Combining Genetic Algorithms with a Water Quality Model to Determine Efficiencies of Sewage Treatment Systems in Watersheds

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Abstract: The implementation and operation of wastewater treatment plants are fundamental actions for environmental water body pollution control that generally involve large amounts of financial resources. Hence, employment of optimization techniques for decisions about the minimum required wastewater treatment plant efficiencies might be very useful. In this study, an optimization technique known as the genetic algorithm (GA) was combined with a water-quality model to determine the minimum efficiencies for sewage treatment in watersheds. Combinations of the optimization technique and models that incorporated environmental quality standards for the parameters of dissolved oxygen (DO), biochemical oxygen demand (BOD), and equity measures among sewage treatment systems, either as constraints or in the objective functions, were developed. These combinations were applied to the Santa Maria da Vitória river watershed, located in the State of Espírito Santo, Brazil, considering possible effluent disposal scenarios and implementation of different established optimization models. The developed combinations of the genetic algorithm and a water-quality model demonstrated to be versatile and efficient tools for determining the minimum sewage-removal efficiencies for wastewater treatment plants in watersheds. Among the developed combinations of optimization models, the best results, or minimum costs, were obtained when the rivers' self-depuration capabilities were taken into account. **DOI: 10.1061/(ASCE)EE.1943-7870.0001048.** *© 2015 American Society of Civil Engineers.*

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Introduction

Planning and management of water resources are very important tools for the establishment of guidelines and actions for water use, control and conservation, particularly in regions where there is a water shortage. The publication of Law No. 9433 in 2007, which established the National Water Resources Policy (PNRH), was a milestone in the evolution of the management of water resources in Brazil. New management tools were introduced as basin plans, granting of right of use, classification of water bodies, information systems, and charging for water use. For proper implementation of these new instruments, it is necessary to develop various computer support decision-making tools (Machado et al. 2012).

Water quality and self-purification mathematical models are important tools for the management of water resources. These models may be used both for prevention and control of water resources degradation. The applications of these models include choice of location for enterprises potentially generating water pollution, definition of minimum wastewater treatment efficiencies for maintaining water-quality parameters inside standard limits, location of the critical sections of river pollution, and forecasting water-quality parameter values over time and space.

The environmental aspects of hydrodynamic and river basins are essential for the modeling of water body quality, in evaluating the pollution control alternatives, as noted by Li et al. (2014), Oliveira et al. (2012), Chen et al. (2011), and Fang et al. (2008). Using water bodies for domestic sewage disposal is one of the primary pathways for environmental degradation. Therefore, the implementation of sewage treatment stations is a primary strategy for pollution control.

A watershed can have several final disposal points for effluents, with considerable qualitative and quantitative variations and watercourses with substantially different hydrodynamic characteristics. Hence, the process of selecting a sewage treatment system is complex, which is why it is useful to combine optimization methods with models for water-quality simulation in this context. Studies by Andrade et al. (2013), Albertin et al. (2006), Tsai and Chang (2001), Zhang et al. (2012), Singh (2011), and Pettelier et al. (2006) provide examples of this approach.

Andrade et al. (2013) found that the application of water-quality simulation models allows the analysis of alternative scenarios and water systems' behavior studies; however, unlike optimization, this method does not seek the best or optimal solution, indicating that a joint application of simulation models and optimization techniques could be useful.

Several methods have been used to solve optimization problems in water resources. Aras et al. (2007) and Cho et al. (2004) noted that conventional mathematical programming methods such as linear programming, nonlinear programming, and dynamic programming have been repeatedly used to solve cost-minimization problems in sewage treatment systems. The development of

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computers and software techniques has contributed to the application of new optimization methods, such as fuzzy logic, artificial neural networks, genetic algorithm, simulated annealing, and ant colony algorithms (Jairaj and Vedula 2000; Reis and Akutsu 2002; Tung et al. 2003; Albertin et al. 2006).

The genetic algorithm (GA) is a research algorithm that is analogous to the theory of the evolution of the species and is used to solve optimization problems. In the water resources field, GA is being used widely to optimize the allocation of limited resources among diversified and typically conflicting uses. Examples of the application of GA in the area of water resources can be found in studies by Chenari et al. (2014), Liu et al. (2014), Nicklow et al. (2010), Carvalho and Kaviski (2009), Aras et al. (2007), Kerachian and Karamouz (2007), Saadatpour and Afshar (2007), Albertin et al. (2006), Park et al. (2006), Yandamuri et al. (2006), Ahmed and Sarma (2005), Cho et al. (2004), Burn and Yulianti (2001), and Vasquez et al. (2000).

In this study, the combined use of a water-quality model and GA was used to select the minimum efficiencies for organic matter removal, which is a preliminary stage in the selection process of sewage treatment systems for a watershed.

Genetic Algorithm

The GA is a direct-search stochastic optimization method that was inspired by the evolutionary mechanisms of species and is based on population genetics, survival, and the adaption processes of individuals.

Studies on the phenomenon of natural evolution and its occurrence in nature have provided characteristic mechanisms of the evolution process that have been incorporated into computational systems. The population size, selection type, crossover, mutation, and stoppage criteria are among the most traditional GA operators and parameters (Nicklow et al. 2010). Fig. 1 shows the generic stages of GA that are used in optimization problems.

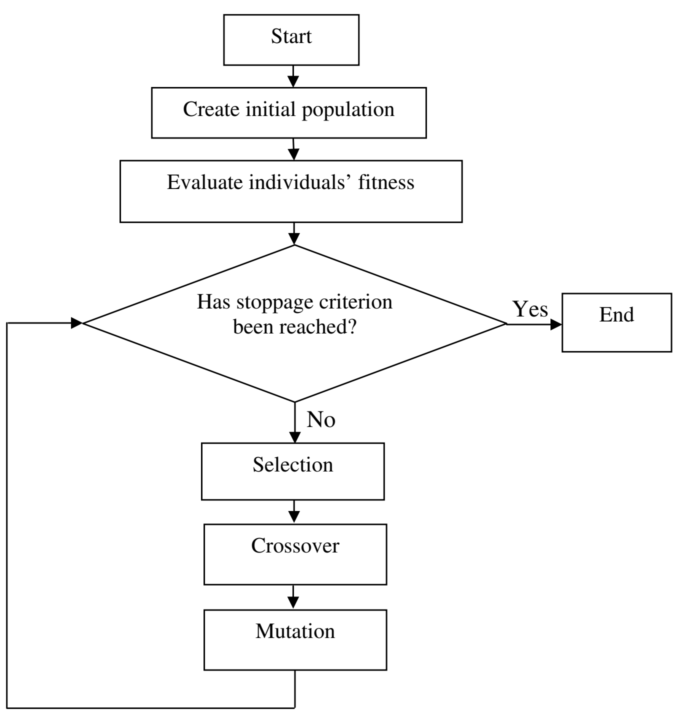

Fig. 1. Generalized chart of GA

Mulligan and Brown (1998) described the implementation of a genetic algorithm as follows: An initial population of a random set of N chromosomes (usually a vector or a chain of bits) is generated that represents possible solutions to the optimization problem. The population size depends on the features of the problem. However, for large populations, the process is similar to an exhaustive search in terms of the processing time. The choice of the population size is usually determined by the user or by using a heuristic technique.

A chromosome usually represents a set of parameters that is used in objective functions whose responses are to be maximized or minimized. Each chromosome is associated with a fitness value, i.e., a grade that indicates the quality of the codified solution, which is used to denominate the individuals in the population. The fitness value of an individual is usually determined from the value of the objective function that is associated with the individual itself; therefore, the fitness value strongly influences the selection process within a population. Lacerda and de Carvalho (1999) indicated that, depending on the problem, it is inadequate to use an objective function value as a fitness value, because objective functions with negative values invalidate some selection methods, and the selection process becomes random if the values of the objective function are very closely spaced. Moreover, an objective function with a very high value may result in premature convergence.

Lacerda and de Carvalho (1999) have identified objective function mapping techniques (fitness scaling) to overcome these problems. Fitness scaling converts the fitness value returned by the objective function into values that can be used to select individuals. Bento and Kagan (2008) used rank to adjust the objective function. In this strategy, the positions of the individuals are ranked according to fitness to determine the selection probability for the next generation. Even if one individual has a much higher fitness than the other individuals, the ranking process can prevent premature convergence in the selection process to a certain extent because this *super individual* will always have the same probability of selection, which is independent of the objective function.

GA was inspired by the natural selection process for living beings and uses different selection methods to choose individuals from the initial population. A fitness ranking is then used to produce an intermediate population, which finally results in a new generation of *offspring individuals*.

Among the different techniques that are available in the literature, one—known as the roulette wheel—is used in the classical algorithm. Grosko et al. (2006) described this technique in terms of assigning a survival probability for the next generation to each individual. This probability is proportional to the fitness, in which the fittest individuals have the highest possibility of being raffled. Deb (1997) observed that one of the problems of this method is the strong selection pressure. That is, there is a tendency among all of the individuals to converge quickly to the same point, which is not necessarily the global maximum, primarily if the fitness value of one individual is much higher than that of the other individuals.

Another commonly used selection strategy is known as *tournament selection*. Lacerda and de Carvalho (1999) stated that in tournament selection, a group of individuals (with equal probabilities) is randomly selected from the population. The group participates in a tournament, and the winner is the fittest individual. This individual is selected for the intermediate population. The process is repeated N times until a new population is obtained.

Lacerda and de Carvalho (1999) stated that after a population is selected, GA applies crossover and mutation operators (the primary GA mechanisms) to generate offspring individuals, thereby exploring unknown regions of the search space.

The crossover operator is applied with a certain probability to each pair of selected individuals of the population (called *parent* individuals), which produces two offspring individuals through the exchange of genetic information. Mutation acts on the population through the insertion of new genetic material into some individuals, and this genetic change provides the algorithm with a larger scope to search for the desired solution.

Different types of crossover are used for both the binary representation and actual representation of chromosomes. The most well-known crossover operators for chains of bits are operators for N points and the uniform crossover. For the crossover of one point, a random cut is applied to the chain of bits that generates two halves in each parent chromosome. These halves are exchanged, thus generating two new offspring individuals. For the crossover of two points, two random cuts are chosen, and the sections between these two points are exchanged between the parents.

Lacerda and de Carvalho (1999) stated that when a uniform crossover is applied, a mask of random bits is generated for each pair of parents. If the first bit of the mask has a value of unity, then the first bit of parent_1 is copied to the first bit of offspring_1. The process is repeated for the remaining bits of offspring_1. The process is inverted in the generation of offspring_2; that is, if the bit of the mask is unity, then the bit of parent_2 is copied. If the bit is zero, then the bit of parent_1 is copied.

Lacerda and de Carvalho (1999) observed that conventional operators (i.e., the crossover of N points and the uniform crossover) work well in binary representation. However, conventional operators exchange gene values in actual representation and therefore do not create new information.

Michalewicz (1994) developed several operators for actual representation, including the arithmetic crossover, the heuristic crossover, the simple crossover, the uniform mutation, the limit mutation, and the nonuniform mutation. Combining these operators into the same GA produced a superior performance than the traditional binary GA.

Study Area

The study area is located in the upper part of the Santa Maria da Vitória River basin, which is an important source of water for the Great Vitoria metropolitan area, located in the state of Espírito Santo, in southeast Brazil.

The Santa Maria da Vitoria river watershed presents a drainage area of approximately 1,660 km^2, with altitudes ranging from 0 to 1,300 m. Its perimeter is equivalent to 291 km. It is limited to the east with Victoria Bay, to the north and west with the Reis Magos and Doce river basins, and to the south with the Jucu, Bubu, and Formate river basins (Habtec 1997).

The region of study lies upstream from the Rio Bonito hydropower plant dam, covering approximately 616 km^2. In this area, the Santa Maria da Vitória reach is 42 km long and presents the Alto Posmoser and São Luiz rivers as main tributaries. Zorzal (2009) highlights, for the study area, the cultivation of vegetables, livestock watering, and agriculture. Fig. 2 shows the location of the study area. Fig. 3 presents a line diagram representing the studied water system.

Methodology

Water Quality Model

A computational model was developed in *MATLAB* to simulate the water quality of the system. This numerical model accounted for the physical interactions in mixing and the biological reactions that characterize the natural self-depuration process of the water body, thus reproducing the mathematic formulations and conceptual and computational structures of the QUAL-UFMG model, which Von Sperling (2007) explained in detail.

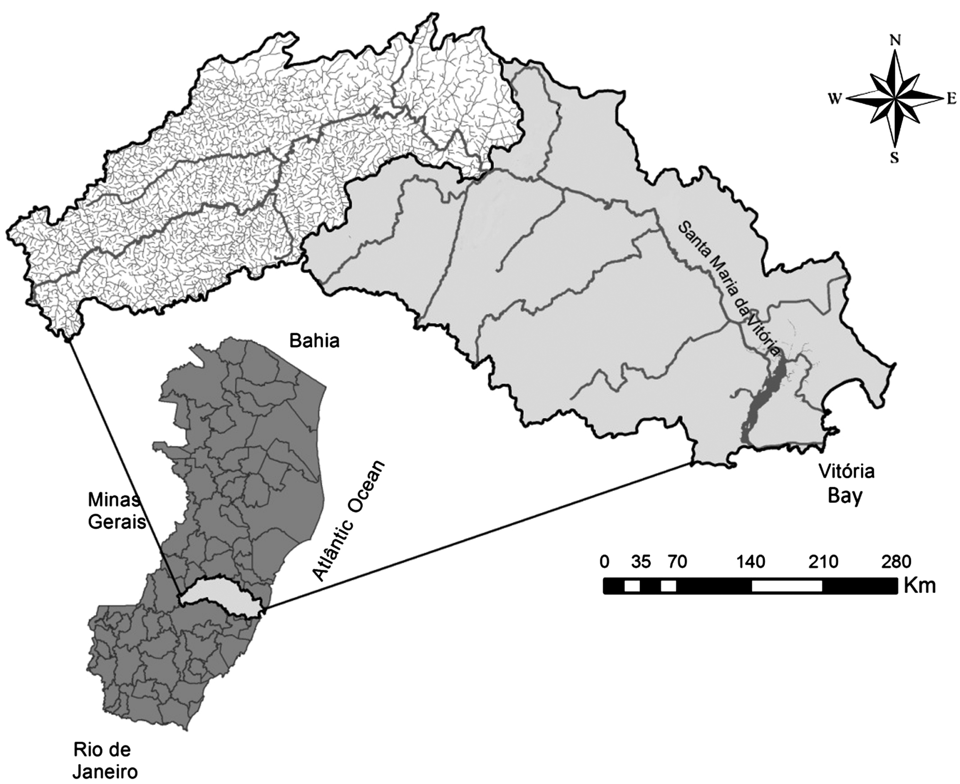

Fig. 2. Location of the study area

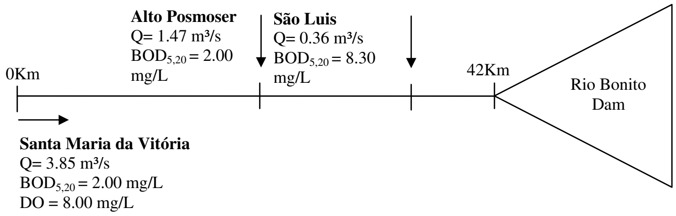

Fig. 3. Diagram of upper part of Santa Maria da Vitória River

The QUAL-UFMG model is based on the QUAL2E model and was implemented using a Microsoft Excel worksheet. The model enables water quality to be simulated by modeling biochemical oxygen demand (BOD), dissolved oxygen (DO), total nitrogen and its fractions, total phosphorus and its fractions, and thermotolerant coliforms. The model is a simplified version of QUAL2E. For example, the interactions between the algae and the other constituents were neglected; longitudinal dispersion was excluded from the mass balance equation; and the Euler method was used to perform the integration.

Von Sperling (2007) noted that the decision to disregard the interactions with algae in the modeling process was based on the knowledge that the processes involving algae are extremely complex and the coefficient values are not easily determined, apart from the fact that interactions with the algae present significant results only in lentic environments.

Integration by the Euler method is the simplest form of integration, and is easily understood by Excel spreadsheet users. In most simulations of varying concentrations of constituents in rivers and pollutant transport in watercourses, steady-state conditions can be modeled by neglecting the longitudinal dispersion term, as the concentration gradients are small for this type of flow.

The QUAL-UFMG model, in addition to not requiring large amounts of data to feed its system, has a good user interface that makes it easy to handle information and to analyze results. For the calculation of constituent concentration profiles, the piston flow reactor dynamics were considered, in which the advection is used as the only transport mechanism.

Computational elements are used in the model to describe incremental flows of tributaries and sewage along the entire extension of the water body, corresponding to contributions from direct drainage or diffuse pollution.

The water quality was modeled by segmenting the river into 42 parts or computational elements (integration units). These computational elements had constant lengths and were considered to be completely mixed. Therefore, the parts represent groups of completely mixed reactors with common hydro-geometrical characteristics and biological rates. The water balance for each element was written as a function of the inflows and outflows.

The water-quality model was used to simulate the concentration profiles for the BOD and the DO, which are the main water-quality parameters for domestic sewage discharges.

Different types of scenarios were simulated considering a combination of different points of domestic sewage disposal with different flows. In the distribution of inflow points, the location of potential places of sewage generation was considered along the studied stretch. The simulation scenarios were characterized as follows:

- Scenario A: Five effluent discharge points presenting the same loads, without any type of treatment ($P1 = P2 = P3 = P4 = P5 = 40$ L/s) into the Santa Maria da Vitória River at 8, 16, 25, 32, and 40 km; and
- Scenario B: Five effluent discharge points presenting different pollution loads. The water-quality parameters of the effluents were the same as those for Scenario A, but with different flows ($P1 = 60$ L/s, $P2 = 50$ L/s, $P3 = 40$ L/s, $P4 = 30$ L/s, and $P5 = 20$ L/s).

For all of the effluents, the raw sewage was considered to have a $BOD_{5,20}$ of 350 mg/L and a DO concentration of zero.

The data for the kinetic constants, hydrodynamics, and water-quality parameters used in this study were the same as those used by Salim (2004) and Mendonça and Almeida (2005) in their analyses of domestic sewage-disposal problems for the same water system.

The kinetic constants for de-oxygenation (K_1) and atmospheric re-aeration (K_2) processes were 0.24 and 0.98 day^{-1}, respectively. The saturation-estimated DO concentration was 8.00 mg/L^{-1}, considering an average altitude of 900 m and water temperature of 21°C for the region under study by using an expression developed by Pöpel (1979).

The scope of the present work does not include the validation of the results with experimental (field) data, because its main objective is to propose an optimization tool, combined with a water-quality model that could be applied generally as a decision-making support for water resources management.

Optimization Models

The following assumptions were made in developing the optimization models in this study:

1. High efficiencies in sewage treatment systems correspond to a higher investment to implement, operate, and maintain these systems. Therefore, it is more convenient to adopt lower treatment efficiencies, which are technologically simpler, thereby enabling public resources to be used in other needed areas;
2. The final disposal of raw sewage in water bodies (BOD removal efficiency = 0%) was considered as an option. Thus, it was assumed that all of the discharged BOD load could be assimilated because of the self-depuration capacity of the stream;
3. The DO and BOD Brazilian environmental quality standards had to be met in the entire water system according to the classification and the preponderant watershed uses, considering the Resolution No. 357/2005 (Brazil 2005) of the National Environment Council (CONAMA);
4. The maximum allowable value for the treated sewage BOD was 120 mg/L, and the minimum allowable BOD removal efficiency was 60%, as recommended by CONAMA Resolution No. 430/2011 (Brazil 2011); and
5. The required removal of organic loads at defined as discharge points along the basin were taken to be proportional to the pollution load at each discharge point. This assumption corresponded to the polluter-payer principle (Luppi et al. 2012) by which higher investments for sewage treatment are imposed on users with higher pollution potential.

Different groups and optimization models were determined for various combinations of the previously mentioned assumptions.

Optimization Model I

In this model, the objective function [Eq. (1)] was formulated to minimize the sum of the treatment efficiencies in the basin. This approach was formulated to lower the expenditures for sewage treatment (Assumption 1). The environmental standards associated with the BOD and DO for CONAMA class 2 rivers were used as constraints on the optimization model [Eqs. (2) and (3)]. The watercourses in the Santa Maria da Vitória river basin were not subjected to a legal framework process and have therefore been classified as class 2 rivers by CONAMA Resolution No. 357/2005.

$$\text{Minimize } f(E) = \sum_{i=1}^{5} E_i \tag{1}$$

Subject to

$$DO_{River} \geq 5 \text{ mg L}^{-1} \tag{2}$$

$$BOD_{River} \leq 5 \text{ mg L}^{-1} \tag{3}$$

In Eqs. (1)–(3), E_i represents the treatment efficiency for the discharge i, DO_{River} is the DO of the watercourse, and BOD_{River} is the BOD of the watercourse.

Additional constraints on the optimization model were incorporated to meet the environmental standards on the effluents. These constraints corresponded to three different optimization groups, which are defined as follows:

- Group 1—$E_i \geq 0$: The minimum BOD removal value (60%) was neglected, and the maximum BOD value of the treated sewage (120 mg/L) corresponded to that from CONAMA Resolution No. 430/2011; final disposal of the raw effluents was an option if these effluents met the conditions, standards, and requirements of CONAMA Resolution No. 430/2011. In this group, all of the BOD load could be assimilated as a result of the self-depuration capacity of the watercourse;
- Group 2—$BOD_{TreatedSewage} \leq 120$ mg/L, according to the maximum raw sewage BOD established by CONAMA Resolution No. 430/2011; and
- Group 3—$E_i \geq 60\%$, according to the minimum BOD removal efficiency established by CONAMA Resolution No. 430/2011. Discharges of treated sewage with BOD concentrations higher than 120 mg/L were allowed in this group.

Equity among discharges was incorporated into the optimization model as an additional constraint [Eq. (4)], which required the highest treatment levels for the highest organic loads.

$$\frac{\text{Load}_{\text{Discharge}\, i}}{E_i} = \frac{\text{Load}_{\text{Discharge}\, n}}{E_n}, \quad \forall\ i \text{ and } \forall\ n \tag{4}$$

In Eq. (4), $\text{Load}_{\text{Discharge}\, i}$ represents the organic load of the raw sewage for discharge i, $\text{Load}_{\text{Discharge}\, n}$ is the organic load of the raw sewage for discharge n, and E_n is the treatment efficiency for discharge n.

Optimization Model II

The second optimization model consisted of an objective function that minimized the inequity among the discharge points. The second optimization model was formulated by assuming that the equity among discharge points was not compulsory, which would only be the case if the equity measure was introduced as a constraint in the optimization problem. The objective function associated with the second optimization model is given by Eq. (5). The constraints on this optimization model were the same those on Optimization Model I

$$\text{Minimise} \sum_{i=1}^{n} \sum_{i=j}^{n} \left[\left(\frac{\text{Load}_{\text{Discharge}\,(i)}}{E_{(i)}} \right) - \left(\frac{\text{Load}_{\text{Discharge}\,(j)}}{E_{(j)}} \right) \right]^2 \tag{5}$$

Optimization Model III

The third optimization model had an objective function with two different objectives. The *cost of treatment versus equity* ratio among the domestic sewage discharges was introduced in the objective function to minimize both the implementation costs of the sewage treatment stations and the inequality among the discharges. The assumption that sources with higher polluting loads were subjected to higher treatment levels was retained.

The multiobjective problem resulting from the third optimization model was solved using the weight method (Gass and Saaty 1955; Zadeh and Desoer 1963; Albertin 2008), in which weights were assigned to the different terms of a single objective function. The choice of weights reflected the *importance* of each of the terms in the objective function. The subjectivity of the weight-selection procedure is one of the disadvantages of this method. Park et al. (2006) emphasized that additional studies are needed to determine the weights for the terms of the objective functions, because weights are typically selected without a specific criterion.

The weight method was applied by first identifying equivalent terms in the objective function by assuming values of p_1 and p_2 that would have the same significance for multiple objectives. Next, alternate values of p_1 and p_2 were used to favor one of the terms in the objective function. Eq. (6) shows the objective function for Optimization Model III

$$\text{Minimise } p_1 \times \sum_{i=1}^{n} E_i + p_2 \times \sum_{i=1}^{n} \left(\frac{\text{Load}_{\text{Discharge}\,(i)}}{E_{(i)}} \right) - \left(\frac{\overline{\text{Load}_{\text{Discharge}}}}{\bar{E}} \right) \tag{6}$$

A preference for the term associated with the sum of the efficiencies corresponded to Optimization Model III-A. Optimization Model III-B corresponded to the preference of the decision makers being oriented to the term for equity among discharges. Optimization Model III-C corresponded to the two terms of the objective function being equally significant.

Lower and upper limits of 0 and 90%, respectively, on the BOD removal were considered for all of the optimization models in this study.

GA Application

The more traditional parameters and AG operators are the population size, type of selection, number of generations, probability of recombination, and mutation probability. The determination of these parameters is one of the main GA difficulties.

Combinations were performed among operators and genetic parameters as generally presented in the literature. Thirty combinations were performed. The algorithm was executed three times for each combination of parameters and operators, and the lowest sum of the efficiencies was recorded. The best combination of parameters and operators was applied to the other optimization methods. Thus, the combination of operators was defined for testing. This stage of the study involved only the first optimization model.

The primary parameters and their values that are most commonly used in water-quality management problems were selected from the current technical literature to determine the GA parameters that were used to solve the optimization problem.

Lianhai et al. (2010), Chen-Guang et al. (2010), and Holenda et al. (2007) showed that a population of 20 individuals was sufficient for the convergence of solutions without requiring a large processing time. In this study, in addition to a population of 20 individuals, the GA responses to populations of 100, 200, 300, and 500 individuals were also evaluated.

The fitness value of the chromosome was used to select individuals from the initial population to create an intermediate population that would undergo the crossover and mutation processes to yield the next generation. The roulette-wheel and tournament strategies were applied in this study. Ten individuals from the initial population were randomly chosen for tournament selection. The individual with the highest fitness was chosen for the intermediate population. Selected individuals from the intermediate population were crossed, and the mutation operator was then applied.

Lacerda and de Carvalho (1999) found that the actual crossover rate varied between 60 and 90%. In this study, crossover rates of 50, 80, and 100% were used, based on studies by Louati et al. (2011), Holenda et al. (2007), Cho et al. (2004), Carvalho and Kavisk (2009), Chen-Guang et al. (2010), Lianhai et al. (2010), and Singh (2011).

The mutation rate should be chosen to ensure the diversity of the individuals. In the current application of the classic GA to optimization problems, a fixed and small value of the mutation rate between 0.1 and 5% is used. However, the adaptive feasible mutation was used in this study. R. Kumar ["System and method for the use of an adaptive mutation operator in genetic algorithms," U.S. Patent No. 7,660,773 (2010)] showed that the use of an adaptive mutation rate is more appropriate for constrained problems.

Elitism was applied to preserve and guide the most adapted individual in each generation to the next generation without being modified by the genetic operators. To avoid the selective pressure caused by the fittest individuals, three individuals were selected for the next population. Table 1 summarizes the different operators and parameters and their values that were considered in this study.

The optimization models used in this study were solved using the GA toolbox in the *MATLAB* software. An exhaustive search algorithm for scanning all of the possible treatment efficiency values for each scenario was developed to determine the global optimum of the optimization problem, which was used to evaluate the results of the application of GA.

Results and Discussion

In this section, the estimated sewage treatment efficiencies of the water systems from GA application are reported for (1) the first optimization model and the three optimization groups for Scenarios A and B of the simulation; and (2) the three optimization models for Scenario B of the simulation.

Table 2 lists the estimated efficiencies that were obtained using the first optimization model for the three different optimization groups with Scenario A.

Table 2 indicates that the lowest sum of efficiencies was produced for Group 1, for which the set of constraints enabled the algorithm to search for the best solution in the entire search space (i.e., efficiencies ranging from 0 to 90%). The second lowest sum of efficiencies was obtained for optimization Group 3 because of the set of constraints on this group that established minimum BOD removal efficiencies of 60% for effluent disposal in water bodies. Group 2 yielded the highest sum of treatment efficiencies, because

Table 1. Operators and Parameters Used in GA Application

Operator/parameter	Value/type
Codification	Real
Population size	300 individuals
Selection type	Tournament (groups of 10 individuals)
Crossover type	Arithmetic
Crossover rate	50%
Mutation type	Adaptive feasible
Stoppage criterion	100 generations or convergence of results
Elitism	Three individuals

Table 2. Estimated Efficiencies of Sewage Treatment Systems for Scenario A Obtained Using First Optimization Model

Optimization groups	Disposal points for treated effluents					$\sum$ Efficiencies
	P_1	P_2	P_3	P_4	P_5	
1	31	60	77	77	67	312
2	66	66	66	66	66	330
3	60	61	69	68	65	323

of the imposition of CONAMA Resolution No. 430/2011 (i.e., sewage disposal in rivers can only be performed after treatment and at BOD concentrations under 120 mg/L). Table 3 summarizes the estimated efficiencies from applying the first optimization model for the three different optimization groups with Scenario B.

For Scenario A, the 6,048 kg/d organic load that was collected from the urban areas of the basin was distributed evenly among the five effluent disposal points (i.e., 1,209.6 kg/d of organic load was treated per discharge point). For Scenario B, 6,048 kg/d of organic load was distributed along the water system; however, each discharge point had a different load because of the decreased flows. The disposed organic loads at the first to the fifth discharge points were 1,814.4, 1,512, 1,209.6, 907.2, and 604.8 kg/d, respectively. The different allocation of loads for discharge into the river reduced the sum of the organic matter removal efficiencies required for the sewage treatment stations (the sum of efficiencies is provided in Tables 2 and 3). This situation occurs primarily when the self-depuration capacity can be assumed to assimilate a considerable part of the organic effluents produced in the basin (Group 1 of the constraints).

This feature suggests that the correct management and/or scaling of the loads along a river may affect the water-quality conditions for water bodies in a watershed, which avoids the selection of a treatment system that underestimates the assimilation capability of rivers and consequently increases the implementation, maintenance, and operation costs of the sewage treatment stations.

Figs. 4–7 show the BOD and DO profiles associated with Scenarios A and B, in which the Santa Maria da Vitória River was considered as a CONAMA class 2 watercourse. Figs. 4–7 clearly show that the BOD concentrations in all of the simulated effluent disposal scenarios did not meet the standards set by CONAMA Resolution No. 357/2005. However, the DO concentration did not meet the environmental quality standards only when the boundary conditions for Scenario B were used.

The pollutant concentrations in the portions of the river in which the water-quality standards were not met could be brought into compliance by incorporating the efficiencies that were estimated using GA, independent of the effluent disposal scenario or the group of constraint considered.

Table 4 summarizes the results that were obtained using the different optimization models described previously for the first group of constraints and the effluent disposal condition for Scenario B.

Table 3. Estimated Efficiencies of Sewage Treatment Systems for Scenario B Obtained Using First Optimization Model

Optimization groups	Disposal points of treated effluents					$\sum$ Efficiencies
	P_1	P_2	P_3	P_4	P_5	
1	90	90	81	14	0	275
2	66	66	66	66	66	330
3	64	64	63	62	61	314

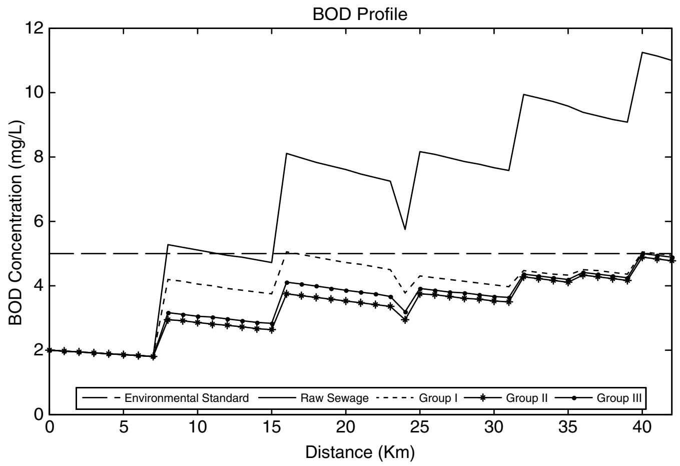

Fig. 4. BOD profile for Scenario A from solution to optimization problem

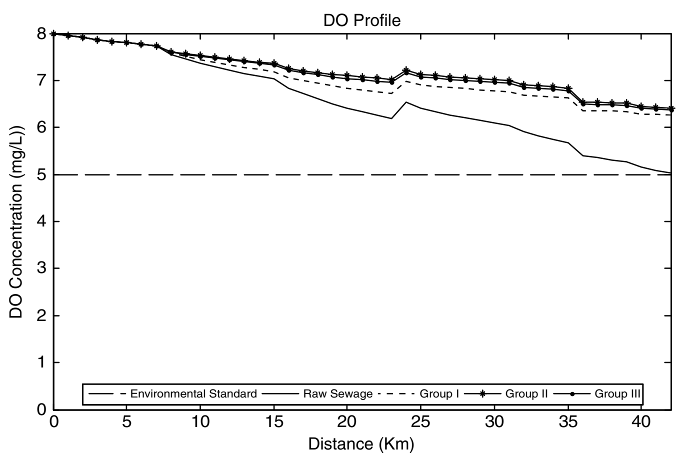

Fig. 5. DO profile for Scenario A from solution to optimization problem

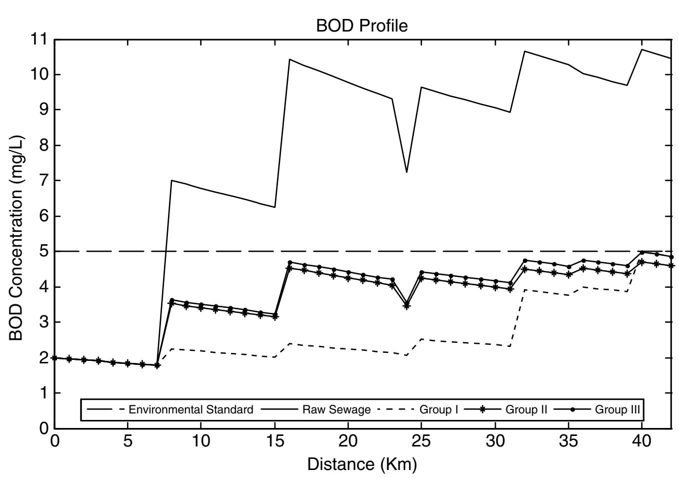

Fig. 6. BOD profile for Scenario B from solution to optimization problem

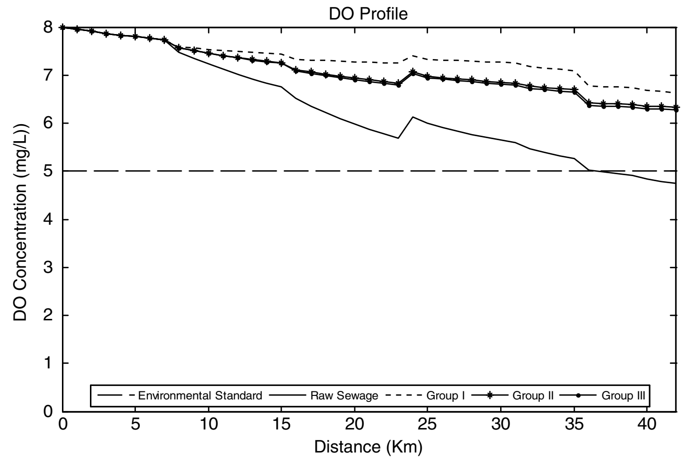

Fig. 7. DO profile for Scenario B from solution to optimization problem

The results in Table 4 show that the equity ratio between discharges was met using three out of the four developed optimization models. Models I, II, and III-B produced identical treatment efficiencies for the different discharges, and therefore the same equity value. Thus, discharges with higher organic loads required higher BOD removal efforts. Consequently, higher inflows of organic loads would require higher investments during the eventual implementation of the sewage treatment stations.

For optimization Model III-B, the minimization term of the sum of efficiencies was penalized; thus, a high weight was assigned to the term in the objective function that was associated with equity among discharges. In this model, the equity ratio was preserved. However, when the term associated with the minimization of the sum of the efficiencies was preferred over the term associated with equity among the effluent discharges (Model III-A), the algorithm produced a solution with the lowest set of estimated treatment efficiencies among the three developed optimization models, and equity was not met. This set of lower estimated efficiencies was quite close to the estimated value obtained for optimization Group 1, which maximized the self-depuration capacity of the rivers, as given in Table 3.

The results obtained using Optimization Model III-C demonstrated that the adopted weights (which did not preferentially give weight to any particular term in the objective function) neither met the equity measure nor significantly reduced the sum of the efficiencies.

Fig. 8 shows the evolution of the maximum fitness (i.e., the fitness of the highest individual in a population of solutions) and the mean fitness (i.e., the mean of the fitness grades of a population of solutions) across generations. The GA iterations shown in Fig. 8 converged rapidly to a solution in the eighth generation.

Table 5 compares the optimal solution that was obtained using the exhaustive search algorithm to that obtained using GA. Although the solutions were quite close in terms of the sum of the efficiencies, the exhaustive search algorithm required substantially higher processing times than the GA.

The percentage differences for the results obtained for the two scenarios were not sufficient to distinguish between sewage treatment systems: Less than 2% differences are not sufficient to differentiate between treatment levels and potential sewage treatment systems for implementation.

Table 4. Estimated Efficiencies for Scenario B Obtained Using Different Optimization Models

Optimization model	P_1	Equity	P_2	Equity	P_3	Equity	P_4	Equity	P_5	Equity	$\sum E_i$
Model I	90	20.16	75	20.16	60	20.16	45	20.16	30	20.16	300
Model II	90	20.16	75	20.16	60	20.16	45	20.16	30	20.16	300
Model III-A	89	20.49	86	17.55	67	18.22	37	24.53	0	—	279
Model III-B	90	20.17	75	20.17	60	20.17	45	20.17	30	20.17	300
Model III-C	90	20.17	83	18.22	61	19.83	40	22.68	12	50.40	286

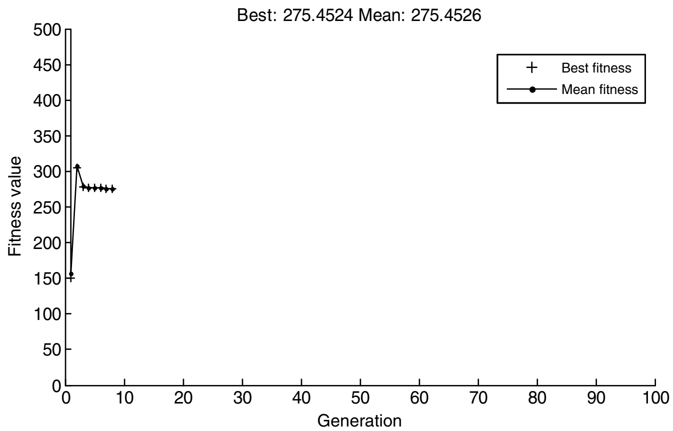

Fig. 8. Evolution of maximum and mean fitness of populations of individuals across generations

Table 5. Comparison of Results from Exhaustive Search and GA

Simulation scenario	Solution technique	Disposal points for treated effluents					$\sum$ Efficiencies	Processing time (s)
		P_1	P_2	P_3	P_4	P_5		
Scenario A	GA	31	60	77	77	67	312	54
	Exhaustive search	8	82	48	82	87	307	6.26×10^5
Scenario B	GA	90	90	81	14	0	275	69
	Exhaustive search	90	89	90	3	0	272	6.42×10^5

Conclusions

The conclusions obtained from the solutions to the developed optimization problems and water quality modeling are summarized as follows:

- The water-quality mathematical model that was used in this study and implemented in the *MATLAB* computational environment produced consistent results that reproduced those obtained using the QUAL-UFMG model. The water-quality model was also versatile, because it could be connected automatically to the optimization toolbox of *MATLAB* for streamlining the GA tests;
- Different optimization models were developed in this study to estimate the minimum efficiencies of the sewage treatment systems for the upper part of the Santa Maria da Vitória River under different scenarios of effluent final disposal. Implementing the proposed system could maintain water-quality standards for BOD and DO along the entire extension of the watercourse under study at the load conditions and self-depuration capacities considered;
- Among all of the optimization models developed in this study, the model that produced the set of lowest efficiencies corresponded to an objective function that minimized the sum of efficiencies, in which the environmental-quality standards were implemented as constraints on the problem. The equity measure was incorporated into the optimization models to distribute the organic load removal efforts proportionally to the organic load at each discharge point along the watercourse;
- The multiobjective optimization model produced results that could enable a decision maker to minimize the sum of efficiencies or maintain equity among discharges; and
- The exhaustive search technique was used to obtain the optimal solution to the problem under consideration. The results obtained using GA were very close to those obtained by using the exhaustive search technique, but required a substantially lower computational processing time.

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