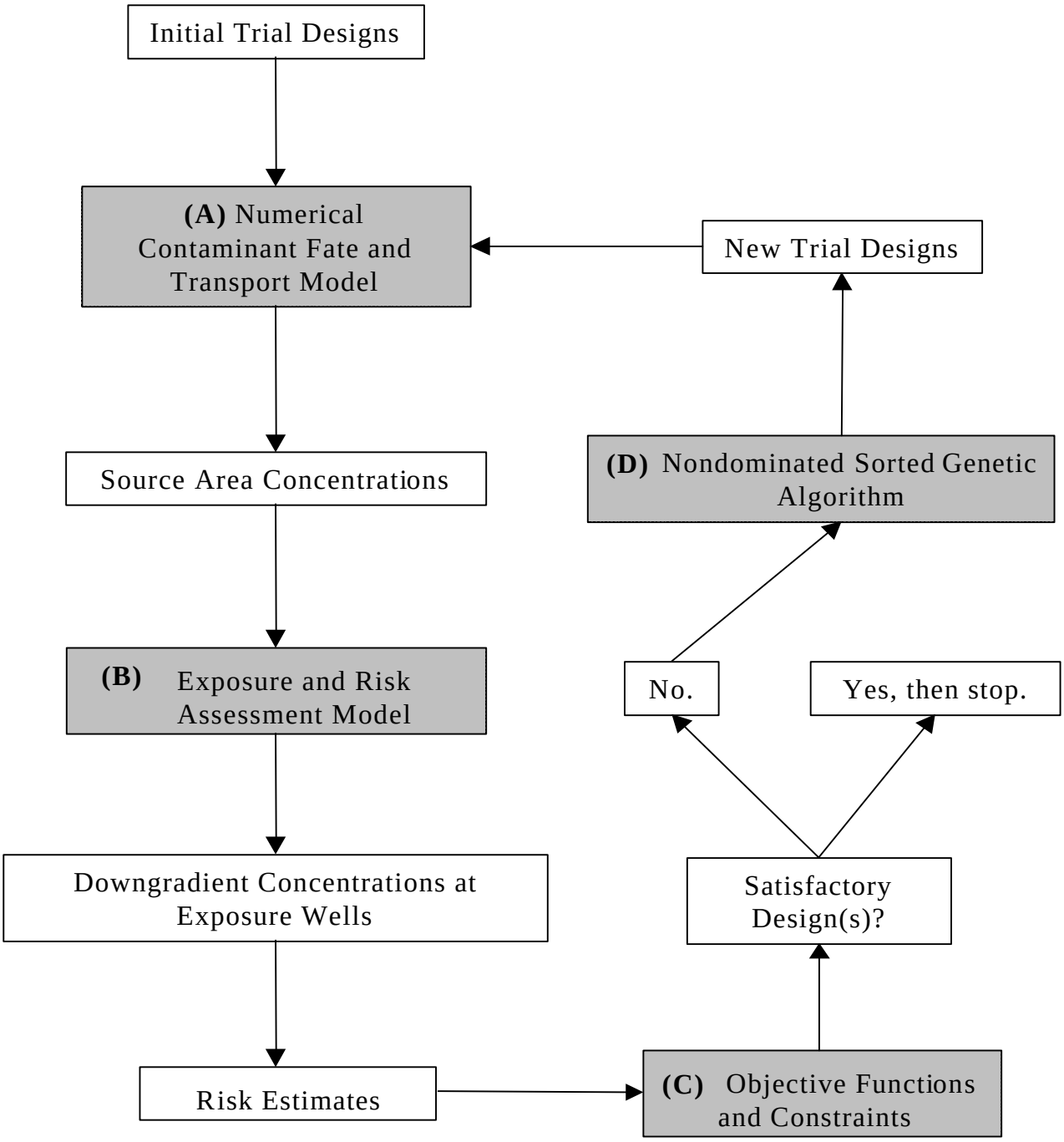


Figure 1. Management Model Components (adapted from Smalley and Minsker, 1999).

human health risk at the exposure wells. Three exposure pathways are considered in the calculation of human health risk: 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 such as dish and clothes washing and cooking. Reference should be made to Smalley and Minsker (1999) for more detailed information about the equations and theory underlying the analytical model and the calculation of human health risk.

2.3 Optimization Model

To identify RBCA designs that minimize both risk and cost, a Nondominated Sorting Genetic Algorithm (NSGA) was implemented in this work. This section describes the objective functions and constraints that were implemented in the NSGA and then explains how the NSGA works.

2.3.1 Objective Function and Constraints

The two goals of the model are to minimize the cost of a bioremediation design solution and to minimize human health risk, represented mathematically in the objective function equations shown below [Equations (1) and (2)].

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

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

C^{TOT} is comprised of three components: the capital and operating costs for the wells, C^{REM}, the cost of site monitoring, C^{MON}, and the additional capital and operating costs for the remediation system, C_{SYST}. $Risk_{t,k}^{TOTAL}$ is the total individual lifetime health risk at time *t* and exposure location *k*; $Risk_{t,k}^{w}$, $Risk_{t,k}^{shw}$, and $Risk_{t,k}^{nc}$ are the risk 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, from concentrations at time *t* and exposure location *k* (see Smalley and Minsker (1999) for details on how these are calculated). The separate cost components are shown in Equations (3) - (5).

$$C_{REM} = \sum_{i=1}^{N} (c_i^{cap,rem} x_i + c_i^{op,rem} \left| u_{i,l} \right| t_{cu}) \tag{3}$$

$$C_{MON} = c^{capsite,mon} + \sum_{j=1}^{M} c_j^{capwell,mon} + \left[c^{samp,mon} + \sum_{j=1}^{M} c_j^{ana,mon} \right] N_{mon} \quad (4)$$

$$C_{SYST} = \left[c^{cap,syst} + \left(\sum_{i=1}^{N} u_{i,l} c^{muni,syst} + c^{op,syst} \right) t_{cu} + c^{main,syst} Y_{cu} \right] X_{syst} \quad (5)$$

In Equations (3) – (5), N represents the total number of remediation wells (injection and extraction), $c_i^{cap,rem}$ is the capital cost of installing each remediation well i ($), x_i is an installation decision variable for remediation well i, $c_i^{op,rem}$ represents the operating cost for remediation well i ($/m^3), $u_{i,l}$ is a pumping rate decision variable for well i ($u_{i,l}$ is positive for injection and negative for extraction) (m^3/day), the decision subscript l is the location of each remediation well, t_{cu} represents the length of the remediation period [a variable calculated as a function of $u_{i,l}$ and l] (days), $c^{capsite,mon}$ represents costs associated with installation of monitoring wells at the site ($), M is the total number of monitoring wells [determined by user], $c_j^{capwell,mon}$ is the capital cost associated with installing each monitoring well j ($), $c^{samp,mon}$ is the sample collection costs ($), $c_j^{ana,mon}$ is the cost to analyze the samples at each monitoring well j ($), N_{mon} is the number of monitoring periods within the remediation period, $c^{cap,syst}$ includes additional capital costs associated with the remedial system ($), $c^{muni,syst}$ is the cost for municipally-supplied water ($/m^3), $c^{op,syst}$ is the additional system operation and management costs ($/day), $c^{main,syst}$ is the equipment maintenance cost ($), Y_{cu} is the number of whole years in the remediation period, and Y_{syst} is a system installation indicator which has a value of 1 if any remediation wells are installed and a value of zero if wells are not installed.

The optimization model searches for solutions, comprised of pumping rates $u_{i,l}$ and well locations l, along the non-inferior frontier. That is, it searches for solutions for which the cost of the total remediation strategy [Equation (1)] cannot be decreased without increasing human health risk [Equation (2)], subject to the following constraints:

$$u_{\min} \le \left| u_{i,l} \right| \le u_{\max} \qquad \forall \quad i \qquad (6)$$

$$l \in \Omega_L \qquad \forall \quad l \qquad (7)$$

$$h_{\min,\,l} \le h_{i,l} \le h_{\max,\,l} \qquad \forall \quad i \text{ at each } l \qquad (8)$$

$$\sum_{i=1}^{N} u_{i,l} \ge 0 \qquad (9)$$

$$x_i = \begin{cases} 0 & \text{then } u_{i,l} = 0 \\ 1 & \text{then } u_{i,l} = u_{i,l} \end{cases} \qquad \forall \quad i \qquad (10)$$

where u_{min} and u_{max} represent the minimum and maximum pumping rates for a given remediation well (m^3/day); Ω_L is a set of possible remediation well locations; and $h_{i,l}$, $h_{min,l}$, 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.

Equations (6) and (8) provide the upper and lower bounds on remediation well pumping rates and hydraulic head at remediation wells, respectively. Equation (7) limits the potential remediation well locations to user-specified locations. Equation (9) restricts the total rate of extraction to be less than that of injection because extracted water is currently assumed to be recycled back into the system via injection. Finally, Equation (10) is the well installation indicator which ensures that pumping cannot occur at a location if there is no well installed at that location (Smalley and Minsker, 1999).

2.3.2.1 Genetic Algorithm Theory

Genetic algorithms (GAs) are based on the notion of "survival of the fittest," and they operate by searching for and choosing optimal solutions in much the same way that natural selection occurs. GAs differ from many other optimization methods in that they only use the objective function, not derivatives, to identify possible solutions. Genetic algorithms start with a randomly selected population of binary decision strings (possible solutions), which hold information about the decision variables and have respective "fitness" values. The fitness of a

decision string is determined by the degree to which it satisfies the objective function and constraints. Thus, if a decision string improves the objective function and satisfies the constraints, then it has a high fitness value. The decision strings that have high fitness are then more likely to be selected as members of a new population. In the new population, there is a random selection of pairs of strings to mate and reproduce, weighted by each string's fitness value. The reproduction process for a pair of decision strings involves duplicating the two individual strings (the "parents") and then choosing a place on the strings to crossover (or switch) information between the strings. This results in two new "children" strings in the population which have equal or higher fitness values than their "parent" strings. Mutation can also occur when string bits are randomly switched. This exchange of information between strings during crossover allows the algorithm to converge to a global, rather than a local, optimum (for reference see Goldberg (1989)).

2.3.2.2 Multi-Objective Optimization Via Non-dominated Sorting Genetic Algorithms

When a problem has several objectives to be satisfied simultaneously, as in Equations (1) and (2), it is called a *multi-objective* optimization problem. Under single objective optimization, the algorithm seeks the best value of the objective function, such as a least cost solution. However, a multi-objective problem requires the algorithm to find solutions that are optimal in several different objectives, such as cost and risk. We are interested in finding the least expensive bioremediation design solutions that have the least amount of human health risk associated with them. Such solutions are referred to as *Pareto optimal* or *nondominated,* because they share the quality that no design in the search space is superior in both cost and risk simultaneously. The set of solutions that is Pareto optimal is known as the *Pareto Frontier,* or the *Nondominated Frontier*. The information provided in the Pareto front shows decision makers the tradeoffs involved in the optimal remedial design selection, which should ultimately lead to improved design selection.

Classical approaches for solving multi-objective optimization problems include the weighting method and the constraint method (for reference, see Revelle, Whitlach, and Wright, 1997). Under the weighting method, all of the objective functions are combined into one overall objective function, *Z,* as below:

$$Z = \sum_{i=1}^{N} w_i f_i(x) \tag{11}$$

where x is contained within the feasible region and the weights w_i are fractional numbers between 0 and 1, and all of the weights sum to 1. This method enables the user to control the emphasis of one objective over another, generating the entire Pareto frontier by varying the relative weights. The constraint method is formulated by solving the model separately for each objective, with the other objective specified as an upper or lower bound constraint. By varying the bounds on the constraint, an approximation of the nondominated set can be generated. These methods are time consuming in that they require multiple optimizations to generate the objective trade-off curve. Identifying appropriate weights or constraint bounds to represent the entire curve is a trial-and-error process that can require numerous model runs. Further, translating an objective function into a constraint may be difficult or impossible for some problems.

Past work in GA multi-objective optimization includes a study performed by Ritzel et al. (1994), in which a genetic algorithm was used to solve for reliable and inexpensive solutions to a groundwater pollution containment problem. This paper compared two variations of a multi-objective GA: the vector-evaluated GA (VEGA) and a Pareto GA. The VEGA approach, developed by Schaffer (1984), differs from a simple GA in that it changes the selection operation to ensure that solutions of each of the objectives are represented in the mating pool. This is accomplished by selecting members from the surviving population that have high fitness for each of the objectives. In essence, this method of selection fosters the mating of individuals belonging to different subpopulations. The Pareto approach (for reference see Goldberg, 1989), involves finding the individuals in a population that are Pareto nondominated and assigning them the highest rank. Ritzel et al. (1994) found that the Pareto approach generated a tradeoff curve over a wider range of objective space than did the VEGA. The NSGA explored in this paper is an extension of the Pareto GA, and like the Pareto approach, the NSGA includes nondomination ranking of the population. The NSGA, however, also introduces a sharing function to ensure diversity of the population in objective space.

The notion of NSGAs was first suggested by Goldberg (1989), and then presented by Srinivas and Deb (1995) for use on multiobjective optimization problems. Based on their findings, Srinivas and Deb (1995) assert that NSGAs can tackle higher dimensional and more difficult multiobjective problems than other multi-objective GAs such as vector evaluated GAs (VEGAs). Further exploration of NSGAs performed by Weile, Michielssen, and Goldberg (1996) compared the Niched Pareto GA (NPGA) and the Crowded Tournament Pareto GA (CTPGA) with the NSGA. Their results indicated that the NSGA was the best performer for their application because it found more of the Pareto front than the other methods, and diversity of the population was maintained throughout subsequent generations. However, the NSGA was more computationally intensive than the NPGA and CTPGA because it includes both the ranking and sharing functions.

Nondominated Sorted Genetic Algorithms (NSGAs) differ from simple GAs in that they direct the algorithm to converge to an optimal set of solutions instead of one optimal solution. NSGAs accomplish this by changing the way selection occurs, while keeping the crossover and mutation operators the same. The NSGA first identifies the nondominated individuals in the population, and then assigns them to the first nondominated front. All of the individuals in the first nondominated front are then given the same large dummy fitness value, thus ensuring their equal reproductive potential. The dummy fitness values for the individuals in the first nondominated front are then shared to ensure representation along the entire frontier. This is achieved by dividing each individual's dummy fitness value by a niche count value, m_i, which is calculated as follows:

$$m_i = \sum_{j=1}^{N_P} Sh(d_{ij}) \tag{12}$$

$$Sh(d_{ij}) = \begin{cases} \left(1 - \dfrac{d_{ij}}{s_{share}}\right)^2 & , if\ d_{ij} \le s_{share} \\ 0 & , otherwise \end{cases} \tag{13}$$

where N_P is the number for individuals in the population, d_{ij} is the distance between individuals i and j in the front, and σ_{share} is the maximum distance allowed between any two individuals to be called a niche. The distance, d_{ij}, between individuals i and j in the front is calculated as follows:

$$d_{i,j} = \sqrt{weight\left(\frac{\text{cost}_i - \text{cost}_j}{\text{cost}^M}\right)^2 + weight\left(\frac{risk_i - risk_j}{risk^M}\right)^2} \qquad (14)$$

The weighting factors can be adjusted if one of the objectives is deemed more important than the other. The variables $cost^M$ and $risk^M$ are constants included to effectively scale both the cost axis and the risk axis to range between 0 and 1. The sharing process effectively reduces the fitness of individuals that are close to other individuals in objective space, ensuring that solutions will be identified across the entire frontier. Once sharing is completed for the first nondominated front, these individuals are temporarily ignored while the rest of the population is assigned into fronts and given shared dummy fitness values (which are kept smaller than the shared dummy fitness of the previous front). Taken from Srinivas and Deb (1995), Figure 2 represents a flow chart of a typical NSGA. The NSGA gives the first nondominated front the best advantage in the selection process, and therefore encourages convergence to an optimal set of solutions (Weile, Michielssen, and Goldberg, 1996; Srinivas and Deb, 1995).

3. Application

3.1 Description of Site and Parameter Values

The model described above was applied to a case study with the aquifer configuration presented in Figure 3. The data were taken from the Borden site, as documented in Smalley and Minsker (1999). The dimensions of the study are approximately 60 m by 20 m, and the aquifer was modeled using a coarse grid of 16 by 8 elements. This coarse grid was derived from a finer mesh of 128 by 64 elements that were used to generate conditional hydraulic conductivity realizations. The hydraulic conductivity generation technique is detailed in Smalley and Minsker (1999) and the aquifer characteristics and Monod kinetic parameters were assumed to have the same values as in that study. To reduce the computational effort in this first application of NSGA, one realization of hydraulic conductivity and mean values for exposure parameters were used in

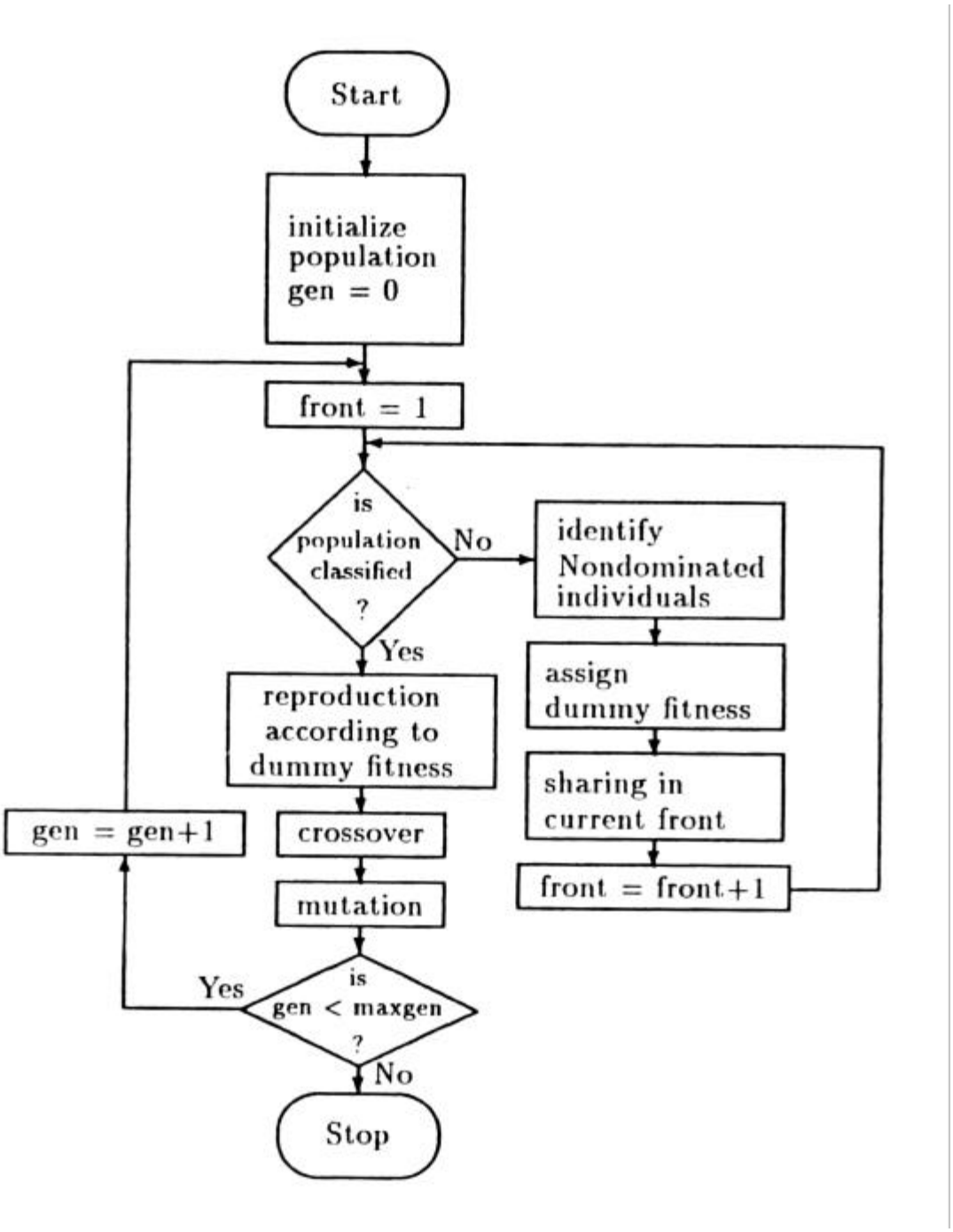


Figure 2. Flow Chart of NSGA (from Srinivas and Deb, 1995).

this work in lieu of the multiple realization noisy GA approach of Smalley and Minsker (1999). Future work will examine performance of the NSGA under noisy (uncertain) conditions, which has not yet been explored.

The contaminant benzene, with an initial peak concentration of 133 mg/L, was assumed to be present on the site and the initial oxygen and biomass concentrations were taken to be 3 mg/L and 0.0026 mg/L respectively, at all nodes. The use of the two-dimensional vertically averaged model (Bio2D) was justified because of the assumption that the benzene, oxygen and biomass concentrations were evenly distributed in the vertical direction throughout the aquifer. As shown in Figure 3, there are four sets of three monitoring wells, at which contaminant concentrations were checked at the end of each 90-day monitoring period. Contaminant concentrations at the boundary wells were used to make sure that the plume did not migrate out of the study area. At the three non-boundary monitoring well sets, maximum levels of benzene observed among each monitoring set were used to determine the human health risk associated with a particular RBCA design. A detailed explanation of the exposure and risk assessment calculations, as well as the cost parameters used, can be found in Smalley and Minsker (1999).

The number of remediation wells that could be installed was set to two, chosen from one of the following three schemes: (1) an injection well located within the upgradient well set and an extraction well in the downgradient well set, (2) an extraction well within the upgradient well set and an injection well in the downgradient set, or (3) an injection well within both the upgradient and downgradient set of wells. It was assumed that all extraction water was re-injected, therefore the scenario of two extraction wells was not possible. Pumping rates were allowed to vary between $u_{min} = 0$ to $u_{max} = 64$ m^3/day, and penalty functions were used to enforce the head constraint, Equation (7) (Smalley and Minsker, 1999). A population size of 100 was used in the NSGA, and it was run until generation 90 with the probability of crossover set to 0.5 and the probability of mutation set to 0.01. As suggested by Srinivas and Deb (1995), the parameter σ_{share} (the maximum distance allowed between any two individuals to be called a niche) in Equation (13) was set at 0.1. The distance function in Equation (14) was calculated with weighting equal between cost and risk distances so that cost and risk would have equal consideration in determining nondominated solutions.

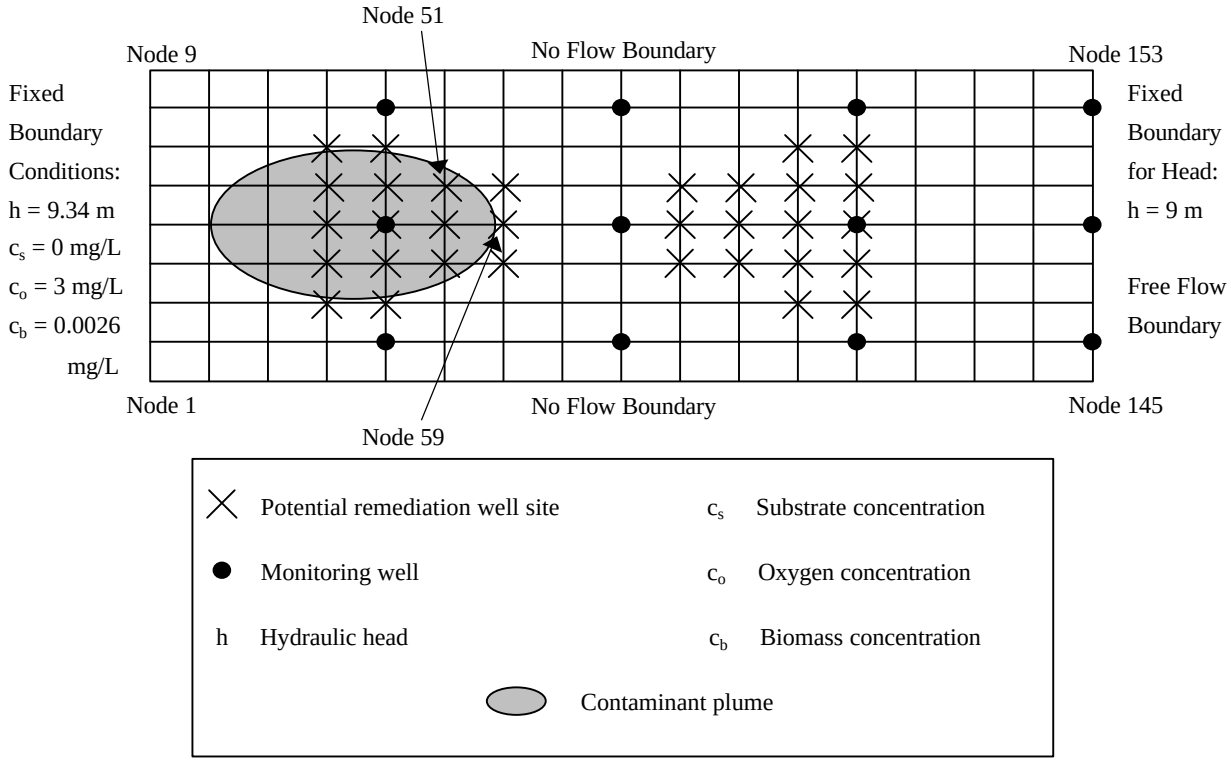


Figure 3. Plan View Schematic of Aquifer (Smalley and Minsker, 1999).

3.2 Results and Discussion

The management model was run with a randomly generated initial population through generation 90, when the number of individuals on the first (optimal) front and the location of the first front had converged. The fronts were plotted for each generation and several of these graphs are presented in Figures 5-7. A tiered effect is apparent in the results, with solutions clustered around three cost levels: $48,000, $65,000, and $80,000. Each cost level corresponds to a different pumping scenario, with the $48,000 solutions representing the scenario in which no pumping wells are installed and only monitoring costs ensue. Therefore the solutions near $48,000 are the "natural attenuation" solutions, considering only oxygen as the electron acceptor. The solutions near $65,000 represent the scenario in which one well is installed and pumping, and solutions near $80,000 represent two pumping well schemes. Solutions contained in the first front of generation 90 were analyzed for their well location and pumping rate configurations. In

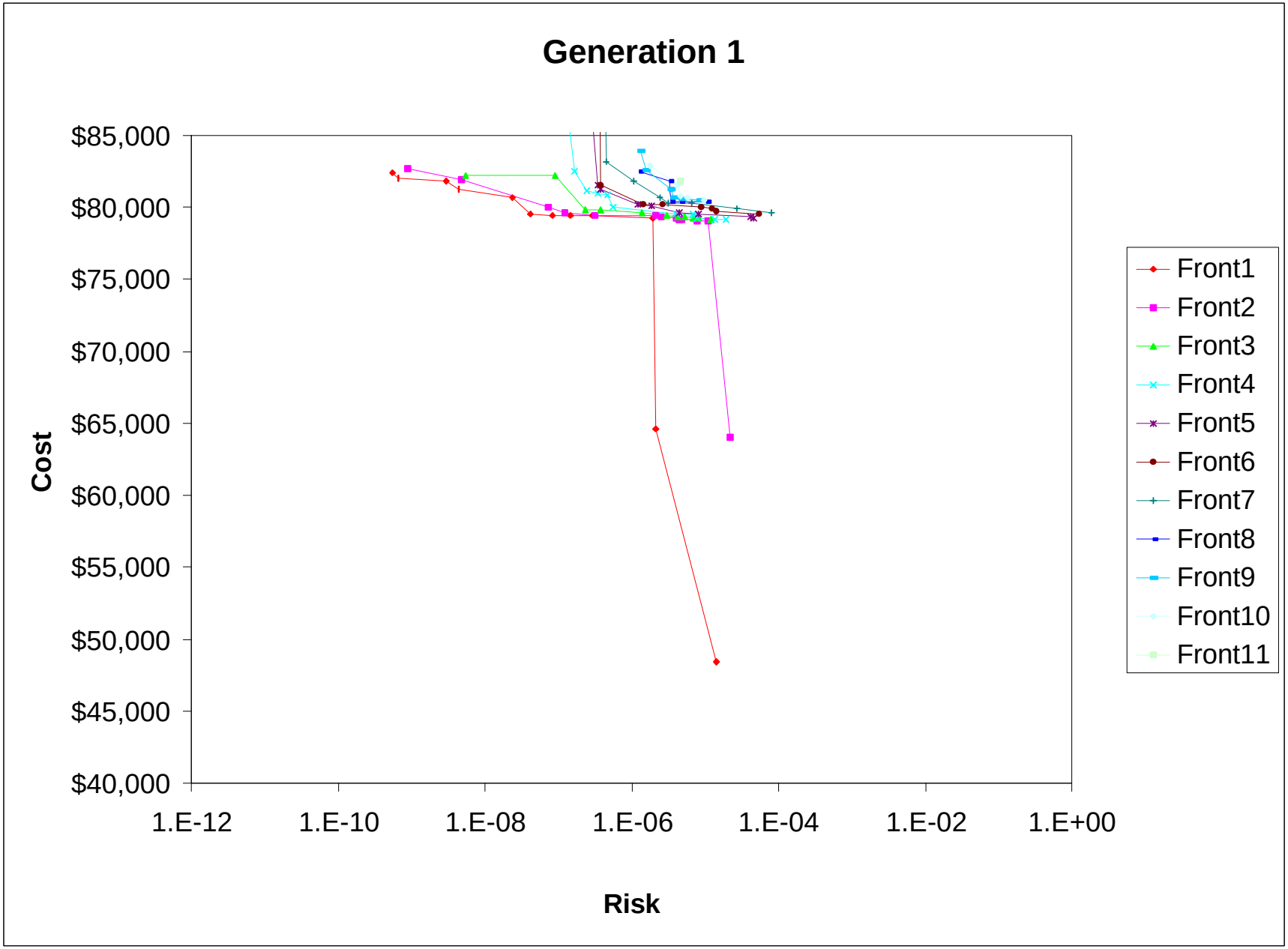


Figure 4. Generation 1 Results.

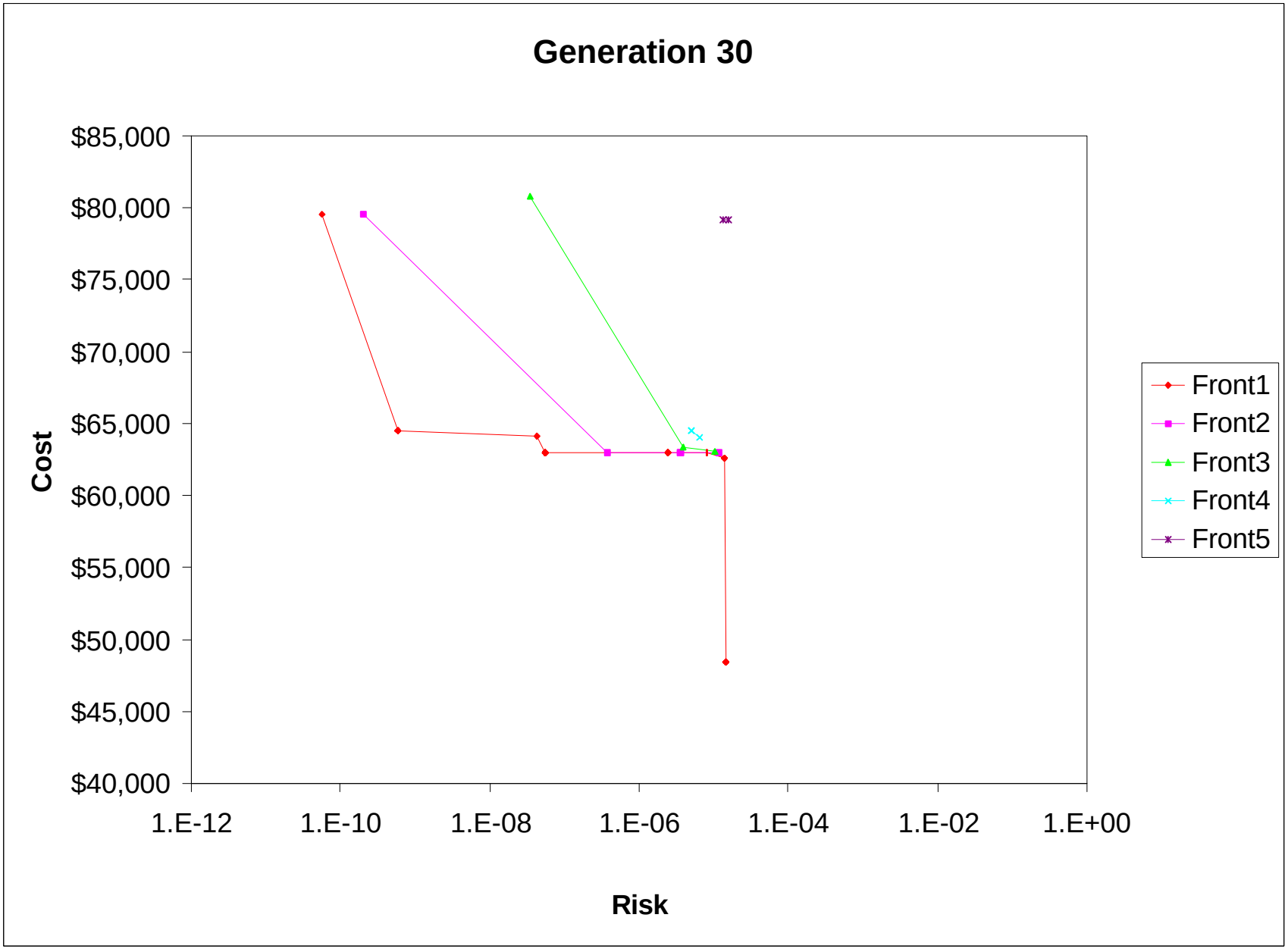


Figure 5. Generation 30 Results.

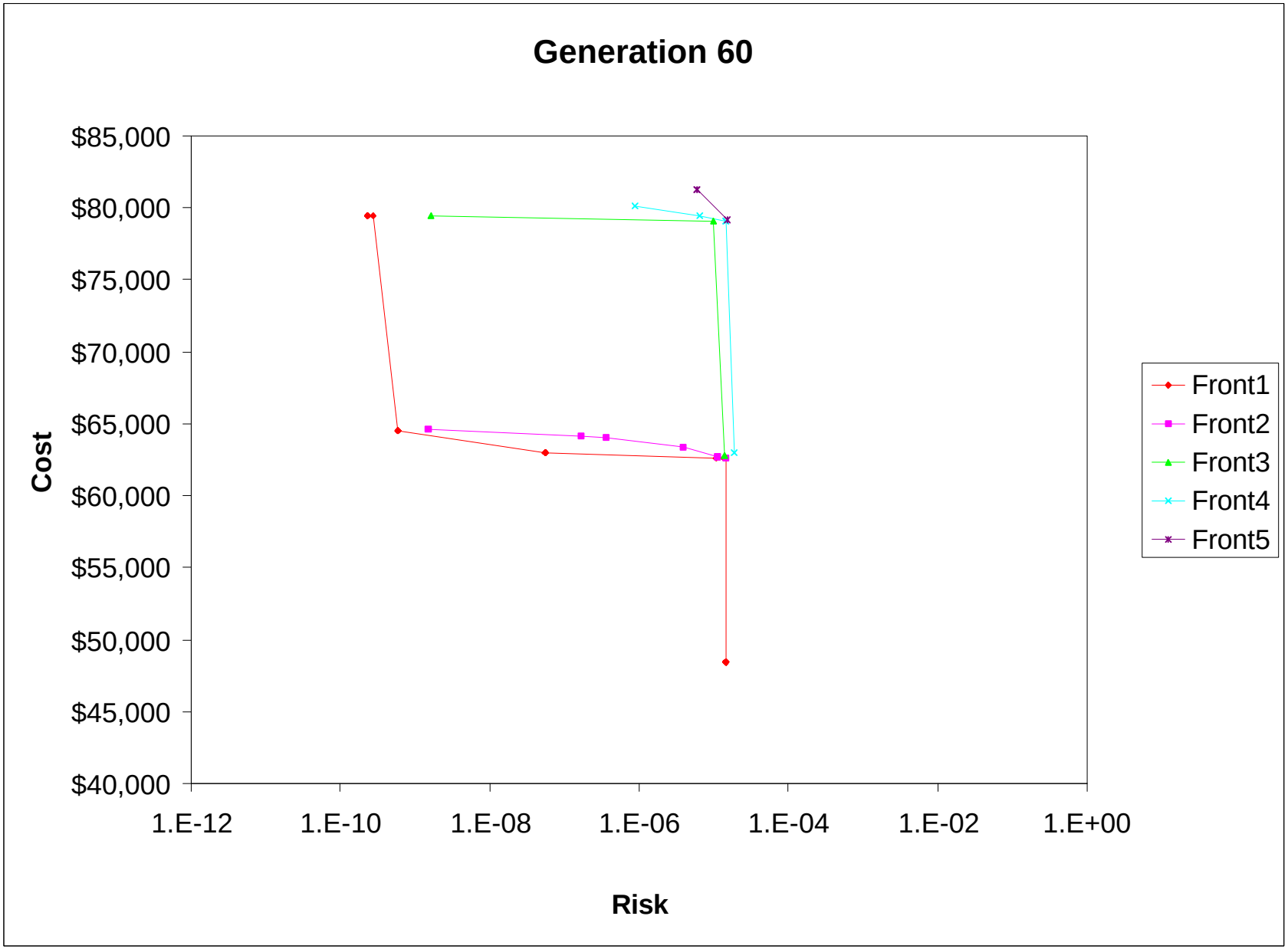


Figure 6. Generation 60 Results.

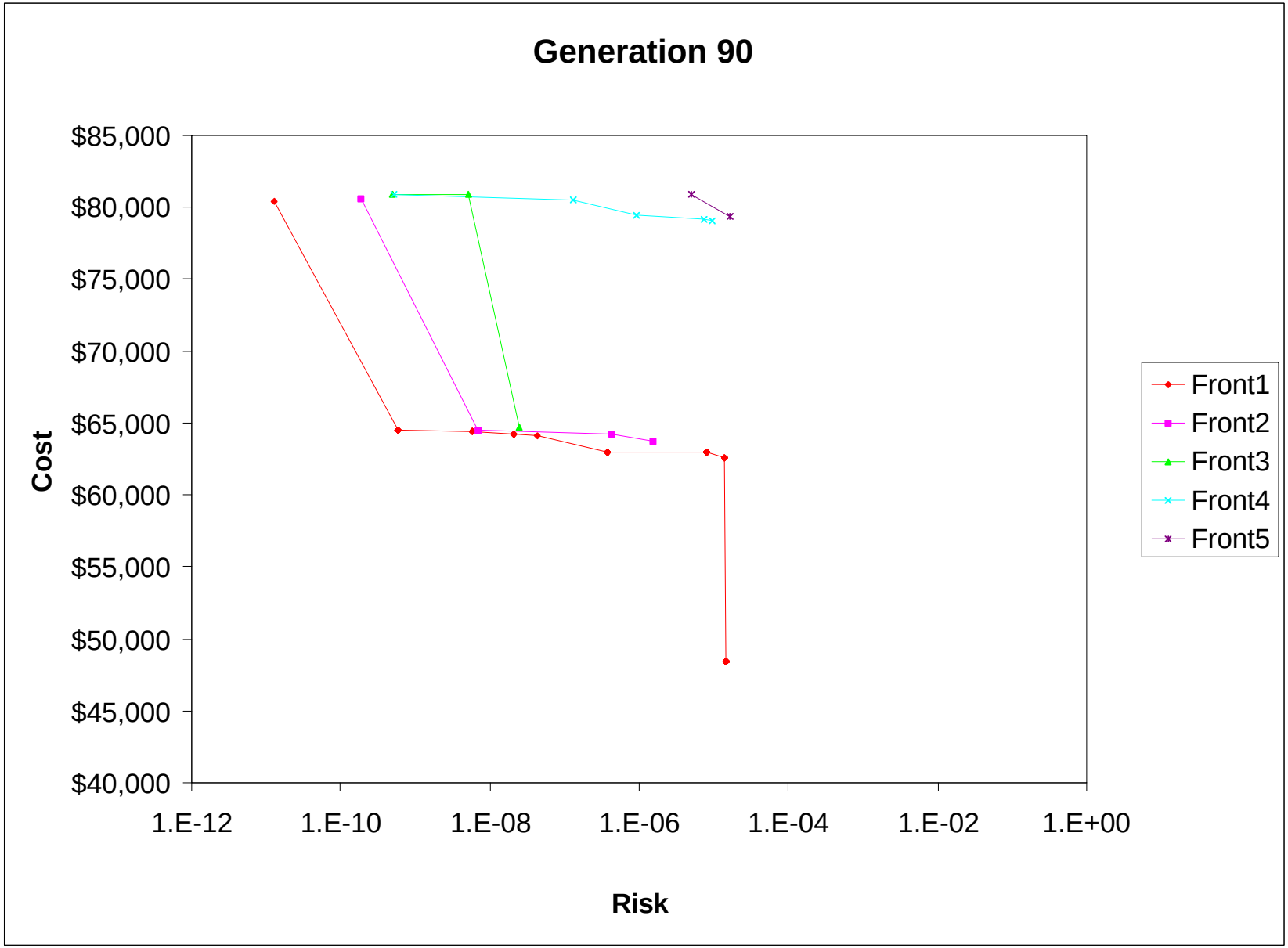


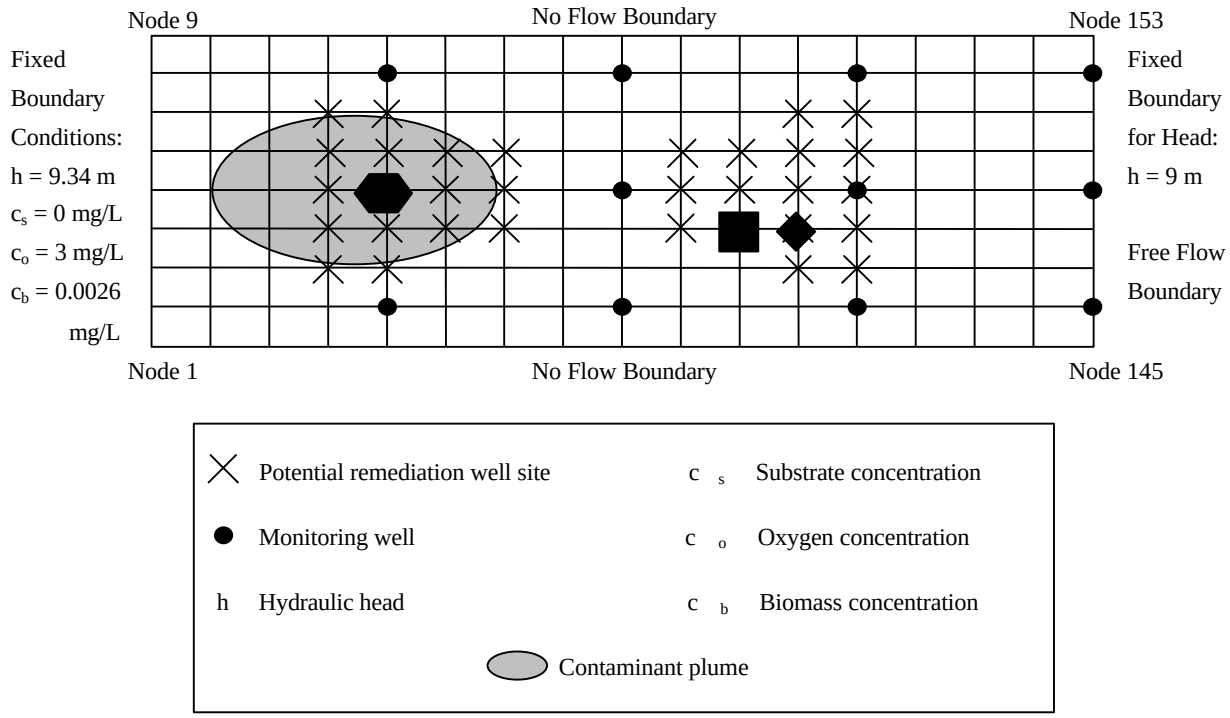
Figure 7. Generation 90 Results.

total, eleven unique solutions were found in the first front of generation 90, including one two-well scenario, nine one-well scenarios and one no-well scenario. Figure 8 shows the locations for the different one-well scenarios. The diamond symbol, representing a well at the downgradient node 103 with a pumping rate of 1.02 m^3/day, corresponds to a cost of $62,609.39 and a risk of 1.40 x 10^{-5}. The rectangle represents a well at the downgradient node 94 with an injection rate of 1.02 m^3/day, a cost of $ 62,609.73 and a risk of 1.37 x 10^{-5}. The hexagonal symbol represents a well at node 41 with pumping rates varying between 8.13 and 42.67 m^3/day, costs ranging from $62,930.89 to $64,515.51, and risks varying from 7.88 x 10^{-6} to 5.88 x 10^{-10}. One of the first front solutions indicated a two-well scenario, where one well is used as an injection well with the other used for extraction (Figure 9). This solution consists of an injection well located at node 41 with an injection rate of 40.63 m^3/day and an extraction well at node 87 with an extraction rate of 16.25 m^3/day. The cost for this scenario is $80,365.26 and the risk is 1.30 x 10^{-11}. The rest of the solutions in the first front of generation 90 do not call for any wells to be installed, and thus consist only of monitoring costs.

Figure 10 depicts the transmissivity field for the aquifer, with the location of the initial contaminant plume and location of the first front wells chosen by the algorithm also represented. The one-well injection scenarios, represented by the square and the diamond symbols, are placed upgradient of a zone of high transmissivity, thus protecting against off-site migration of the contaminant. The other one-well scenario, represented by the hexagon shape, places an injection well within the contaminant plume to decrease concentrations around the area of the spill before the plume can migrate into zones of higher transmissivity. The two-well injection/extraction scenario represented by the hexagon and the triangle again places emphasis on degrading the plume near the spill area, and provides for capture of the remaining contaminant downgradient, before the plume enters a zone of high transmissivity.

One of the tradeoffs between the single-objective optimization approach and the multi-objective approach is the difference in computational time. Experiments were run timing the NSGA model versus the simple GA model used in Smalley and Minsker (1999). All runs of the models were done on an HP 9000-C160 Workstation. It was found that the multi-objective NSGA approach used only slightly more computational time than the single-objective simple GA

model. For the case formulated above, with a population size of 100 through generation 90, the NSGA run lasted approximately 90 hrs, while the simple GA run took 84 hours. Therefore, the



Well Location	Injection Rate (m3/day)	Cost	Risk
103	1.02	$62,609.39	1.40213E-05
94	1.02	$62,609.73	1.37449E-05
41	8.13	$62,930.89	7.87910E-06
41	10.16	$63,023.21	3.76918E-07
41	34.54	$64,140.53	4.24005E-08
41	35.56	$64,187.35	2.06859E-08
41	40.63	$64,421.67	5.77345E-09
41	42.67	$64,515.51	5.87666E-10
41	42.67	$64,515.51	5.87666E-10

Figure 8. First Front Results for Generation 90, One-Well Scenario.

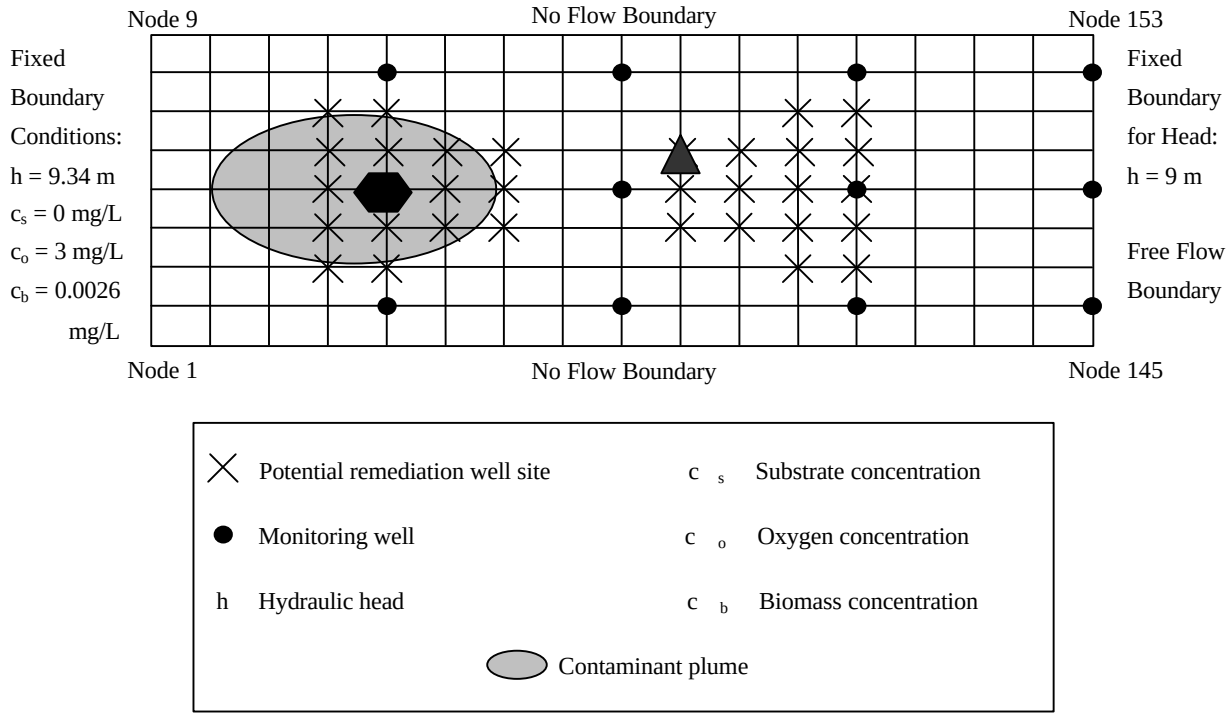


Figure 9. First Front Results for Generation 90, Two-Well Scenario.

difference between generating one point on the cost/risk tradeoff curve and generating the entire curve is only six hours. If the Smalley and Minsker (1999) model were to be reformulated as a multi-objective problem using either the weighting method or the constraint method, multiple runs of the model would be necessary (as outlined in Section 2.3.2.2). In order to reproduce the NSGA's eleven unique solutions in the first front of generation 90, the simple GA would need to be run at least eleven times under the weighting or constraint method, assuming perfect knowledge of the appropriate weights or constraint bounds to obtain these solutions. This would amount to a computational time of at least 924 hours, as compared to the 90 hours of computational time used by the NSGA approach. Therefore, the efficiency of the NSGA as compared with the weighting or constraint methods is substantial.

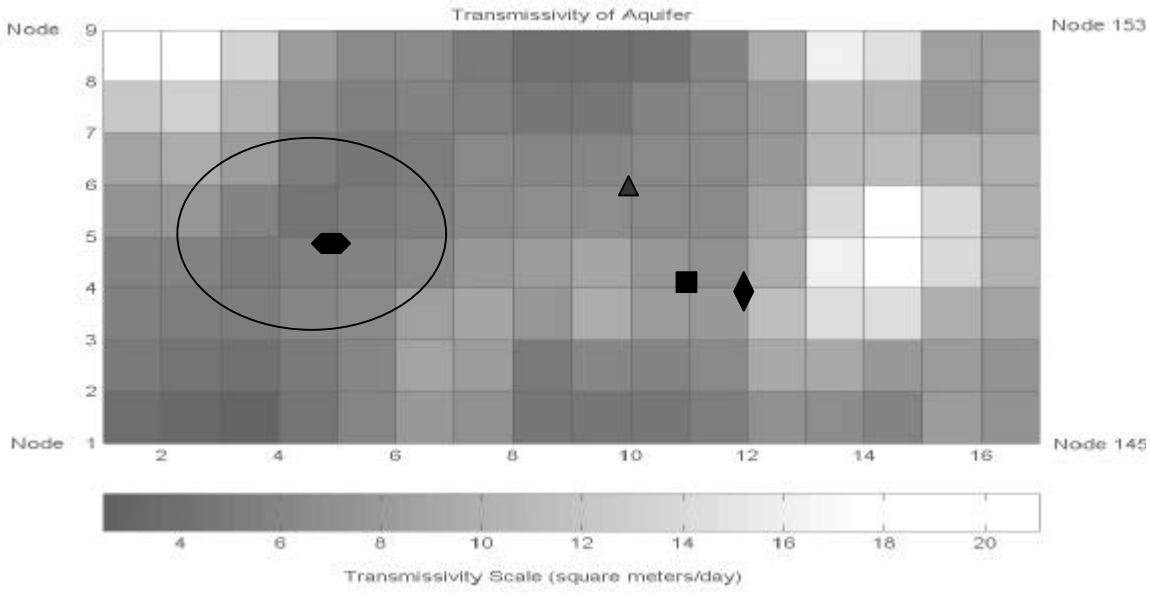


Figure 10. Transmissivity of Aquifer.

4. Conclusions

An improved multi-objective approach to the previous work done by Smalley and Minsker (1999) was presented and applied to a case study. The noisy genetic algorithm used in the previous work was changed to a Non-dominated Sorted GA, which enables the algorithm to determine risk and cost tradeoffs. This ultimately leads to more information for design selection than was available under previous approaches. The disadvantages of this method, namely the increased computational time, relative to generating designs for a single risk level, are small compared to the increase in the amount of information produced under the NSGA method. The efficiency of the NSGA method in generating multiple solutions on the non-inferior frontier relative to more traditional multi-objective approaches was also demonstrated.

Studies in the area of risk-based corrective action will become increasingly important in the wake of the emerging acceptance of RBCA in the environmental industry. This paper has demonstrated that the use of NSGAs for identifying multiple cost-effective risk management

designs is a promising approach. Future work will examine the effect of uncertainty on the non-inferior frontier, allowing the designer to identify reliable solutions to achieve desired objectives. Methods for improving computational efficiency of the model are also being developed so that large-scale field sites can be modeled more accurately.

5. Acknowledgments

I would like to thank my research advisor, Dr. Barbara Minsker for her guidance, support and insight to this project. I am grateful to have the opportunity to work with her on this project which has challenged and excited me from the beginning. I would also like to acknowledge my office mates Patrick Reed and Yong Liu for their support, help and discussions about our research, which have been enormously helpful to me. Dr. David Goldberg provided me with background material and code for NSGAs for which I am grateful. Finally, I would like to thank my family, especially my parents, for loving and supporting me throughout my educational journeys.

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