Multiscale Island Injection Genetic Algorithm for Ground Water Remediation

Eva Sinha[1], Barbara Minsker[2] and Meghna Babbar[3]

[1]Graduate Research Assistant, Dept of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N. Matthews Avenue, Urbana, IL 61801; Ph (217)369-4993; evasinha@uiuc.edu
[2]Associate Professor, Dept of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N. Matthews Avenue, Urbana, IL 61801; Ph (217)333-9017; minsker@uiuc.edu
[3]Graduate Research Assistant, Dept of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N. Matthews Avenue, Urbana, IL 61801; Ph (217)493-0515; mbabbar@uiuc.edu

Abstract

Genetic algorithms have been shown to be powerful tools for solving a wide variety of water resources optimization problems. Applying these approaches to complex, large-scale applications, which is usually where these methods are most needed, can be difficult due to computational limitations. Large grid sizes are often needed for solving field-scale groundwater remediation design problems. Fine grids usually improve the accuracy of the solutions, but they are also computationally expensive. Multiscale parallel genetic algorithms have been shown to improve the performance of engineering design problems that use spatial grids. In this paper we present multiscale island injection genetic algorithms (IIGAs), in which the optimization algorithm has different multiscale populations working on different islands (group of processors). Each island has a fraction of its population on the coarse grid and a fraction on the fine grid. Different islands exchange the best individuals, at the same scale, after a fixed number of generations and thus drive the GA towards better and more accurate solutions faster. The performance of this approach is compared to a single population multiscale approach developed previously, using a field-scale pump-and-treat design problem at the Umatilla Army Depot.

Introduction

According to a study by the U.S. Environmental Protection Agency (*USEPA, 1997*), remediation costs for contaminated soil and groundwater in the United States are estimated at $187 billion in 1996 U.S. dollars. The majority of the cleanup sites use the pump and treat methodology for the removal of contaminants. A recent study showed that improved designs for field-scale pump and treat systems can be found using optimization tools along with numerical transport models (*Minsker et al. 2003*). Many studies including *Culver and Shoemaker* (1992), *Karatzas and Pinder* (1993), *Ritzel et al* (1994), *Rizzo and Dougherty* (1996), *McKinney and Lin* (1995) and *Minsker and Shoemaker* (1998 have implemented various optimization methods for groundwater remediation management.

The degree of accuracy of these numerical models is a function of several factors including the size of numerical grid used in the simulation model. Fine grids usually improve accuracy but can increase computational effort substantially. Coarse grids, though computationally less intensive, tend to produce less reliable solutions because of the numerical inaccuracies faced in calculating the fitness function (*Babbar et, al* 2003).

Babbar and Minsker (2003) tested two different multiscale strategies on a hypothetical test case. In this paper we will test multiscale strategy formulated by *Babbar et, al* (2003) on a real life case at Umatilla Army Depot. . A new island injection genetic algorithm approach is also presented, with results to follow at the conference.

Case Study-Umatilla Chemical Depot

Umatilla is a 19,728-acre ordnance depot established in 1941 for storing and handling of military supplies. From the 1950s until 1965, the depot operated an onsite explosives washout plant. The wash water from the plant was disposed in two unlined lagoons, where wash water infiltrated into the soil. Explosives contained in the wash water migrated into the soil and groundwater at the site. The major contaminants are RDX (Hexahydro-1,3,5-trinitro-1,3,5-triazine, and commonly referred to as Royal Demolition Explosive) and TNT (2,4,6-Trinitrotoluene). The site was placed on EPA's National Priorities List (NPL) in 1984 because of the soil and groundwater contamination of the lagoons.

A pump-and-treat system was designed by the U.S. Army Corps of Engineers (USACE, 1996 and 2000) to contain and remove the RDX and TNT plumes (Fig.1). The total cost of this design was $ 3.8 million. Fig. 1 shows the remediation system, which has three extraction wells and three injection basins. Injection basins were used to return the extracted water to the aquifer after treatment with activated carbon columns. The design of the system was performed by trial-and-error using a simulation model designed to predict the groundwater flow and contaminant transport. The USACE (2000) evaluated flow and contaminant transport at the site using the simulation models MODFLOW 2000 (Harbaugh et al., 2000) and MT3DMS (*Zheng and Wang*, 1999).

The entire site was divided into 5 model layers with 132 rows and 125 columns. The first layer is an alluvial aquifer, and the last four layers were in silt and weathered basalt unit. The alluvial aquifer was divided into approximately 12 homogenous hydraulic conductivity zones, with hydraulic conductivity ranging from 10^{-6} to 10^{-3} m/s.

This site was chosen by an Environmental Security Technology Certification Program (ESTCP) project as one of the three demonstration sites for transport optimization of pump and treat systems (*Minsker et al.*, 2003). Three optimization formulations were developed for the site in that project. Our research is focused on formulation one, the primary objective of which was to minimize the total cost.

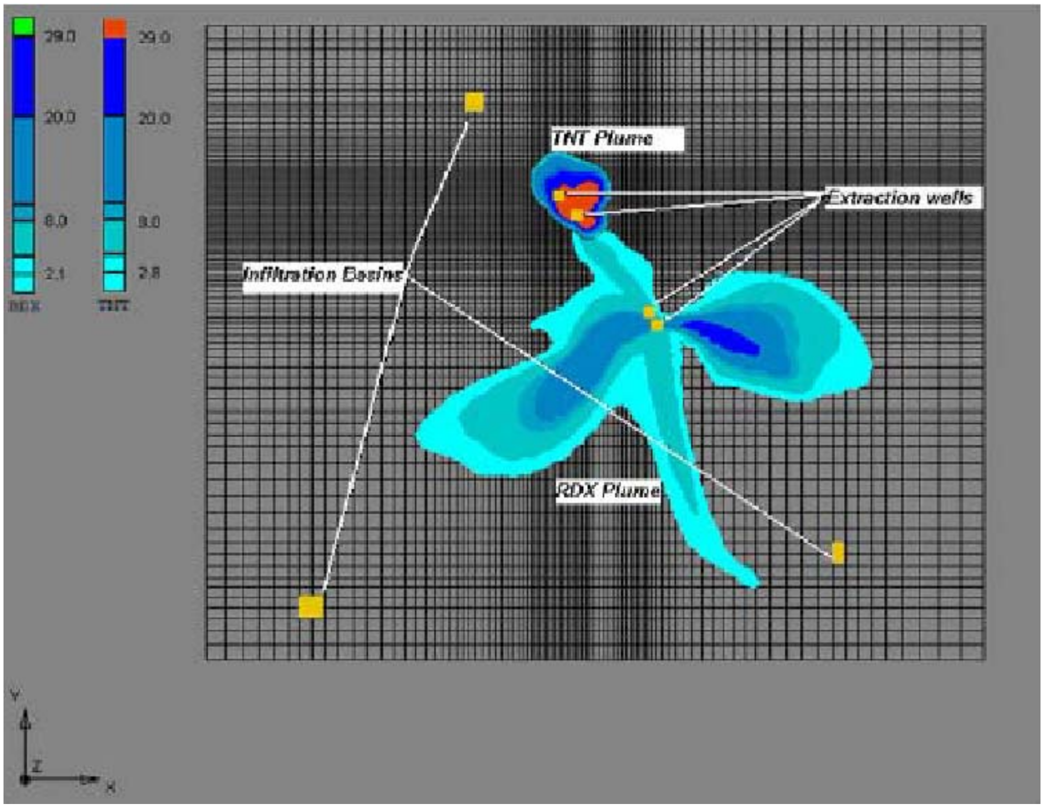

Figure 1. Existing RDX and TNT plume at the Umatilla site along with the pumping wells and infiltration basins
Source: ESTCP (2003)

Thus the objective function of Formulation 1 can be expressed as follows:
Minimize: $CCW + CCB + CCG + FCL + FCE + VCE + VCG + VCS$

CCW: Capital costs of new wells
CCB: Capital costs of new recharge basins
CCG: Capital cost of new GAC unit
FCL: Fixed cost of labor
FCE: Fixed costs of electricity
VCE: Variable electrical costs of operating wells
VCG: Variable costs of changing GAC units
VCS: Variable cost of sampling

The various constraints are:

1) $Q_1 + Q_2 \leq 1170$ gpm
2) $Q_1 \leq 360$ gpm
3) $Q_2 \leq 900$ gpm
4) $C_{RDX} \leq 2.1$ μg/l
5) $C_{TNT} \leq 2.8$ μg/l
6) Total injection = total extraction

where: Q_1 and Q_2 are the total pumping rates from two different hydrogeological zones identified in the area of study and C_{RDX} and C_{TNT} are the RDX and TNT concentrations.

The specific conditions we used for the design were a maximum of four new extraction wells, three new injection basins and a maximum cleanup time of five years. The five-year limit was imposed to reduce computational effort, since the optimal solutions found in the ESTCP project were all less than five years (ESCTP, 2003).

Multiscale Strategy Implementation on Umatilla Case

Simple genetic algorithms (SGA) are search algorithms that evolve a population of solutions to the optimal solution(s) using principles of natural selection ('survival of the fittest') with three basic operators: reproduction, crossover and mutation. Genetic algorithms are theoretically and experimentally proven to provide robust search in complex spaces (*Holland, 1975*). Their main advantage over conventional gradient based methods lies in their ability to solve discrete, non-convex and discontinuous problems (*Goldberg, 1989*).

The efficiency of SGA can be improved by using a combination of fine and coarse numerical grids in the embedded simulation model. The coarse grid leads to the better solution at a faster rate while the fine grid improves the quality of the solution found by the coarse grid. *Babbar et al* (2003) formulated a multiscale strategy that first used the coarse grid numerical model for an initial evaluation of the entire population. Then, a specified percentage of best individuals in the population are evaluated on the fine numerical grid. For crossover, tournament selection uses a biased technique to select the individual for mating. This biased technique prefers individuals tested on the fine grid over individuals tested on the coarse grid, even if the apparent fitness of individual tested on the coarse grid is better than that tested on the fine grid. The proportion of individuals selected from the fine grid size group in the final population is slowly increased to allow the individuals tested on the fine grid to take over the population after sufficient exploration using the coarse grid numerical model. This approach was shown to be significantly faster than the SGA on a hypothetical test case (*Babbar et al* 2003).

In this study, this strategy was tested on the Umatilla Case to evaluate its performance at the field scale. A population injection method that has proved to be very effective in solving the simple GA problem for different building block orders (*Espinoza et al,* 2003) was used with a building block order of 'k=3'. The multiscale strategy was used with three different percentages (10%, 15%, and 20%) of the coarse population being tested on the fine scale. The results are shown in Figures 2 and 3.

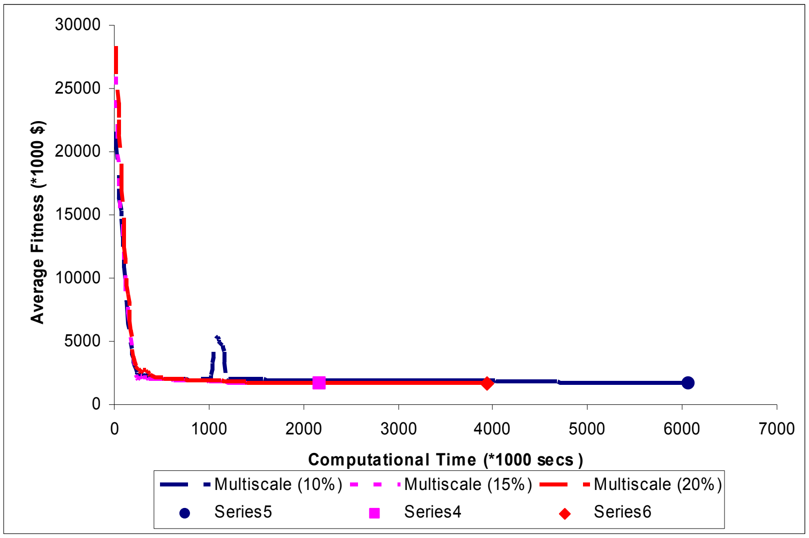

Figure 2. Multiscale Approach (10%, 15% and 20%).

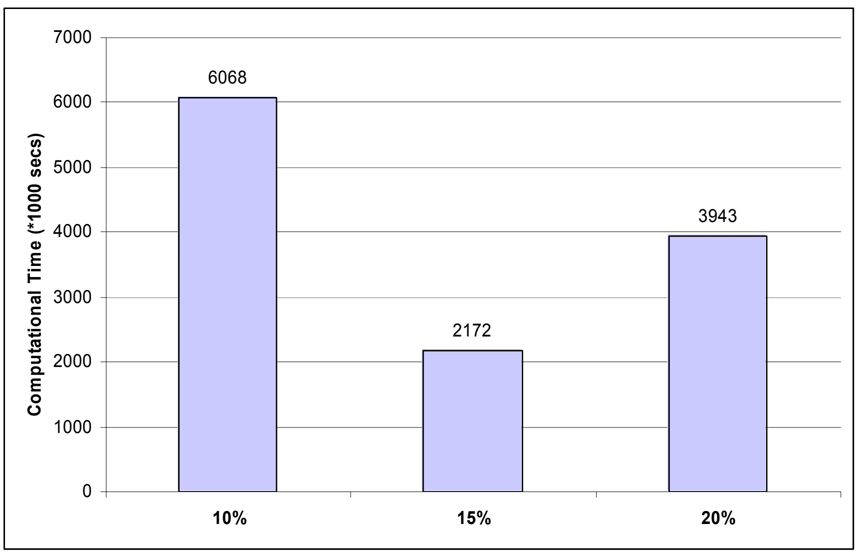

Figure 3. Comparison of Different Multiscale Strategies.

From Figures 2 and 3, we can observe that the multiscale strategy (all percentages) led to the same final solution. However, the strategy with 15% of the individuals evaluated on the fine scale reached the optimal solution in much less time than the other two approaches. The approach with 20% evaluated on the fine scale was 45% more computationally expensive, while the 10% fine-scale approach was 64% more computationally expensive than the 15% fine-scale approach.

Island Injection GA's with Multiscale Strategy

The strategy outlined above operates with a single population genetic algorithm. An alternative approach is to use island injection genetic algorithms (IIGAs), which have multiple subpopulations performing independent GA runs and exchanging the best individuals after a few generations. *Goodman et al* (1997) used an island injection topology that comprised of low resolution islands injecting solutions into a set of high resolution nodes in the optimization of composite structures. *Eby et al* (1997) used an IIGA to search at various levels of resolution within a given space for the optimal design of elastic flywheel. *Lin et al* (1997) tested several models and scales of parallel GAs in the context of job shop scheduling problems. *Babbar et al* (2002) used an IIGA which consisted of three islands, two of them working with the coarse grid and one on the fine grid. The islands working on the coarse grid periodically injected their best solutions into the fine grid population while also exchanging solutions among themselves after a specific number of generations. However, this approach produced results that were much more computationally intensive than the SGA using the fine grid alone. Our hypothesis is that the failure may be due to inefficiencies in load balancing among the parallel processors when 2 of the 3 populations are using the fast coarse grid and one population is using the slower fine grid.

In this study the IIGA consist of three islands (depicted in Figure 4), each searching for the optimal solution using the multiscale strategy described above. The percentage of the total population tested on the fine grid is varied on the different islands. The islands will exchange their best individuals at the higher resolution (fine scale) after a fixed number of generations. Best individuals of fine scale migrate from one island to other and replace the worst individuals of the same scale there. Though transferring of individuals should result in exchange of good building blocks, excessive migration would lead to premature convergence (Cantu'-Paz, 1999). Thus different migration rates would be tested to observe their effect on the attainment of the final solution.

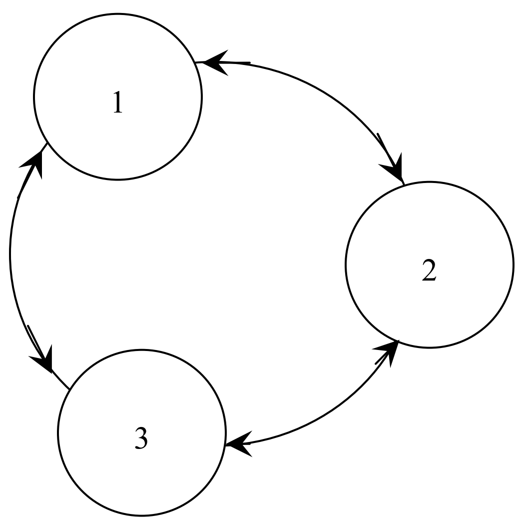

Figure 4. Island Injection Topology

Future Work and Conclusion

From the results of the single-population multiscale approach, it is observed that the approach with 15% of the population evaluated at the fine scale performed much better than the other two approaches. However, the results obtained may vary depending on the starting population or the case study considered. Results with different starting populations, along with the new IIGA scheme, will be presented at the conference.

Acknowledgements

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