

OPTIMIZATION OF WASTEWATER DESIGN USING GENETIC ALGORITHMS

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Abstract

Recently, at Brigham Young University, graduate students in the Environmental Engineering Laboratory have been exploring the possibility of using Genetic Algorithms for the optimization of wastewater treatment design. This research applies the IAWRC ASM no. 1 model for solving a four-stage Bardenpho process system using a tournament style selection genetic algorithm. The mathematical model was solved in Maple, and programmed in C++ using a Gauss-Seidel iterative method. Final results will be available in June 2003.

Introduction

“If we knew what is was we were doing, it would not be called research, would it?” – Albert Einstein, 1941

In recent years, there has been much debate and speculation about the exploration of the planet Mars, manned and unmanned. Eventually, the United States will send human explorers to Mars. As with any prolonged human voyage, whether a family road trip to Disney World, or manned interplanetary travel, problems associated with waste and waste disposal have to be solved. However, unlike the family road trip, any waste that is generated will have to be reclaimed of its constituents to the maximum extent possible because a spaceship is a closed environment.

Interplanetary space travelers do not have the option of obtaining more resources when needed.

The most essential resource needed for interplanetary space travel, besides oxygen, will probably be water. Water is essential to all life forms. In the future, most prolonged space flights will require some sort of treatment and recycling of water. This research paper explores the application of genetic algorithms to the optimization of wastewater treatment design.

First, the International Association on Water Pollution Research and Control's (IAWRC) Activated Sludge Model no. 1 will be discussed, along with the mathematical solution to the model. Next, the design that will be optimized in this problem, the four-stage Bardenpho process, is explained. Finally, the genetic algorithm being used is explored, with some consideration given to future directions in the research.

Background

Activated Sludge Model no. 1

In 1983, the IAWRC formed a task group to “facilitate the application of practical models to the design and operation of biological wastewater treatment systems (Grady et al., 1986).” The task group recognized that although physical models are useful in design, the cost of lab-scale reactors is still sufficient to prevent the exploration of

all potentially feasible solutions. Mathematical models allow the engineer to quickly explore other possible solutions and designs.

Although models had been used for years in biological wastewater design, most models were based on empirical models, developed by using a statistical approach to make end results of the model match measured results from the physical model. This approach had two main limitations. First, predictions could only be reasonably extrapolated to designs that were physically similar to the test physical model, and to where the governing assumptions were still valid. Second, many of these models and design methods were proprietary, and their use and application was very limited. In 1986, the task group released their report, including the IAWRC Activated Sludge Model no. 1 (ASM coefficients in the column times their respective reaction rates.

no. 1). ASM no. 1 presents the constituents of wastewater, along with the associated reaction rates and processes. By the promulgation of a kinetically based mathematical model, new, non-traditional system designs could be explored by researchers and engineers across the field.

The ASM no. 1 matrix format model is presented in Figure 1. below. It is in a convenient matrix format that allows for easier programming and understanding. In the left-most column are the eight kinetic processes modeled. For the complete ASM no. 1, please see Grady et al., 1986, or Grady, Daigger, and Lim, 1999. Across the top are the constituents of wastewater the model accounts for. On the rightmost column are the eight process rate equations. In order to calculate the rate of change in a constituent, one sums the kinetic

Figure 1. Process Kinetics and Stoichiometry for Heterotrophic Bacterial Growth in an Aerobic Environment (Grady et al., 1986)

		1	2	3	Process rate, r_{ji} $\text{ML}^{-3}\text{T}^{-1}$, p_j
j	Component → i	X_B	S_S	S_O	
j	Process				
1	Growth	1	$-\frac{1}{Y_H}$	$\frac{1-Y_H}{Y_H}$	$\hat{\mu} \left(\frac{S_S}{K_S + S_S} \right) X_B$
2	Decay	-1		1	bX_B
Observed conversion rates, $\text{ML}^{-3}\text{T}^{-1}$		$r_i = \sum_j r_{i,j}$			
Stoichiometric Parameters:					Kinetic Parameters:
True Growth Yield: Y		Biomass $\text{M}(\text{COD})\text{L}^{-3}$	Substrate $\text{M}(\text{COD})\text{L}^{-3}$	Oxygen (Neg. COD) $\text{M}(\text{COD})\text{L}^{-3}$	Maximum specific growth rate: μ Half-velocity constant: K_S Specific Rate Constant: b

Genetic Algorithms

Genetic Algorithms vs. Classical Optimization

Genetic Algorithms mimic natural evolutionary principles in order to find optimal solutions for given design problems. These stand in stark contrast to classical optimization techniques. Most classical optimization techniques use a deterministic procedure for approaching an optimal solution. These types of algorithms start with a random guess solution. Then, based on a pre-determined transition rule, a search direction is determined. A unidirectional search is then performed along this direction to find a best solution. This solution then becomes the starting point for a new search. Usually, the new search direction is determined from local conditions. Algorithms of this type differ mainly in the way the search direction is computed at each intermediate solution.

Classical optimization techniques have several weaknesses that make them difficult to apply to wastewater optimization problems.

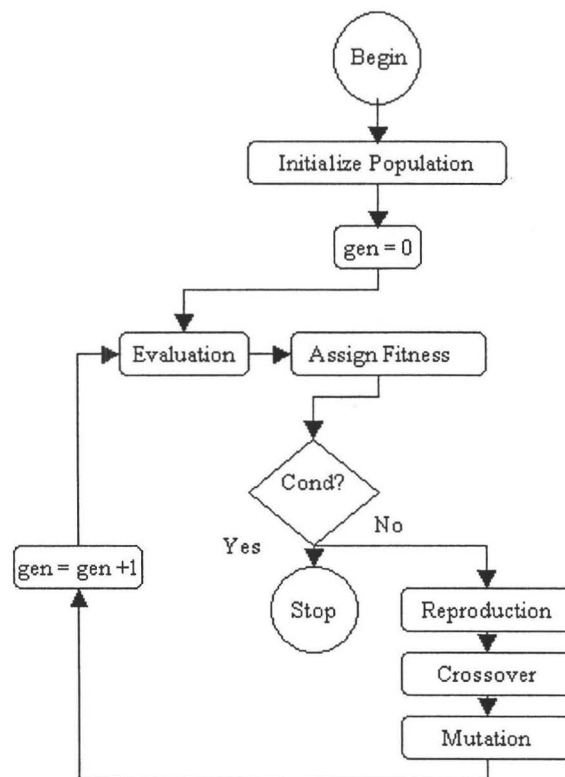
First, the convergence to an optimal solution depends on the chosen initial solution. Although this may not matter as much when the problem is a straightforward optimization of a chosen design, and not a typology problem, our eventual plans are to be able to solve typological design problems. Second, most classical algorithms become “stuck” in local maximums or minimums, whereas designers are generally seeking the global maximum or minimum. Third, classical algorithms are not as effective at handling a discrete search space (Deb 2001).

As their name suggests, Genetic Algorithms (GA) borrow their working principles from the principles of natural genetics. The overall algorithm can be seen in Figure 2. GA's begin by randomly creating an initial population of designs (solutions).

Every parameter needed to define a solution is represented as a binary number. An arbitrary, although finite precision for any decision variable can be achieved by simply using a long enough string. The decision variable strings are then put in a predefined order to create a pseudo-chromosomal representation of a solution. The initial population of designs is created by making arbitrary strings of ones and zeros.

Each design is then evaluated, and a fitness is assigned based on the underlying objective and constraint functions. In most cases, where there may be one objective function, the fitness is made equal to the objective functions value. At this point, the genetic operator parts of the algorithm come into play.

Figure 2. A flowchart of the principle of a GA (Deb 2001).



Although there are many methods in the literature used to create a "mating pool" for the next generation of design, we used the 'tournament' style of selection. First, each of the designs were randomly paired against another solution. The solution with the lowest fitness number (in our case, we are minimizing our objective equations) was copied, and the copy of its 'DNA' was placed in the gene pool. Next, each of these winners was randomly paired against another solution from the winner pool. Copies of the winners from this tournament round are placed in the gene pool. Finally, a consolation tournament round is created by randomly pairing each of the first round losing solutions, and a copy of the winners of this round are placed in the reproducing pool. The end result of the tournament is that of a population of sixteen solutions, four solutions would get two copies of their DNA in the gene pool, eight solutions would get a single solution, and the four double 'loser' solutions would be eliminated from the gene pool all together.

Next, two strings of DNA are randomly selected to be "mated." Their binary DNA strings are placed side-by-side, and a bit-wise swapping operation is performed from a randomly selected crossover site.

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110100110010 | 1110011110
110010100101 | 0110111001

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This operation forms two new designs, which would appear as

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110100110010 | 0110111001
110010100101 | 1110011110

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The reproduction algorithm continues until a new population of designs is generated. In order to perform a search operation, an element of variability is introduced by allowing a small probability of a mutation occurring for a given solution. If a mutation

occurs, a site on the DNA strand is randomly selected, and the binary 1 or 0 is switched to a 0 or 1. For example,

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1101001100 | 0 | 110111001
              | 10 |

```

becomes

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1101001100 | 1 | 110111001
              | 10 |

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after a mutation operation. The process of the GA is repeated until the specified number of generations is reached.

As can be seen above, the GA is more powerful than classical optimization techniques for problems that form a Pareto set, where there may be more than one non-dominating solution. Furthermore, convergence on the optimal set of solutions does not depend on a correct initial guess. The introduction of random mutations also prevents the algorithm from being trapped by local minima or maxima.

Methods and Materials

For initial testing of our concept of using GA for the optimization of wastewater design, we chose to optimize a four-stage Bardenpho process. The Bardenpho process was created to achieve ammonification and denitrification of wastewater without the need of an additional carbon source. A limitation of this type of design for space-based application is the fact that it is gravity driven. But the strength of the GA is that it can be applied to forced-flow systems with some sort of non-gravity-driven filtering system.

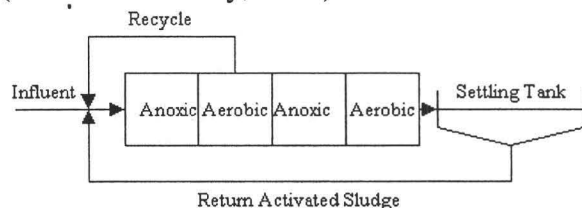
All programming was accomplished using Microsoft Visual C++ Studio 6.0.

Four Stage Bardenpho Process

The Bardenopho process is one example of process designs that use a series of

anoxic and aerobic reactors in series. An anoxic reactor is not an anaerobic condition, but rather it uses available nitrates as the electron acceptor for respiration rather than oxygen. As the influent enters the second stage reactor, any ammonia is converted into nitrate and nitrite, which are recycled back to the first reactor. In the first reactor, anoxic bacteria breakdown organic waste using nitrogen compounds as the electron acceptor, and also form denitrification by converting the nitrogen into the N_2 form. In the settling tank, the microorganisms are settled out of the effluent, and are recycled to the beginning of the process.

Figure 4. Four stage Bardenpho process (Metcalf and Eddy, 2003).



Gauss-Seidel Method

Because the ASM no. 1 is a system of partial differential equations, the system mass balance was solved for the steady state condition. Using Maple, each constituent was isolated, and a Gauss-Seidel iterative method using C++ was used to solve for the steady-state effluent of each reactor.

C++ Code

C++ coding was used for its ease in data management and storage. Two separate classes were created, a design class, and a reactor class. The design class included four reactor class member functions, along with a constructor that creates the design from the DNA string.

Results

This research project is still being developed. Results will be available in May, 2003.

Future Directions

Ultimately, for a given wastewater and its associated kinetic parameters, the GA will be able to create a population of optimal designs that will be able to optimize non-traditional aspects of plant design. For example, in space-based applications, it will be very important to minimize parameters such as size and weight, oxygen requirements, electrical power requirements, etc. This research project explores the feasibility of applying GA's for the optimization of a pre-defined process. The next step will be allowing the GA to solve a typology problem, which will create new and novel processes. Furthermore, GA's can be used to optimize the operation of a design for a different wastewater condition other than what it was initially designed for.

Literature Cited

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