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Waste-Load Allocation Model for Seasonal River Water Quality Management: Application of Sequential Dynamic Genetic Algorithms

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In this paper, an extension of classical waste-load allocation models for river water quality management is presented to determine the monthly treatment or removal fraction of wastewater to evaporation ponds. The dimensionality of the problem, which is due to a large number of decision variables, is tackled by developing a new GA based optimization model, which is called a Sequential Dynamic Genetic Algorithm (SDGA). This is a deterministic multi-objective optimization model, which is linked to an unsteady water quality simulation model. The model minimizes the total losses incurred during the optimization time horizon, including the treatment or removal fraction costs and the costs associated with the deviation from water quality standards. The proposed model has been used for the water quality management and salinity reduction of the Karoon River in Iran. The results show the proposed model can effectively reduce the computational burden of the seasonal waste-load allocation problem. It is also shown that the seasonal waste-load allocation can significantly reduce the number and duration of standards violations.

INTRODUCTION

Optimal waste-load allocation in river systems has been given considerable attention in the literature. Waste load allocation models determine the required removal fraction or treatment level at a set of point sources, not only to maintain water quality standards, but also to search the optimal values of other objectives, such as the minimization of the treatment cost and the magnitude or frequency of water quality violations.

Traditional waste-load allocation models have been formulated to minimize the total effluent treatment cost, while satisfying water quality standards throughout the system (see [1-3] for more details). Most of the classical models incorporate the uncertainties of waste-load allocation problems by choosing one set of design conditions that include particular low flow values, such as the seven-day average low flow with a 10-year return period (7Q10) and the maximum observed water temperature. In recent efforts (such as those developed by Ellis [4], Burn [5] and Fujiwara et al. [6]), some sources of uncertainty, such as decay and reaeration rates have been explicitly considered. In these works, the chance constraint method is used to develop the stochastic waste-load allocation model for low flow conditions. Sasikumar and Mujmadar [7] developed a fuzzy linear optimization formulation for classical waste-load allocation. They incorporated the objective functions of different decision-makers as a fuzzy utility function, but their model was linear and deterministic. Takyi and Lence [8] used a multiple realization approach to calculate the trade-off between treatment cost and the reliability of maintaining the river water quality standards. They used a heuristic and a neural network technique to reduce the computational time required to solve multiple realization, but their model was linear and non-seasonal.

In conventional waste-load allocation schemes, static treatment levels are determined at individual point sources that typically involve high capital investment. Variable strategies allow for different operations, depending on the season, stream-flow, temperature and current water quality levels [9]. The economic efficiency of seasonal waste-load allocation models has been demonstrated by Boner and Furland [10], Herbay et al. [11], Ferrera and Dimino [12], Lence and Takyi [13]

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and Takyi and Lence [14]. Because of the dimensionality problem of the seasonal waste-load allocation due to large number of decision variables in all previous works, different scenarios have been developed to approximate the seasonal treatment levels. Karamouz et al. [15] proposed a GA based optimization model to estimate the long-term average monthly treatment levels. In this study, a new multi-objectives waste-load allocation model is proposed, which can consider the temporal variations of climatic and hydrologic conditions of the system and the qualitative and quantitative characteristics of the point loads. In their model, the monthly treatment or fraction removal policies can be determined.

In this paper, varying assimilative capacity of river systems are also explicitly considered in the development of the removal fraction policies of point sources using an unsteady water quality simulation model.

Genetic algorithms (GAs), which were initially introduced by Holland [16], have been converted to a powerful and attractive optimization approach by many investigators, but there have been limited pieces of literature describing the application of GAs to water quality management problems.

Ritzel et al. [17] developed a multi-objective model using Genetic Algorithms for the groundwater pollution problem. They showed that this search-based optimization method can be effectively used for the operation of complex water resources systems. Burn and Yulianti [18] have shown the capabilities of genetic algorithms for identifying solutions to classical waste-load allocation problems. They showed that GAs provide the robust and non-inferior solutions for deterministic waste-load allocation in low flow conditions.

In this study, the model proposed by Burn and Yulianti [18] and Karamouz et al. [15] are extended to provide the monthly removal fraction policies for point loads, using a combination of simulation and a new GA based optimization model. Other optimization methods, such as dynamic programming, cannot be easily used to solve monthly waste-load allocation problems because of the dimensionality problems. In the application of the dynamic programming method in waste-load allocation problems, the decision variables can be the treatment efficiency (removal fraction) of point loads and the state variables are the concentration of water quality variables across the river. Spatial dynamic programming can be easily used for traditional waste-load allocation in low flow conditions. In such a case, the temporal variation of the quantitative and qualitative characteristics of the system are not considered and there is only one state variable, which is the concentration of water quality variable just upstream or downstream of the point load at each spatial stage of the system. In seasonal waste-load allocation problems, the state variable is the spatial variation of the concentration of the water quality variable along the river. Therefore, the state of the system, at each time step (stage), can be shown by a set of values for the concentration of the water quality variable at just the upstream or downstream of each point source along the river. In such a case, the computational burden considerably limits the application of DP models.

In this study, the significant dimensionality problem of the seasonal waste-load allocation is tackled using a proposed Sequential Dynamic Genetic Algorithm (SDGA) optimization model. In this new model, the number of decision variables and the length of chromosome (set of decision variables) are sequentially increased and the capability of classical GA models in solving the complex problems is effectively improved. The SDGA can be easily linked to water quality simulation models and can, also, incorporate different conflicting objectives. The model is used for TDS load allocation in the Karoon River. The results show that the seasonal waste-load allocation can significantly reduce the number and duration of violating the standards.

MODEL FORMULATION

In this section, formulation of a multi-objective optimization model is presented for providing the monthly waste-load allocation policies in a river system. This optimization model determines the optimal removal fraction at point sources to minimize two different objectives, namely, the total treatment cost and the loss associated with the positive deviation from water quality standards. When evaporation ponds are used instead of treatment plants, the model formulation is as follows:

$$\text{Minimize } Z_1 = \sum_{i=1}^{NS} C(a_i), \tag{1}$$

$$\text{Minimize } Z_2 = \sum_{t=1}^{WE} \left(\sum_{j=1}^{NR} (V_{jt})^2 \right), \tag{2}$$

Subject to :

$$c_{j,t} = f(\overline{x}_i, \overline{q}_i, \overline{c}_i, \overline{q}_u, \overline{c}_u, \overline{D}_s, \overline{k}_s, \overline{q}_s, \overline{c}_s) \quad \forall j, t, s, \tag{3}$$

$$V_{jt} = \begin{cases} c_{j,t} - c_{\text{std}} & \text{if } (c_{j,t} - c_{\text{std}}) > 0 \\ 0 & \text{if } (c_{j,t} - c_{\text{std}}) \leq 0 \end{cases}, \tag{4}$$

$$S_{i,m+1} = S_{i,m} + Q_{i,m} x_{i,m} - a_i l_{i,m}, \tag{5}$$

$$S_{i,m} \leq a_i d_{\max,i}, \tag{6}$$

where:

- WE number of weekly time steps (known),
- NS number of point sources (known),
- $C(a_i)$ removal fraction cost of point load i during the planning horizon, which is equal to the construction cost of evaporation pond i with an area of a_i (\$, unknown),
- NR number of check points along the river (known),
- V_{jt} the magnitude of the positive water quality deviation from standards in point j at time step t (mg/L, unknown),
- c_{jt} concentration of the water quality variable in point j at time step t (mg/L, unknown),
- $\overline{x}_i$ time series of monthly removal fraction at point source i (percent, unknown),
- $\overline{q}_i$ time series of the average monthly flow rate of point load i before diversion to evaporation ponds (m^3/s, known),
- $\overline{c}_i$ time series of the concentration of water quality variable in point load i (mg/L, known),
- $\overline{q}_u$ time series of the daily flow rate of the headwater (m^3/s, known),
- $\overline{c}_u$ time series of the daily concentration of water quality variable in the headwater (mg/L, known),
- $\overline{k}_s$ time series of decay and growth coefficients in reach s of the river for non-conservative constituents (1/day, known),
- $\overline{D}_s$ time series of dispersion coefficients in reach s of the river (m^2/s, known),
- c_{std} standard level for the water quality variable (mg/L, known),
- q_s time series of the average monthly lateral flow due to local flows, surface and groundwater interaction or water withdrawal in reach s of the river (m^3/s, known),
- $\overline{c}_s$ time series of the average monthly quality of $\overline{q}_s$ (mg/L, known),
- f a non-linear function that is defined using an unsteady water quality simulation model (known),
- $l_{i,m}$ monthly average depth of water loss due to evaporation and infiltration in evaporation ponds i in month m (m/month, known),
- $S_{i,m}$ volume of evaporation pond at the end of month m (m^3),
- $Q_{i,m}$ flow volume of point load i in month m before diversion to evaporation ponds (m^3, known),
- $d_{\max,i}$ maximum depth of the evaporation pond i (m, known).

Equation 1 defines the removal fraction cost of the system, during the planning horizon. Equation 2 defines the sum of the square of the weekly positive violations from the water quality standards during the planning horizon. Equation 3 defines the time series of the concentration of the water quality variable at each point, j, which is evaluated using a one-dimensional unsteady simulation model. In Equation 2, negative violation (i.e., when total dissolved solids (TDS) concentration is less than the TDS standard level) is assumed to be zero (Equation 4). As the evaporation and infiltration volumes of each evaporation pond are related to its area, the maximum area of each evaporation pond, i, is calculated, using a trial and error process, considering the maximum depth of each pond as ($d_{\max,i}$).

The results of this optimization-simulation model can be used to derive the monthly treatment or removal policies at each point source, considering the long-term quantitative and qualitative conditions of the river and the point loads.

In this study, a combination of the ε-constraint method and a proposed genetic algorithm is used to provide the optimal solution considering different objectives. The ε-constraint method is one of the most powerful techniques for generating the non-dominated set, when the objective functions and constraints are non-linear. In this method, the basic strategy is to transform a multi-objective problem into a series of single-objective problems that can be solved using single objective optimization methods such as genetic algorithms. The ε-constraint method offers the advantage of better control over search algorithms for the non-dominated set. This method for a maximization problem with m objectives can be summarized as follows:

Step 1 Solve m individual maximization problems to find the optimal solution for each of the individual m objectives;

Step 2 Compute the value of each of the objectives and determine the potential range of values for each of the m objectives;

Step 3 Select a single objective (Z_h) to be maximized. Transform the remaining $m-1$ objectives in the form of:

$$Z_k \geq L_k, \quad k = 1, 2, \cdots, h-1, h+1, \cdots, m. \tag{7}$$

Add these new $m-1$ constraints to the original set of constraints, where L_k represents the right-hand-side values that will be varied;

Step 4 For each of the objectives and the associated range of potential values, select the desired level of resolution and divide the range into the number of intervals determined by this level of resolution in order to find L_k;

Step 5 Solve the problem of Step 3 for every combination of right-hand-side values determined in Step 4. These solutions form the approximation for the non-dominated surface. (For more details see [19,20].)

In this study, the non-dominated solution of the ε-constraint method are calculated using the proposed SDGA model.

SIMULATION MODEL FORMULATION

The basic equation of the water quality simulation model developed in this study is based on a one-dimensional advection-dispersion mass transport equation, which is numerically integrated over space and time for each water quality constituent. This equation includes the effect of advection, dispersion, dilution, constituent reactions and interactions and the flow sources and sinks. For any constituent concentration, c, the mass transport can be written as follows:

$$\frac{\partial M}{\partial t}=\frac{\partial\left(A_x D_L \frac{\partial c}{\partial x}\right)}{\partial x}-\frac{\partial\left(A_x u c\right)}{\partial x}+\left(A_x d_x\right)\frac{dc}{dt}+S, \tag{8}$$

where:

- M the pollutant mass in the control volume (M),
- x the distance along the river (L),
- t time,
- c the concentration of the pollutant (ML^{-3}),
- A_x the cross sectional area (L^2),
- D_L the dispersion coefficient ($\mathrm{L}^2\mathrm{T}^{-1}$),
- u the mean velocity (LT^{-1}),
- S the external source or sink (MT^{-1}),
- d_x the computational element length (L).

Considering $M = Vc$, where V is the incremental volume ($V = A_x d_x$) and the steady state condition of the flow in the stream, namely $\frac{\partial Q}{\partial t}=0$, Equation 8 can be written as follows:

$$\frac{\partial c}{\partial t}=\frac{\partial\left(A_x D_L \frac{\partial c}{\partial x}\right)}{A_x \partial x}-\frac{\partial\left(A_x u c\right)}{A_x \partial x}+\frac{dc}{dt}+\frac{S}{V}. \tag{9}$$

The terms on the right-hand side of the equation represent dispersion, advection, constituent changes and external sources/sinks, respectively. dc/dt refers only to the constituent changes, such as growth and decay and should not be confused with the term $\partial c/dt$, the local concentration gradient. The term $\partial c/dt$ includes the effect of constituent changes, as well as dispersion, advection, source/sinks and dilutions. Changes that occur to individual constituents or particles independent of advection, dispersion and waste input are defined by the term [21]:

$$dc/dt = rc + p, \tag{10}$$

where r is the first order rate constant (T^{-1}) and p is the internal constituent sources and sinks ($\mathrm{ML}^{-3}\mathrm{T}^{-1}$) (e.g., nutrient loss from algal growth, benthos sources, etc.).

For numerical solution of the above equations, an implicit backward finite difference method, developed by Brown and Barnwell [21], is used in this study.

SEQUENTIAL DYNAMIC GENETIC ALGORITHM

Genetic algorithms are adaptive methods trying to imitate biological and genetic processes and can be successfully applied to optimization problems. The main field of application of GAs includes problems with high complexity and non-linear behavior, such as seasonal waste-load allocation. More details of genetic algorithms can be obtained from publications such as [22,23]. Genetic algorithms usually consist of the following steps:

Step 1 Representation or encoding of the decision variables and joining them in a chromosome, which is a string of encoded decision variables,

Step 2 Creating an initial population (first generation),

Step 3 Determination of the fitness of every chromosome (set of decision variables) in the current population (fitness evaluation),

Step 4 Selection of the better chromosomes to mate and perform the crossover operator for shuffling the selected chromosomes (genetic operator 1),

Step 5 Performing mutation for selected chromosomes (genetic operator 2),

Step 6 Repeating Steps 3 to 5 to obtain the optimal or near optimal solutions.

In other words, GAs start with a population of chromosomes and combines them through genetic operators to produce better or fitter chromosomes. GAs do not guarantee that a new solution will be better than the ones before, but they guarantee that the probability of being better is higher [24].

Simple Genetic Algorithms can be easily used for seasonal waste-load allocation in short term planning [15], but the chromosome length and the dimensionality problems of the model are considerably increased in a long-term river water quality management. In this study, a new GA based optimization algorithm is proposed, based on the sequential game theory. In this new methodology that is called Sequential Dynamic Genetic Algorithm (SDGA), the number of chromosome genes (chromosome length) is sequentially increased to effectively lead the initial feasible solutions to the global optimal solution. As can be seen in Figure 1, in the first step, a small record of quantitative and qualitative characteristics of stream-flows and point loads (and, therefore, a small chromosome length) are selected and the optimal levels of the monthly removal fraction for point loads are obtained using the traditional GA-based optimization model. Then, the chromosome length is increased sequentially and the optimum solution of the first step is placed in the first part of the new chromosomes. Each step (length of chromosomes) can vary from one month to 1 or 2 years. The step length is determined, based on the convergence characteristics of the GA model. This sequential method effectively reduces the computational burden of GA-based models in the long-term planning and management of water resources. As shown in Figure 1, this proposed SDGA model is used in the ε-constraint multi-objective method and each optimal solution of the SDGA model provides one non-dominated point on the trade-off curve of the two objectives.

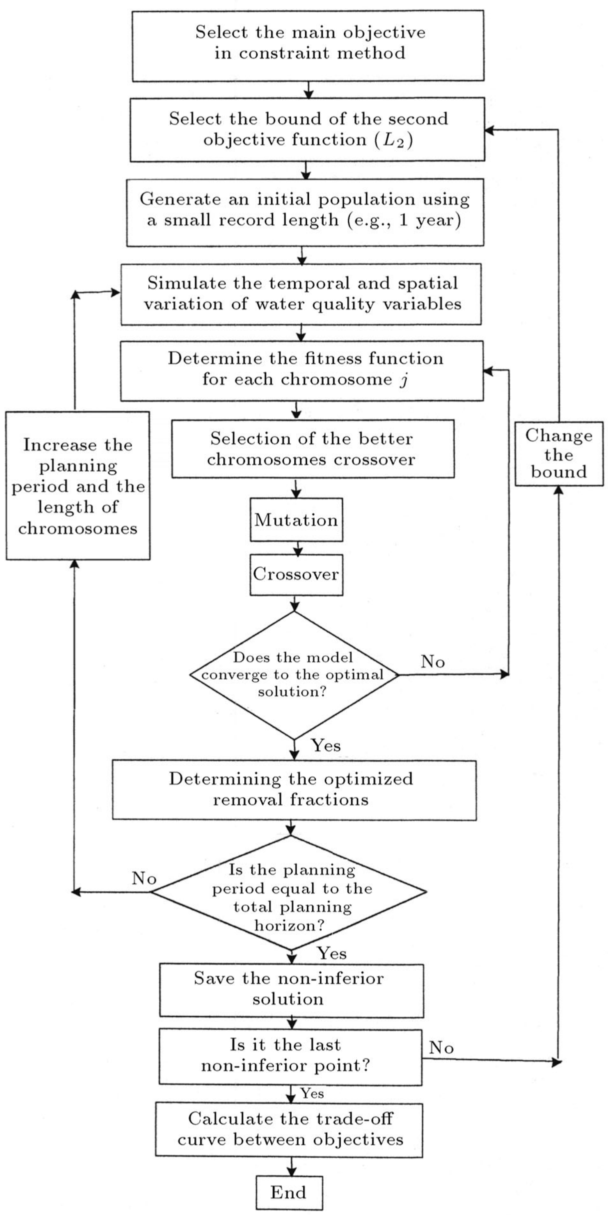

Figure 1. The flowchart of multi-objective Sequential Dynamic Genetic Algorithms (SDGA).

In this study, different components of the SDGA model for waste-load allocation in river systems have been developed with the following characteristics.

Decoding and Creating an Initial Population

The prior requirement for coding a problem is to represent every potential solution by finding a suitable representation of the parameters of the problem and joining them in a string. The common representation method is to use the binary values. An overview of other possible methods is given in [23]. The encoded parameter is referred to a gene and a string of genes (chromosome) represents one possible solution to the problem. A solution vector represents the required pollutant removal level at each point source in different months of the planning horizon. Therefore, each chromosome consists of $NS \times NY \times 12$ genes, where NS is the number of point sources and NY is the number of years in the planning horizon.

Over the last 10 years, various encoding methods have been proposed to provide effective GA models. In this study, binary coding is used to represent treatment levels. In this binary coding, 00, 01, 10, 11 are used to represent 0, 0.25, 0.50 and 0.75 treatment levels, respectively. Burn and Yulianti [18] have used a similar encoding method. In the binary encoding method, the large jumps in variable values between generations, proposed by Goldberg [25], can be limited using gray coding. In this method, which has been used in this study, the binary representation of each variable changes in each sequence with no more than one binary digit. This binary encoding and discretization of decision variables can reduce the computational burden of the seasonal waste-load allocation problem effectively. Details of encoding methods can be obtained in the work of Gen and Cheng [23].

The initial population of chromosomes is selected randomly. These strings are, then decoded to corresponding nodal removal fractions to calculate the fitness value of each chromosome in the population.

Fitness Evaluation and Selection of Chromosome

The actual evolutionary process consists of several steps. In the first step, the fitness of each chromosome (the goodness of each solution) in the population is determined. In the second step (the selection phase), the better chromosomes for next generations are selected. Mimicking the biological process of the survival of the fittest, as stated by Burn and Yulianti [18], the solution that has higher fitness is more likely to be selected. In the next step, the selected chromosomes are shuffled or recombined using crossover and mutation reproduction operators.

In this study, the fitness of each chromosome in the population is calculated using an unsteady water quality simulation model. The simulation model, which will be described in the next section, calculates the daily concentration of different water quality variables along the river. The fitness of each chromosome is calculated, based on the required removal cost or the loss corresponding to violating water quality standards.

One of the important operators that are generally used in the GA-based optimization is the niche operator [25-27]. In the simple GAs, selection drives the evolving population toward a uniform distribution of the copies of the most fitted chromosomes that could reduce the diversity of the population and cause a premature convergence. Niching induces restoration pressure to balance the convergence pressure of the selection. Investigators have proposed many different methods for the niche operator. Goldberg and Richardson [28] have detailed a practical scheme that directly uses the sharing metaphor to induce niche and species. In this method, a sharing function is defined to determine the neighborhood and degree of sharing for each chromosome in the population. The basic idea of the fitness sharing method is to restrict the unlimited growth of certain individuals by enforcing each chromosome to share its fitness with other nearby chromosomes in the same niche. In the fitness sharing method proposed by Goldberg and Richardson [28], the fitness of each chromosome in the population is modified according to the following fitness sharing scheme:

$$\text{Modified fitness function of choromosome } n = \frac{\text{fitness function of choromosome } n}{\sum_{j=1}^{npop} Sh(d_{jn})}, \tag{11}$$

where *npop* is the population size in each generation and $Sh()$ is the sharing function of a measure of distance, (d_{jn}), between two chromosomes, j and n. The measure of distance between two chromosomes, j and $n, (d_{jn})$, is determined as follows:

$$d_{jn} = \frac{\sqrt{\sum_{i=1}^{\text{ngens}} ((P_{ij} - P_{in})/(P_{\max_i} - P_{\min_i}))^2}}{ngens}, \quad \forall j \in \text{choromosome population}, \tag{12}$$

where:

P_{ij}	value of gene i in chromosome j,
P_{in}	value of gene i in chromosome n,
$P_{\max_i}/P_{\min_i}$	maximum/minimum value of gene i in all of the chromosomes,
ngens	total number of genes in each chromosome.

The sharing function is as follows:

$$Sh(d_{jn}) = \begin{cases} 1-(d_{jn}/L_{\min}) & \text{if } d_{jn} < L_{\min} \\ 0 & \text{otherwise} \end{cases} \quad \forall j, n, \tag{13}$$

where $L_{\min}$ is a constant controlling the size of niches (see [29] for more details). The chromosomes separated by $L_{\min}$ do not degrade the fitness of each other.

Useful selection methods, such as Roulette Wheel, Tournament, Linear Ranking, Exponential Ranking and Truncation Selection and their properties, were discussed by Cantu'-Paz [30]. The more general methods are the Tournament and Roulette Wheel selection. In the first method, a group of individuals are chosen randomly and the individual with the highest fitness is selected for inclusion in the next generation. This process is repeated until appropriate numbers of individuals are selected for the new generation. The Roulette Wheel selection is the simplest method that selects the best chromosome according to the ratio of the fitness of each chromosome to the sum of all the fitness values related to all chromosomes.

In this paper, the Tournament selection, which is widely used in literature such as [31], is selected for the SDGA model.

Crossover and Mutation

The reproduction operators, known as crossover and mutation, create new chromosomes. Crossover operators randomly take one pair that performs well from the mating pool and by exchanging important building blocks between two chromosomes, a new pair is obtained. It is assumed that the good performance of a chromosome is due to good sub-chromosomes, namely, the crossover operator combines the good building blocks (with better fitness) of chromosomes, which is likely to provide better solutions. Michalewicz [22] described three crossover methods, namely, one-point, two-point and uniform crossover, but there is no consensus among investigators whether there is a generally superior crossover method. Crossover occurs between two selected chromosomes with a specific probability (P_c). In other words, the probability of the crossover of two selected chromosomes is P_c. The one-point crossover, which has been selected for this study, randomly chooses a position (gene) in the chromosome, and new chromosomes are obtained by swapping all genes after that position. In binary encoding, the crossover should occur only at gene boundaries to protect the splitting of genes. Each gene consists of two bits in this study.

Mutation is an important process that can provide diversity and new genetic information to the population and prevents premature convergence to local optimal solutions. The mutation operator changes randomly the bit value (e.g., number one becomes zero and vice-versa) with a probability of P_m [23].

CASE STUDY

The Karoon River, being more than 450 km long (between the Gotvand Dam and the Persian Gulf) and with an annual average discharge of 11891 MCM, is the biggest river in Iran, located in the southwestern part of the country. A part of the river that is located downstream of the Gotvand Dam supplies the water demands of more than 700,000 hectares of agricultural networks, eight cities and several industries. The domestic and agricultural waste-loads and agricultural return flows, as well as interaction between the river and aquifer, have severely decreased the water quality of the river. Recent investigations on the river have shown that concentrations of most of the water quality variables, such as Total Dissolved Solids (TDS), Chemical Oxygen Demand (COD), Coliform bacteria, total phosphorus, Cd, and Ni, have deviated adversely from the stream water quality standards and more than 90 percent of industrial effluents, agricultural or agro-industrial return flows violate the effluent standards. As salinity is the most devastating problem of the system, TDS concentration is considered as an indicator of the water quality variable [32].

In this study, an important section of the Karoon River, with a length of 190 km, between the Gotvand Dam and the Ahvaz metropolitan area, is considered to evaluate the effectiveness of the seasonal policies developed by the multi-objective GA-based waste-load allocation model for river water quality management. Some important cities, such as Gotvand, Shooshtar, Mollasani, Weis and Ahvaz are located in the study area and their domestic demands are supplied from the river. The river also provides the water demands of two major agro-industries and several strategic steel and petrochemical heavy industries in this region and two important cities, Khoramshahr and Abadan, at the downstream end of the river.

As shown in Figure 2, there are two important tributaries, namely, the Dez and Gargar Rivers. The Gargar is actually a branch of the main river, but is considered as two tributaries for modeling purposes. As water treatment plants in the cities cannot remove the salinity of the water supplied from the river, it has caused many complaints from the people in the study area. Therefore, water pollution control projects, such as the relocation or transfer of agricultural return flows to evaporation ponds, have been proposed and implemented.

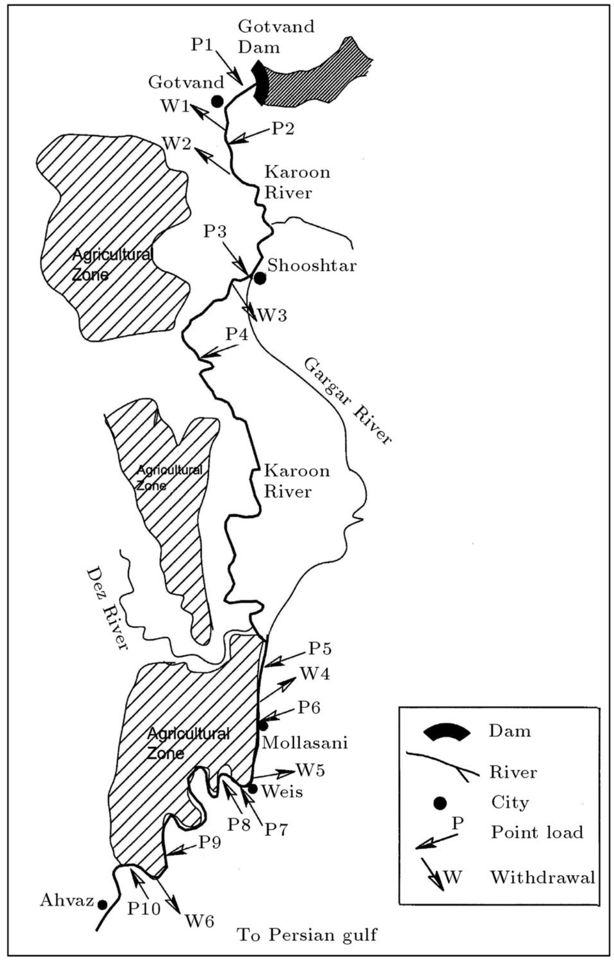

Figure 2. A part of the Karoon River system located in the study area [15].

The TDS concentration of the groundwater in the study area varies from 1500 to 9000 mg/L and groundwater resources are rarely used for water supply purposes. The high potential of evaporation (more than 3200 mm/year) and considerable cost of TDS removal, justify the diversion of a fraction of the point loads flow rate to the evaporation ponds, as a practical method for the Karoon River pollution reduction.

In this study, considering the spatial distribution of discharge points, 10 point loads, including the return flows of agriculture networks and agro-industrial sectors, are used for waste-load allocation in the Karoon River. The location and characteristics of these point loads are presented in Figure 2 and Table 1.

The daily data of river flow and the monthly quantitative and qualitative data of the point loads have been used in this study for the period 1992-2001. Even though the available data of the quality and

Table 1. The characteristics of point loads of the Karoon River in the study area.

Point Loads	Location (Km) (Distance from the Gotvand Dam)	Average Annual Discharge (m^3/sec)	Average Conc. of TDS (mg/lit)
P1	3	5.52	2102
P2	10	0.094	2004
P3	46	0.04	1901
P4	50	0.045	1889
P5	124	0.535	6155
P6	131	0.127	2093
P7	146	0.159	1911
P8	152	0.07	2691
P9	179	0.004	1457
P10	186	0.22	2508

quantity of point loads is monthly, the time step of the simulation model is selected to be daily to consider the short-term variations of the quality and quantity of the headwater. Local flows and their quality and the quantitative-qualitative interaction between the river and the aquifer have been estimated using the mass balance of water and total dissolved solids. The water quality simulation model has been developed and calibrated using the observed qualitative and quantitative data of the river, point loads and the estimated discharge and quality of the local and return flows. As an example, Figure 3 shows the observed and simulated concentration of TDS along the river in the month of July, which is a critical month, due to less river flow, high volume of withdrawal and return flows. As can be seen in this figure, the simulation model can be used for the evaluation of water quality management policies. The proposed model is applied to the Karoon River to obtain the optimal monthly removal fraction policies at the point sources considering different objectives, namely, minimization of the construction cost of evaporation ponds and the loss of violation from water quality standards. In this study, each gene, which shows the removal fraction, has two bits. Therefore, for a 10-year planning horizon, each chromosome has 1200 genes and 2400 bits for 10 point loads. In order to find a more stable solution, the probability of mutation and crossover were obtained using a trial and error process as 0.009 and 0.8, respectively. As mentioned before, the optimal volume of evaporation ponds is calculated using a search-based optimization model and considering the time series of removal fractions (corresponding to simulating chromosomes) and monthly evaporation and infiltration rates. The maximum water depth of each evaporation pond has been limited to 2 m, suggested as a standard of practice in the region. The construction cost of the evaporation ponds is also considered, based on the ongoing cost in Iran.

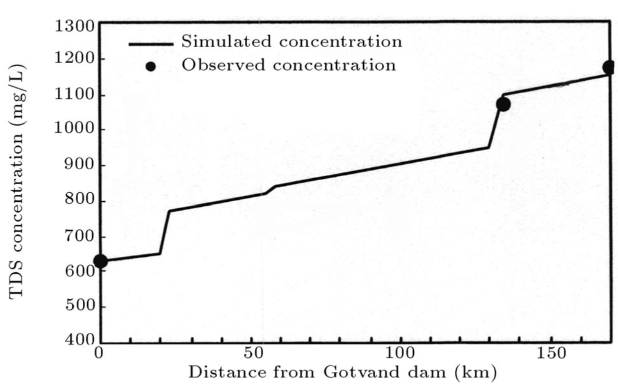

Figure 3. The observed and simulated concentration of TDS in month of July, 1999.

RESULT AND DISCUSSION

In this study, in the ε-constraint multi-objective method, minimization of the deviation of TDS concentration from water quality standards is considered as the main objective. As the river is supplying the drinking water of the cities and villages located in the study area, the maximum concentration of TDS is considered as 1200 mg/L. In the proposed SDGA model, at each step, the fraction of the planning horizon and the chromosome length is increased as one year or 120 genes, respectively. The number of generations at each step of the SDGA model is considered to be 150.

Figure 4 shows the fitness improvement and reduction of the total loss due to deviations from the water quality standard in the last step of the calculation of the SDGA model (with full length chromosomes). The

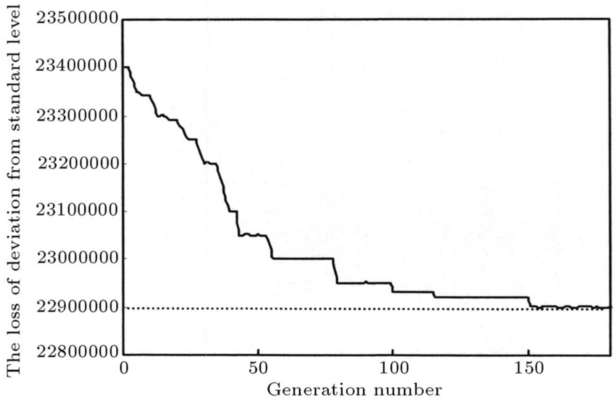

Figure 4. Fitness improvement in the last step of SDGA evolutionary process.

GA-based optimization model has found the optimal, or near optimal, solution after 150 generations.

To control the global optimality of the solution, as mentioned by Gen and Cheng [23], the evolutionary process is evaluated with a high probability of mutation and with a high number of generations. As shown in Figures 4 and 5, increasing P_m from 0.009 to 0.1 results in instability of the solutions, but does not provide a solution with a smaller violation loss (a violation loss less than the dashed lines in Figures 4 and 5). It is also demonstrated that by increasing the number of generations, the minimum loss is not improved, therefore, a global, or near to global, minimum has been reached. In this study, the effects of population size and the probability of crossover are also controlled. Having a larger population in each generation does not improve the fitness of the optimal solution, but it can reduce the required number of generations to find the global or near global solutions. Furthermore, decreasing the probability of crossover (P_c) can increase the required number of generations for finding the optimal solution.

The runtime of the described model is about 5 hours using a Pentium IV (1400 MHz) computer. To evaluate the effectiveness of the SDGA model in

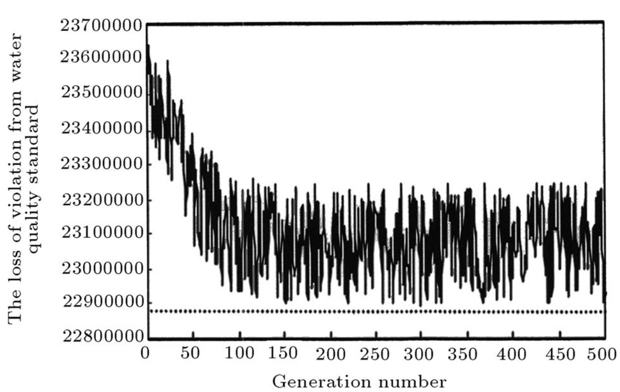

Figure 5. Fitness improvement in evolutionary process with high mutation probability ($P_m = 0.1$).

reducing computational time, it has been compared with the traditional genetic algorithm optimization model. As mentioned before, the SDGA can provide the optimal solution after 150 iterations in the last step of computations when the chromosomes have their maximum length. As shown in Figure 6, the traditional GAs can provide this solution with 3000 generations and a computational time of about 2.5 times the proposed method. Therefore, the SDGA can effectively reduce the computational time of classical GAs.

The ε-constraint method provides the trade-off curve between the selected objectives. As can be seen in Figure 7, the violation from the standard level is unavoidable because of the high TDS concentration in the headwater (in some months in the planning horizon), local flows and interactions between surface and saline groundwater in certain months during the computational time horizon.

In general, frequency, duration and magnitude of the violation of water quality standards are performance indicators that present the reliability, resiliency and vulnerability of pollution management policies. The reliability indicator describes how likely or of-

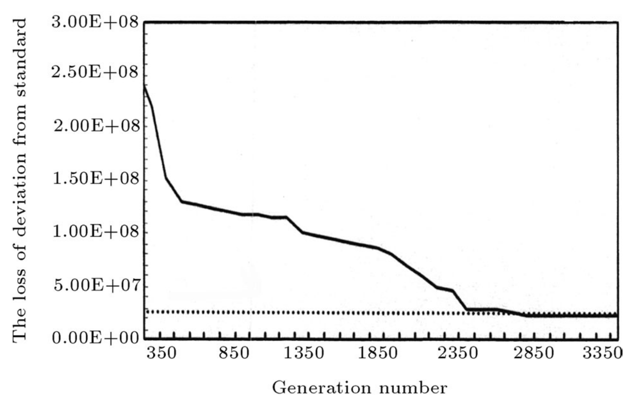

Figure 6. Fitness improvement in traditional GA model (chromosome length = 1200 genes, $P_m = 0.009$).

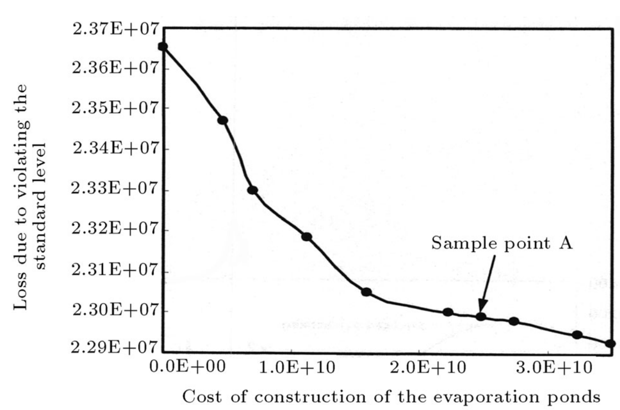

Figure 7. Trade-off curve between TDS removal cost versus the loss associated with violating the standard level of 1200 mg/L.

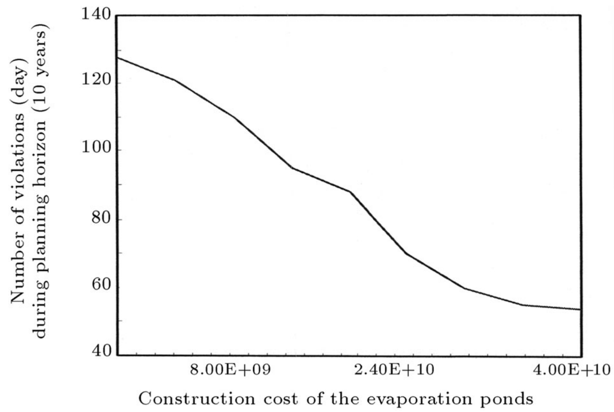

Figure 8. Trade-off curve between construction cost of evaporation ponds and number of violations (day) during planning horizon.

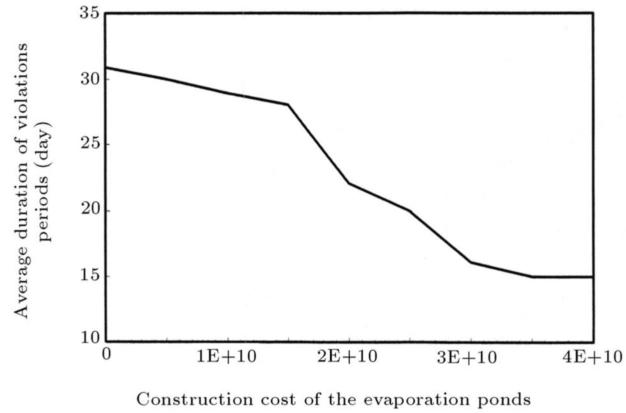

Figure 9. Trade-off curve between construction cost of evaporation ponds and the average duration of violation periods (day).

ten the water quality goals may be achieved, while resiliency and vulnerability indicators represent how quickly the water quality systems recovers from a failure and the severity of the consequences of violations of water quality standards, respectively. As shown in Figure 8, by increasing the construction costs of the evaporation ponds, the number of days, within which the river water quality in the study area violates from the water quality standards, is decreased from 127 to 52 days. In such a case, the average duration of water quality violation, which is an indicator of the resiliency of the system, is decreased from 32 to 15 days (Figure 9). As the maximum violation is not directly considered as an objective function of the model, the maximum violation reduction is equal to 30 mg/L. Figures 7, 8 and 9 could help the decision-makers to select the most favorable solution, based on their own set of priorities.

Table 2 presents the statistical characteristics of the monthly removal fraction for different point sources. The proposed GA-based waste-load allocation model can provide the optimal value of the monthly removal fractions at each point source and the optimal area and the depth of evaporation ponds. The values of standard deviation present the variations of the monthly removal fractions. High variations of the average monthly removal fraction of each point load and, also, the high values of the standard deviation of the monthly removal fractions show the significance of considering the seasonal waste-load allocation approach.

The statistical characteristics of the removal fraction of point sources in the month of July and the optimal volume of evaporation ponds corresponding to an arbitrary point, A, in Figure 6, are presented in Tables 3 and 4. The high variation of the average monthly removal fractions and, also, the high value of their standard deviations, shows the significance of

Table 2. The statistical characteristics of the monthly removal fraction of point source P1, downstream of the Gotvand Dam, corresponding to the arbitrary point, A, in Figure 7.

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	July	Aug.	Sep.	Oct.	Nov.	Dec.
Average Removal Fraction (%)	35	40	30	30	35	52	48	52	40	40	43	27
Standard Deviation (%)	26	24	23	26	24	20	32	25	31	31	28	24

Table 3. Statistical characteristics of the monthly removal fraction of point sources in the month of July, corresponding to the arbitrary point, A, in Figure 7.

Point Load	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Average Removal Fraction (%)	48	50	35	38	23	33	38	35	23	48
Standard Deviation (%)	32	20	32	32	25	24	34	27	18	28

Table 4. The optimal area of evaporation ponds corresponding to the arbitrary point, A, in Figure 7.

Point Load	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Area (km^2)	9.8	0.18	0.07	0.09	1.28	0.22	0.4	0.18	0.01	0.49

the seasonal waste-load allocation, because, in the conventional waste-load allocation methods, the treatment plants (or, in this case, the evaporation ponds) are designed based on the critical condition of the system.

Based on the results of the model, the optimal monthly removal fraction polices have been developed for each point source. Table 5 presents the removal fraction policies derived for arbitrary point source P1, downstream of the Gotvand Dam, corresponding to point A in Figure 7. The equations in Table 5 provide the removal fraction policies at each point source, based on the quantitative and qualitative characteristics of the point load and the river at a section just upstream of the wastewater discharge point. As can be seen in this table, increasing the mass transport rate in the stream flow and the point load will increase the required removal fraction.

SUMMARY AND CONCLUSION

In this paper, the model developed by Burn and Yulianti [18] is extended to include the seasonal variations of the quantitative and qualitative characteristics of the river and point sources. It is also demonstrated that the proposed SDGA optimization model can provide a robust and acceptable solution for a deterministic monthly waste-load allocation problem. This problem would be very difficult to solve using other optimization methods, such as the family of dynamic programming models, due to computational difficulties. The proposed model uses the long-term qualitative and quantitative data of the river and its pollutants to derive the monthly fraction removal of the point sources. The proposed algorithm is applied to the monthly data of the Karoon River system in Iran. The algorithm has been tested using different probability for genetic algorithm operators and different population sizes, to reach the global or near global optimal solutions.

The approach can readily handle discrete decision variables and can effectively identify the trade-off between objectives, which are the removal cost and the sum of the square of the violations from water quality standards. The trade-off curves that show the variations of reliability, resiliency and vulnerability of the model based on different values of construction costs, can be a useful means for decision-makers to select the most favorable treatment levels considering the two objectives.

Table 5. The monthly removal fraction policies for point load P_1 downstream of the Gotvand Dam, corresponding to the arbitrary point, A, in Figure 7.

Month	**Policy**	**R**
January	$rf_{\text{Jan.}} = 1 \times 10^{-5} q_{1,\text{Jan.}} \times c_{1,\text{Jan.}} + 1.1 \times 10^{-4} q_{0,\text{Jan.}} \times c_{0,\text{Jan.}}$	0.8
February	$rf_{\text{Feb.}} = 34 \times 10^{-4} q_{1,\text{Feb.}} \times c_{1,\text{Feb.}} + 1 \times 10^{-4} q_{0,\text{Feb.}} \times c_{0,\text{Feb.}}$	0.85
March	$rf_{\text{Mar.}} = 13 \times 10^{-4} q_{1,\text{Mar.}} \times c_{1,\text{Mar.}} + 1 \times 10^{-4} q_{0,\text{Mar.}} \times c_{0,\text{Mar.}}$	0.80
April	$rf_{\text{Apr.}} = 2.6 \times 10^{-3} q_{1,\text{Apr.}} \times c_{1,\text{Apr.}} + 1.1 \times 10^{-4} q_{0,\text{Apr.}} \times c_{0,\text{Apr.}}$	0.80
May	$rf_{\text{May}} = 22 \times 10^{-4} q_{1,\text{May}} \times c_{1,\text{May}} + 1.2 \times 10^{-4} q_{0,\text{May}} \times c_{0,\text{May}}$	0.96
June	$rf_{\text{Jun.}} = 36 \times 10^{-4} q_{1,\text{Jun.}} \times c_{1,\text{Jun.}} + 1 \times 10^{-4} q_{0,\text{Jun.}} \times c_{0,\text{Jun.}}$	0.92
July	$rf_{\text{Jul.}} = 12 \times 10^{-4} q_{1,\text{Jul.}} \times c_{1,\text{Jul.}} + 2 \times 10^{-3} q_{0,\text{Jul.}} \times c_{0,\text{Jul.}}$	0.86
August	$rf_{\text{Aug.}} = 53 \times 10^{-4} q_{1,\text{Aug.}} \times c_{1,\text{Aug.}} + 1 \times 10^{-4} q_{0,\text{Aug.}} \times c_{0,\text{Aug.}}$	0.91
September	$rf_{\text{Sep.}} = 2.8 \times 10^{-4} q_{1,\text{Sep.}} \times c_{1,\text{Sep.}} + 1.3 \times 10^{-4} q_{0,\text{Sep.}} \times c_{0,\text{Sep.}}$	0.84
October	$rf_{\text{Oct.}} = 36 \times 10^{-4} q_{1,\text{Oct.}} \times c_{1,\text{Oct.}} + 1.1 \times 10^{-4} q_{0,\text{Oct.}} \times c_{0,\text{Oct.}}$	0.86
November	$rf_{\text{Nov.}} = 169 \times 10^{-4} q_{1,\text{Nov.}} \times c_{1,\text{Nov.}} + 13 \times 10^{-5} q_{0,\text{Nov.}} \times c_{0,\text{Nov.}} - 2.14$	0.81
December	$rf_{\text{Dec.}} = 45 \times 10^{-4} q_{1,\text{Dec.}} \times c_{1,\text{Dec.}} + 10 \times 10^{-5} q_{0,\text{Dec.}} \times c_{0,\text{Dec.}}$	0.84

rf_t = removal fraction of point source P1 in month t (percent),

$q_{1,t}$ = streamflow of point source P1 at month t (m^3/s),

$q_{0,t}$ = streamflow in upstream of point-load P1 at month t (m^3/s),

$c_{0,t}$ = concentration in upstream of point-load P1 at month t (mg/L),

R = correlation coefficient.

The proposed model can be easily applied to a problem with more point sources, smaller time steps and a longer time horizon. The results show that the removal of all the point sources will not completely improve the quality of the streamflow, due to interaction between the river and saline groundwater, local flows and the low quality of headwater during some months of the planning horizon. Therefore, waste-load allocation models may not have a considerable effect on the improvement of water quality in the study area. However, the results of this study show that the proposed model can be easily used for water quality management of river systems and can provide optimal monthly operating polices. The results also show the significant value of using the modified genetic algorithm in reduction of the burden of dimensionality of the seasonal waste-load allocation problems.

This is, perhaps, the first time that monthly waste-load allocation policies are determined by linking the simulation and optimization models, considering the dynamic characteristics of the system. Another promising area of investigation is the development of monthly fraction removal policies, considering the uncertainties of system parameters and the vagueness of the water quality criteria and standards.

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NOMENCLATURE

A_x	cross sectional area (m^2)
a_i	area of evaporation pond i (m^2)
c_{jt}	concentration of the water quality variable in point j at time step t (mg/L)
$C(a_i)$	removal fraction cost of point load i during the planning horizon, which is equal to the construction cost of evaporation ponds, i, with area of a_i ($)
c_{std}	water quality standard level (mg/L)
$\overline{c}_s$	time series of the quality of $\overline{q}_s^{\mathrm{int}}$ (mg/L)
$\overline{c}_i$	time series of the concentration of water quality variable in point load i (mg/L)
$\overline{c}_u$	time series of the daily concentration of the headwater (mg/L)
$\overline{D}_s$	time series of dispersion coefficients in reach s of the river (m^2/day)
D_L	dispersion coefficient (m^2/day)
d_{jn}	measure of distance between two chromosomes, j and n
d_i	depth of evaporation pond, i (m)
$d_{\max,i}$	maximum depth of the evaporation pond, i (m)
d_x	computational element length (m)
f	a non-linear function that is defined using an unsteady water quality simulation model
$\overline{k}_s$	time series of decay and growth coefficients in reach s of the river for non-conservative constituents (1/day)
L_k	kth right-hand-side value
$l_{i,m}$	monthly average depth of water loss due to evaporation and infiltration in evaporation ponds, i, in month m (m/month, known)
$L_{\min}$	specific distance criterion
M	pollutant mass in the control volume (kg)
m	number of objective functions
N	number of time steps
NR	number of checkpoints along the river
NS	number of point sources
$ngens$	number of genes (parameters) in each chromosome
$npop$	population size in each generation
p	internal constituent sources and sinks ($\mathrm{mg/m^3s}$)
P_c	probability of crossover
P_{ij}	value of gene i in chromosome j
P_{in}	value of gene i in chromosome n
P_m	probability of mutation
$P_{\max_i}$	maximum values of gene i
$P_{\min_i}$	minimum values of gene i
$Q_{m,i}$	flow volume of point load, i, in month m before diversion to evaporation ponds (m^3, known)
$\overline{q}_i$	time series of the flow rate of point load, i, before diversion to evaporation ponds ($\mathrm{m^3/s}$)

$\overline{q}_s$	time series of the lateral flow due to local flows, surface and groundwater interaction or water withdrawal in reach s of the river (m^3/s)
$\overline{q}_u$	time series of the daily flow rate of the headwater (m^3/s)
r	first order rate constant (1/day)
rf_t	removal fraction of point source P1 in month t (percent)
S	external source or sinks (mg/s)
$S_{m,i}$	volume of evaporation pond at the end of month m (m^3)
Sh	sharing function
t	time (s)
u	mean velocity (m/s)
V	incremental volume (m^3)
V_{jt}	the magnitude of water quality deviation from standards in point j at time step t (mg/L)
WE	number of weekly time steps
$\overline{x}_i$	time series of monthly removal fraction at point source, i (percent)
x	distance along the river (m)
Z_k	kth objective function

REFERENCES

1. Liebman, J.C. and Lynn, W.R. "The optimal allocation of stream dissolved oxygen", *Water Resources Research*, **2**(3), pp 581-591 (1966).
2. Loucks, D.P., ReVelle, C.S. and Lynn, W.R. "Linear programming models for water pollution control", *Mgmt. Sci.*, **14**(4), pp B-166-B-181 (1967).
3. ReVelle, C., Loucks, D.P. and Lynn, W.R. "Linear programming applied to stream dissolved oxygen", *Water Resources Research*, **4**(1), pp 1-9 (1968).
4. Ellis, J.H. "Stochastic water quality optimization using imbedded chance constraint", *Water Resources Research*, **23**(12), pp 2227-2338 (1987).
5. Burn, D.H. "Water quality management through combined simulation-optimization", *Journal of Environmental Engineering, ASCE*, **115**(5), pp 1011-1024 (1989).
6. Fujiwara, O., Puangmaha, W. and Hanaki, K. "River basin water quality management in stochastic environment", *Journal of Environmental Engineering, ASCE*, **114**(4), pp 869-877 (1988).
7. Sasikumar, K. and Mujmadar, P.P. "Fuzzy optimization model for water quality management", *Journal of Water Resources Planning and Management, ASCE*, **124**(2), pp 79-84 (1998).
8. Takyi, A.K. and Lence, B.J. "Surface water quality management using a multiple-realization chance constraint method", *Water Resources Research*, **35**(5), pp 1657-1670 (1999).
9. Cardwell, H. and Ellis, H. "Stochastic dynamic programming models for water quality management", *Water Resources Research*, **29**(4), pp 803-813 (1993).
10. Boner, M.C. and Furland, L.P. "Seasonal treatment and variable effluent quality based on assimilative capacity", *Res. J. Water Pollution Control Fed.*, **54**, pp 1408-1416 (1982).
11. Herbay, J.P., Smeers, Y. and Tyteca, D. "Water quality management with time varying river flow and discharger control", *Water Resources Research*, **19**(6), pp 1481-1487 (1983).
12. Ferrara, R.A. and Dimino, M.A. "A case study analysis for seasonal nitrification: Economic efficiency and water quality preservation", *Res. J. Water Pollution Control Fed.*, **57**, pp 763-769 (1985).
13. Lence, B.J. and Takyi, A.K. "Data requirements for seasonal discharge programs: An application of a regionalized sensitivity analysis", *Water Resources Research*, **28**(7), pp 1781-1789 (1992).
14. Takyi, A.K. and Lence, B.J. "Markov chain model for seasonal water quality management", *Journal of Water Resources Planning and Management, ASCE*, **121**(2), pp 144-157 (1995).
15. Karamouz, M., Kerachian, R. and Mahmoodian, M. "Seasonal waste-load allocation model for river water quality management", *Proceedings of 2003 World Water and Environmental Resources Congress*, Philadelphia, USA (2003).
16. Holland, J.H., *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, Mich, USA (1975).
17. Ritzel, B.J., Eheart, J.W. and Ranjithan, S. "Using genetic algorithms to solve a multiple objective groundwater pollution problem", *Water Resources Research*, **30**(5), pp 1589-1603 (1994).
18. Burn, D.H. and Yulianti, S. "Waste-load allocation using genetic algorithms", *Journal of Water Resources Planning and Management, ASCE*, **127**(2), pp 121-129 (2001).
19. Karamouz, M., Szidarovszky, F. and Zahraie, B., *Water Resources System Analysis- with Emphasis on Conflict Resolution*, CRC Publishing, Boca Raton, Florida, USA, 33431 (2003).
20. ReVelle, C. and McGarity, A.E. "Design and operation of civil and environmental engineering systems", John Wiley and Sons, New York, NY, USA 10158-0012 (1997).
21. Brown, L.C. and Barnwell, O., *The Enhanced Stream Water Quality Models, QULA2E and QUAL2E-UNCAS: Documentation and User Manual*, U.S. Environmental Protection Agency Publication (1987).

22. Michalewicz, Z., *Genetic Algorithms + Data Structures = Evolutionary Programs*, Springer, New York, USA (1992).

23. Gen, M. and Cheng, R., *Genetic Algorithm and Engineering Optimization*, John Wiley & Sons (2000).

24. Oliveira, R. and Loucks, D.P. "Operating rules for multi-reservoir systems", *Water Resources Research*, **33**(4), pp 839-851 (1997).

25. Goldberg, D.E., *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Reading, Mass, USA, p 399 (1989).

26. Horn, J. and Nafpliotis, N. "Multi-objective optimization using the niched pareto genetic algorithm", *Proceeding of the First IEEE Conference on Evolutionary Computation*, **1**, pp 82-87 (1993).

27. Mahfoud, S.W. "Niching methods for genetic algorithms", Ph.D. Thesis, University of Illinois, IL, USA, p 251 (1995).

28. Goldberg, D.E. and Richardson, J. "Genetic algorithms with sharing for multimodal optimization", *Proc. 2nd Int. Conf. on Genetic Algorithms*, Cambridge, MA, USA, pp 41-49 (1987).

29. Fonseca, C. and Fleming, P. "Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization", *Proceedings of the 5th International Conference on Genetic Algorithms*, San Mateo, California, USA, pp 416-423 (1993).

30. Cantu'-Paz, E. "Order statistics and selection methods of evolutionary algorithms", *Information Processing Letters*, **82**, pp 15-22 (2002).

31. Karamouz, M., Khodatalab, N., Araghi Nejad, Sh. and Kerachian, R. "Operation of multi-purpose reservoirs: Application of genetic algorithms", *Conference on Water Resources Planning and Management, ASCE*, May 19-22, Virginia, USA (2002).

32. Karamouz, M. "A master plan for water resources pollution control in the Karoon River", *Report prepared for Environmental Protection Agency*, Tehran, Iran (2002).