Proceedings of the 6th WSEAS Int. Conf. on EVOLUTIONARY COMPUTING, Lisbon, Portugal, June 16-18, 2005 (pp384-391)

Simulation-Optimization Model For Fuzzy Waste Load Allocation

M. SAADAT POUR, A. AFSHAR, O. BOZORG HADDAD
Department of Civil Engineering
IRAN University of Science and Technology
Narmak, Tehran
IRAN

***Abstract*:** A simulation-optimization model is developed for waste load allocation in a fuzzy optimization framework. The model provides the best compromise solution to the pollution dischargers and pollution control agencies. To deal with uncertainties due to randomness and vagueness of the goals and parameters, fuzzy sets with appropriate membership functions are introduced. The fuzzy waste load allocation model (FWLAM) incorporate QUAL2E as a Water Quality Simulation Model and GA (Genetic Algorithm) as an optimization tool to find the optimal fraction removal level to the dischargers and pollution control agency (PCA).The GA directs the decision variables in a real-value form to QUAL2E as an input file. QUAL2E simulates the decision variables and calculates the state variables. Penalty functions are employed to control the infeasible solutions. This fuzzy optimization model with genetic algorithm has been used for a hypothetical problem. Results demonstrate a very suitable convergence of proposed optimization algorithm to the global optima.

Keywords: Optimization, Waste Load Allocation, Genetic Algorithm, Fuzzy, QUAL2E.

Introduction

The determination of an optimal waste load allocation for a river basin is an aspect of water quality management that has received considerable attention. Optimal waste load allocation implies that the treatment vector selected not only maintains the water quality standards, but also results in the best value for the objective function defined for the manager problem.

A WLA model is, in general, a mathematical model incorporating a water quality simulation model within the framework of multi-objective optimization. It normally consists of three components:(1) an optimization model expressing the objectives, goals, and constraints of the water quality management problem; (2) a water quality simulation model that simulate the water quality constituents in the river system; and (3) means of addressing uncertainty inherent in the system. Generally, two sets of objectives are considered in the decision-making process for water quality management of a river system. The first set of objectives is determined by the pollution control agency (PCA) that deals with satisfying water quality standards. The second set of objectives deals with the minimization of waste treatment cost ,which is paid by the dischargers in the river system. These two sets of objectives are often in conflict with each other.

Most WLA models employ the well known Streeter-Phelps (S-P) equations (Streeter and Phelps 1925) with Camp-Dobbins (Camp 1963; Dobbins 1964) modifications to simulate biodegradation and to map waste loads into downstream constituents. While S-P equations are effective in modeling DO and biochemical oxygen demand (BOD), they cannot be extended to model transport of other constituents (e.g., nitrogen, phosphorus and chlorophyll). Several simulation models are now available (e.g., QUAL2K, QUAL2E and WASP4) for modeling transport of most pollutants in a river system. Efforts to incorporate such simulation models in WLA models began with Cardwell and Ellis (1993) who addressed model uncertainty considering different models [S-P equations, QUAL2E (Brown and Barnwell 1987) and WASP4 (Robert et al,1988) simultaneously in a single framework.

Optimization methods have been developed to incorporate multiple and conflicting goals of the dischargers and the PCAs. Recently, Suresh and Mujumdar (1999), Sasikumarand Mujumdar (2000), and Mujumdar, Sasikumar (2002) and Mujumdar, Vemula (2004) have incorporated multiple and conflicting goals in the WLA models and addressed uncertainty due to both randomness and

Proceedings of the 6th WSEAS Int. Conf. on EVOLUTIONARY COMPUTING, Lisbon, Portugal, June 16-18, 2005 (pp384-391)

imprecision. In this paper, we try to use a Simulation-Optimization (S-O) approach to integrate the Fuzzy Waste Load Allocation model with a water quality simulation Model.

Several advantages of the S-O methodology have been realized in various fields of water resources, including groundwater management (Gorelick et al. 1984; McKinney and Lin 1994), reservoir operation (Oliveira and Loucks 1997), surface water quality and quantity management (Dai and Labadie 2001), water distribution systems (Sakarya and Mays 2000) and waste load allocation (Lence (1993), Burn (2001)). A major advantage of the S-O methodology proposed in this paper is that the physical processes such as the mass and temperature balance are accounted through simulation outside the optimization model, thus reducing the size and complexity of the optimization model.

In this paper GA (Genetic Algorithm) is used as an optimization tool which is linked to QUAL2E FORTRAN source code. For a given pollution abatement matrix, the water quality model, QUAL2E, calculates the Jacobian matrix whose elements represent the marginal effects of increase in each pollutant load on downstream DO levels of the river.

It is well known that classical, nonlinear optimization method pose a difficulty in achieving global or near global optimal solutions. As an alternative, therefore, the genetic algorithm (GA) assures global or near global solutions, has been employed to solve the fuzzy optimization problem.

Description of the River System

Table 1 gives the description of a river system to which FWLAM is applied for water quality management. The relevant components of the system are identified as sets. Set *Q* represent the collection of mesh point (water quality check points) where the water quality is of interest in the river system. Set *D* is the collection of dischargers (e.g. industries). Set *T* is the collection of uncontrollable source of pollutant in the system (e.g. BOD addition due to runoff and scour in a stream). Set *P* is the collection of the pollutants in the river system (e.g. point source of BOD, a mixture of toxic substance, etc). Set *V* is the collection of water quality parameter with a desirable level greater than the permissible level (e.g. dissolved oxygen concentration). Set *S* is the collection of water quality parameters with the desirable level less than permissible level (e.g. toxic pollutant concentration). A pollutant is assumed to affect one or more than one water quality parameter in the sets *V* or *S* or both. Note that no water quality parameter is common to sets *V* and *S*.

Table1.River System Description

Set	Description of the set	Element representation	Number of elements
Q	Water quality mesh point	l	N_q
D	Dischargers	m	N_d
P	Pollutants	n	N_p
T	Uncontrollable source of pollutants	p	N_t
V	Water quality parameters: desirable level>permissible level	i	N_v
S	Water quality parameters: desirable level<permissible level	j	N_s

Genetic Algorithms

Evolutionary Algorithms can be divided into three main areas of research: Genetic Algorithms (GA), Evolution Strategies (ES) and Evolutionary Programming (EP). Genetic Programming began as a general model for adaptive process but has since become effective at optimization while Evolution Strategies was designed from the beginning for variable optimization. The schematic diagram of these algorithms which are made of the several iterations of basic Evolution Cycle is shown below:

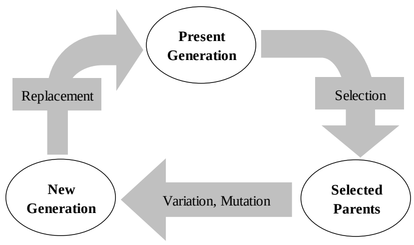


Figure1: Schematic Diagram of Evolution Cycle

A GA is a robust method for searching the optimum solution to a complex problem, although it may not necessarily lead to the best possible solution. A GA generally represents a solution using strings (also referred to as chromosomes) of variables that represent the problem.

A GA starts with a population of chromosomes, which are combined through genetic operators to produce successively better chromosomes. The genetic operators used in the reproductive process are selection, crossover and mutation. Chromosomes in the population with high fitness values have a high probability of being selected for combination rather than chromosomes with low fitness. Combination is achieved through the crossover of pieces of genetic material between selected chromosomes. Mutation allows for the random mutations of bits of information in individual genes. Through successive generations fitness should progressively improve. Various schemes for selection, crossover, and mutation exist.

Max-Min Formulation

Different goals associated with water quality management in the river system are considered in this section. The quantities of interests are the concentration levels, C_{il} and C_{jl} of the water quality parameters, and the fraction removal levels (treatment levels), x_{imn} and x_{jmn}, of the pollutants.

The pollution control agency sets a desirable level, C_{il}^{D}, and a minimum permissible level, C_{il}^{L} for the water quality parameter i at the mesh point l ($C_{il}^{D} > C_{il}^{L}$). Similarly, C_{jl}^{D} and C_{jl}^{H} represent respectively, the desirable and maximum permissible levels of the water quality parameter j at the mesh point l ($C_{jl}^{D} < C_{jl}^{H}$). The quantities x_{imn} and x_{jmn} are the fractional removal levels of the pollutant n from the discharger m to control the water quality parameters i and j, respectively. The aspiration level of the discharger m with respect to x_{wmn} (w stand for either i or j) is represented as x_{wmn}^{L}. The corresponding maximum fraction removal level acceptable to the discharger m is represented as x_{wmn}^{M}.

The first goal, E_{il} is defined that the concentration level, C_{il} as close as possible to the C_{il}^{D}.The desirable level, C_{il}^{D} is assigned a membership value of 1. The minimum permissible level, C_{il}^{L}, is assigned a membership value of zero.

Goal E_{jl} is similar to the goal E_{il} but with respect to water quality parameter j. The desirable level, C_{jl}^{D}, for the water quality parameter j at the mesh point l is assigned a membership value of 1. The maximum permissible level, C_{jl}^{H} is assigned a membership value of zero. The goal F_{imn} is defined as making fraction removal level x_{imn} as close as possible to the x_{imn}^{L}. The fraction removal level, x_{imn}^{L}, corresponding to the aspiration level of the discharger m with regard to x_{imn} is assigned a membership value of 1.The maximum acceptable level, x_{imn}^{M}, is assigned a membership value of 0.

This membership function may be interpreted as the variation of satisfaction level of the discharger m in treating the pollutant n to control the water quality parameter i in the river system.

Goal F_{jmn} and membership function $\mu_{F_{jmn}}(x_{jmn})$ is similar to the goal F_{imn} and the membership function $\mu_{F_{imn}}(x_{imn})$ but with respect to water quality parameter j.

Non increasing or non decreasing membership function are assigned to each of the fuzzy sets. The non increasing membership function reflect the premise "the less the better or at least not the worse," whereas the non decreasing membership function reflect the premise "the more the better or at least not the worse.

Based on the membership function for the fuzzy goals, the MAX-MIN formulations of FWLAM are presented in this section. Shape of the membership function may be chosen by the decision maker. The crisp equivalent of the fuzzy multiple-objective optimization problem provides the basis for the MAX-MIN formulation of FWLAM. The model maximizes the satisfaction level, λ, in the system. The model is expressed as

$$\text{Max } \lambda \qquad (1)$$

$$\mu_{E_{il}}(C_{il}) \geq \lambda \qquad \forall\, i,l \qquad (2)$$

$$\mu_{E_{jl}}(C_{jl}) \geq \lambda \qquad \forall\, j,l \qquad (3)$$

$$\mu_{F_{imn}}(x_{imn}) \geq \lambda \qquad \forall\, i,m,n \qquad (4)$$

$$\mu_{F_{jmn}}(x_{jmn}) \geq \lambda \qquad \forall\, j,m,n \qquad (5)$$

$$C_{il}^{L} \leq C_{il} \leq C_{il}^{D} \qquad \forall\, i,l \qquad (6)$$

$$C_{jl}^{D} \leq C_{jl} \leq C_{jl}^{H} \qquad \forall\, j,l \qquad (7)$$

$$\boldsymbol{x}_{imn}^{L} \le \boldsymbol{x}_{imn} \le \boldsymbol{x}_{imn}^{M} \qquad \forall\, i,m,n \qquad (8)$$

$$\boldsymbol{x}_{jmn}^{L} \le \boldsymbol{x}_{jmn} \le \boldsymbol{x}_{jmn}^{M} \qquad \forall\, j,m,n \qquad (9)$$

$$\boldsymbol{x}_{imn}^{MIN} \le \boldsymbol{x}_{imn} \le \boldsymbol{x}_{imn}^{MAX} \qquad \forall\, i,m,n \qquad (10)$$

$$\boldsymbol{x}_{jmn}^{MIN} \le \boldsymbol{x}_{jmn} \le \boldsymbol{x}_{jmn}^{MAX} \qquad \forall\, j,m,n \qquad (11)$$

$$0 \le \lambda \le 1 \qquad (12)$$

$\mu_{E_{il}}$ and $\mu_{E_{jl}}$ are the membership functions of goals $\boldsymbol{E}_{il}$ and $\boldsymbol{E}_{jl}$ and $\mu_{F_{imn}}$ and $\mu_{F_{jmn}}$ are the membership functions of $\boldsymbol{F}_{imn}$ and $\boldsymbol{F}_{jmn}$.

The crisp constraints (6) through (12) determine the feasible space of alternatives. The constraints (6) through (7) determine the water quality requirements set by the pollution control agency. Constraints (8) and (9) determine the aspiration level and maximum acceptable level of pollutant treatment efficiencies set by the dischargers. Constraints (10) and (11) determine the minimum levels of pollutant efficiencies which are expressed by the pollution control agency as a lower bound , $\boldsymbol{x}_{imn}^{MIN}$ and $\boldsymbol{x}_{jmn}^{MIN}$, and maximum acceptable treatment levels. It may be noted that the constraints (2) through (5) define the parameter λ as the minimum satisfaction level in the system.

The concentration level, $\boldsymbol{C}_{wl}$, of the water quality parameter *w* (the index *w* stands for either *i* or *j*) at the mesh point *l* can be related to the fraction removal level, $\boldsymbol{x}_{wmn}$, of the pollutant *n* from the discharger *m* to control the water quality parameter *w*.

Water Quality Simulation Model

As environmental controls become more costly to implement and the penalties of judgment errors become more severe, environmental quality management requires more efficient management tools based on greater knowledge of the environmental phenomena to be managed. In this paper, the most recent modification QUAL2E (version 3.22) is used.

QUAL2E , which can be operated as a steady state is intended for use as a water quality planning tool. The model can be used for example, to study the impact of waste load in stream water quality or to identify the magnitude and quality characteristic of non point waste loads as part of field sampling program.

QUAL2E have the capability to model physical, biological and chemical process take place in a water body. QUAL2E are developed based on the conversation of mass. QUAL2E is a multi-constituent water quality model which can predict the physical, chemical and biological interaction of many constituents and organisms found in natural water bodies. The basic equation solved by QUAL2E, in steady state, is the one dimensional advection- dispersion equation as

$$\frac{\partial C}{\partial t} = \frac{\partial (A_x . D_L . \frac{\partial C}{\partial x})}{A_x . \partial x} dx - \frac{\partial (A_x . \bar{U} . C)}{A_x . \partial x} + \frac{s}{V} \qquad (13)$$

The finite–difference form of Eq.(13), is successively applied to all computational elements of the river system. If any computational element is subjected to an external Load, the mass released from that load is added to system

Simulation-Optimization

The coupling between simulation and optimization allows the advantages of both modules to be retained within a single framework. The S-O approach, in this paper work interfaces QUAL2E and GA to solve the Fuzzy optimization problem. A simulation model generally needs a large amount of data for calculating the response of the system. This data consist of details of river discretization, location of headwaters, effluent flow, effluent loads and junctions, length of reaches and computational element, simulation type (Steady State or dynamic), units(metric or English), water quality constituents to model (DO,BOD),…. The data are incorporated into the input file of QUAL2E and remain fixed for all simulations. The input file also consists of the fraction removal levels, which are the decision variables of the fuzzy optimization model. During each call to QUAL2E, the set of fractional removal levels of the dischargers in the input file is replaced with the set provided by GA. Each runs of QUAL2E result in the system response in terms of the concentrations of the water quality indicators (state variables), which are written to an output file. This state variable required by Fitness Evaluation programming is taken from this QUAL2E output file. The main objective of interface among GA and QUAL2E is to evaluate the Fitness Function of the chromosomes. Fitness Function evaluation is performed after any generation.

Model Application

The application of FWLAM is demonstrated with a hypothetical river network (Figure.2). The river network is applied to a 500 km reach of the river, which stem from four headwaters and nine point loads. For simplicity no incremental flow or withdrawal along the stream is assumed to influence the flow in the river system. In QUAL2E, a reach is defined as a stretch of river which model input parameters or coefficients (physical, chemical and biological) remain constant. A new reach is defined at a location where a new junction is encountered or a significant change in model input coefficient occurs or the number of computational elements in the reach will be 20. Accordingly, the 500-km long stretch of the river is discretized into 16 reaches of varying lengths, each of which is further discretized into computational elements of 2 km, following the QUAL2E restriction of twenty computational elements within each reach. Nine reaches receive a point source of BOD waste load from the dischargers located at the beginning of them. The only pollutant in the system is the point source of BOD waste load. The water quality parameter of interest is dissolved oxygen deficit (DO deficit) at a finite number of mesh points due to these point sources of BOD. Water quality is checked at 23 mesh points. A trapezoidal cross-sectional shape with side slope 1:1 is considered for the river.

It may be noted that since the desirable level of the DO deficit is smaller than the permissible level, this water quality parameter belongs to the set *S* described in table 1. The set *V* and *T* are empty sets. The elements in the sets *P*, *D* and *Q* are, respectively, BOD point sources, nine dischargers, and 23 mesh points. Since the sets *P* and *S* contain only one element each, the suffixes *j* and *n* are dropped from the constraints and objective function for convenience. Denoting the DO deficit at the water quality mesh point *l* by $\boldsymbol{C_l}$, and the fractional removal level for the *m*th discharger by $\boldsymbol{x_m}$, and using linear membership function for the fuzzy goals. The MAX-MIN formulation can be simplified as follows:

Max λ

Subject to

$$\left[\frac{\boldsymbol{C_l^H} - \boldsymbol{C_l}}{\boldsymbol{C_l^H} - \boldsymbol{C_l^D}}\right] \geq \lambda \qquad \forall\, l$$

$$\left[\frac{\boldsymbol{x_m^M} - \boldsymbol{x_m}}{\boldsymbol{x_m^M} - \boldsymbol{x_m^L}}\right] \geq \lambda \qquad \forall\, m$$

$$\boldsymbol{C_l^D} \leq \boldsymbol{C_l} \leq \boldsymbol{C_l^H} \qquad \forall\, l$$

$$\text{Max}[\boldsymbol{x_m^L}, \boldsymbol{x_m^{MIN}}] \leq \boldsymbol{x_m} \leq \boldsymbol{x_m^M} \forall\; m$$

$$0 \leq \lambda \leq 1$$

Two typical membership functions corresponding to the fuzzy goals $\boldsymbol{E_l}$ (goal of the pollution control agency related to the DO deficit at mesh point *l*), and $\boldsymbol{F_m}$ (goal related to the fraction removal level for discharger *m*) .A minimal fraction removal level of 0.25 is imposed by the pollution control agency on all dischargers (i.e., $\boldsymbol{x_m^{MIN}}$ =0.25, $\forall$ *m*).

For this simulation-optimization model, we use GA as an optimization method. The GA process is done corresponding to the follow illustration**.**

Step1: Generating initial random populations with N chromosomes.

Step2: Simulating these chromosomes; in simulation process, the state variables are calculated in water quality simulation model (QUAL2E) and written in output file.

Step3: Evaluating the fitness functions of chromosomes. Minimum nonzero membership of these chromosomes divided by penalty coefficient that the times which state variables (dissolved oxygen deficit) are more than permissible level is exponent of it, is introduced as a fitness function of any chromosome**.**

Step4: Sorting the fitness functions of all chromosomes in decreasing fashion.

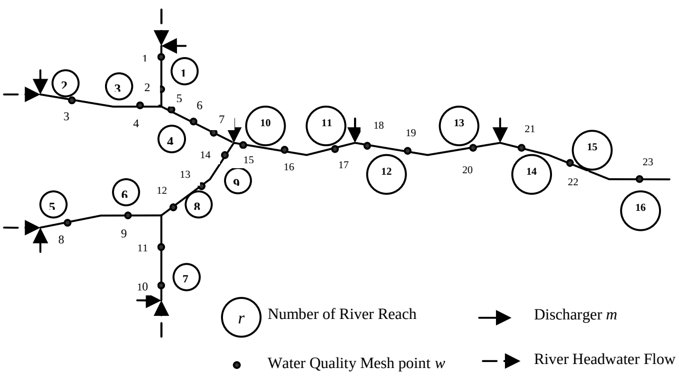
Step5: Choosing N chromosomes for participation in reproduction process in roulette wheel approach.

Step6: Permitting to some of the chromosomes to participate in crossover process and swap some of their gens together.

Step7: Permitting random mutation to be made to individual gens in some chromosomes.

Therefore, new populations are generated and then we go to step2 and go on until the termination criteria met. In this study, the fitness function is very small and the algorithm is sensitive to penalty coefficient. When we use a small penalty coefficient, we have a lot of infeasible solution. Because we reduce the elimination of infeasible chromosomes and we have extra space for searching and the time for achieving to the best solution is increased. In other word, we will be far off the best solution. On the other hand, when we choose a high penalty coefficient, we limit the search space and the good chromosomes with high fitness functions have more probability to be selected for next generation and the chromosomes with small fitness functions which may have good gens in some of their bits, have low probability for choosing and may be, they are eliminated. Therefore, the number of good chromosomes in next generation will be high and it causes the crossover not to have an important role in GA process. We try to survey the penalty coefficient with number 1.1 and 1.5, also we change the crossover and mutation probability and crossover type, too. We change the crossover type to one-cut point and two-cut point and crossover probability (Pc) to 40%, 60% and 80%. We change mutation probability (Pm) to 2%, 5% and 10%, too. Generally, we have 36 states and we survey the results of any states in 10 Runs. With comparison Convergence, Standard deviation, Maximum, Average and Minimum diagrams of fitness functions and Standard deviation, Maximum, Average and Minimum of final fitness function in 10 Runs in any states, we choose the best state which follow us to the optimal solution. The state was Pc=40%, Pm=2%, penalty coefficient =1.5 and Crossover type=two-cut point. The best fitness function which is obtained through 1000 generation and 80 populations, is $\lambda^* = 0.22$ In comparison between 36 states, which discussed in this section, we choose the state, which has maximum fitness function and minimum standard deviation of final fitness function in 10 Runs. The diagrams of these 36 states are shown in figure.3. through 5 and figure.6. through 11.

Figue.2: Hypothetical River Network



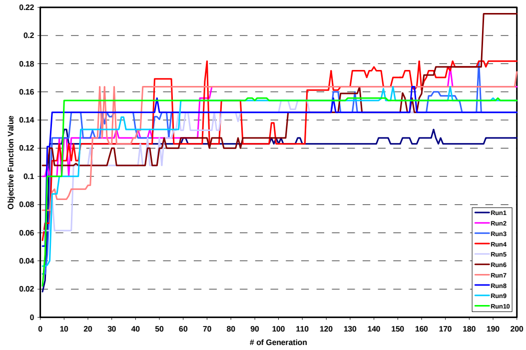


Figure.3: Maximum of Objective FunctionValue Obtained in Each Generation Over 10 Runs

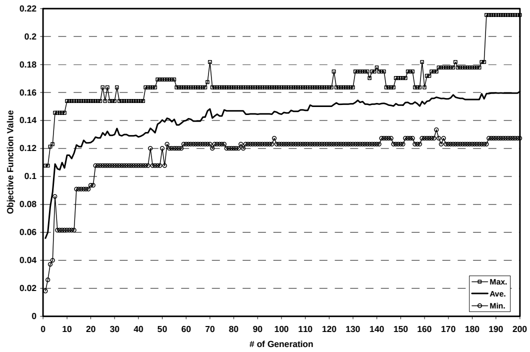


Figure.4: Maximum, Average and Minimum Objective Function Value Obtained in Each Generation Over 10 Runs

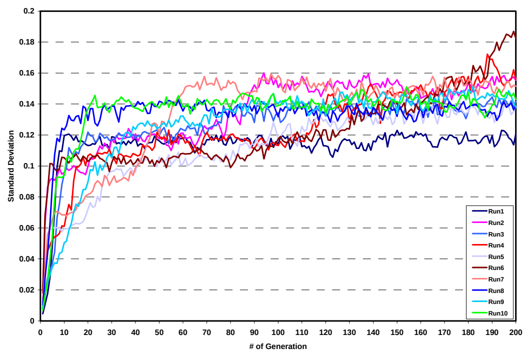


Figure.5: Standard Deviation of Objective Function Values Obtained in Each Generation Over 10 Run

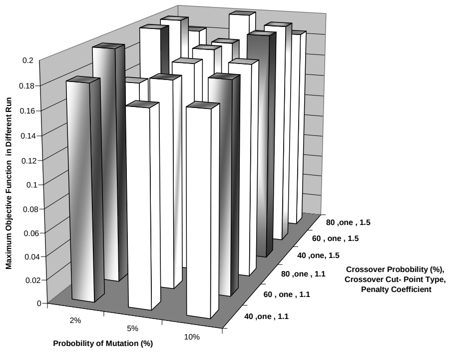


Figure.6: Maximum of Final Objective Function Values Obtained Over 10 Runs in One-Point Cut Crossover

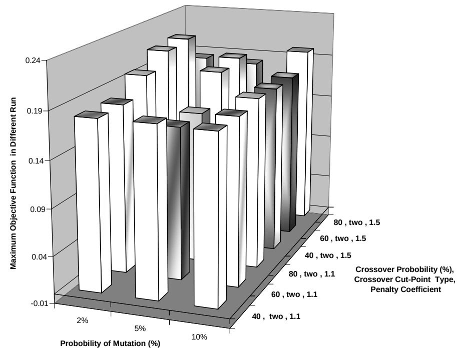


Figure.7: Maximum of Final Objective Function Values Obtained Over 10 Runs in Two-Point Cut Crossover

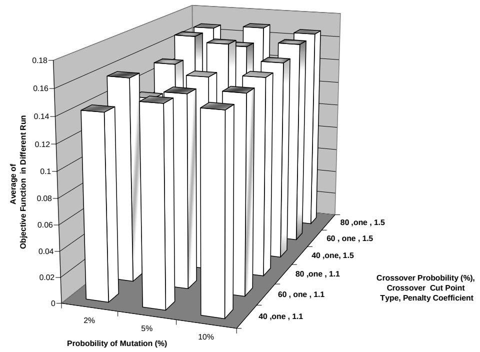


Figure.8: Average of Final Objective Function Values Obtained Over 10 Run in One-Point Cut Crossover

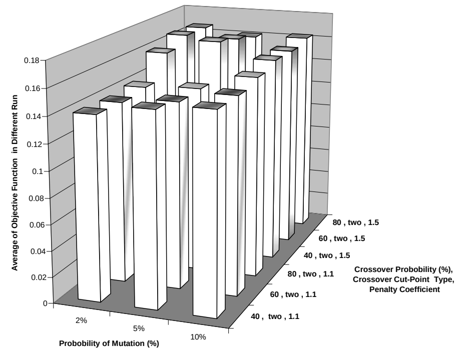


Figure.9: Average of Final Objective Function Values Obtained Over 10 Runs in Two-Point Cut Crossover

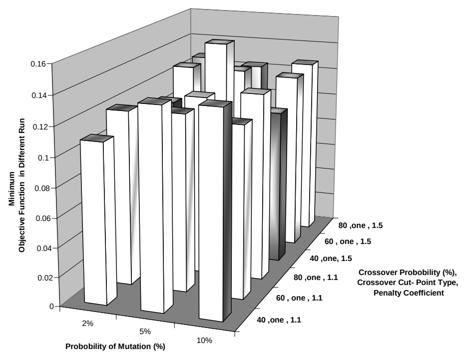


Figure.10: Minimum of Final Objective Function Values Obtained Over 10 Runs in One-Point Cut Crossover

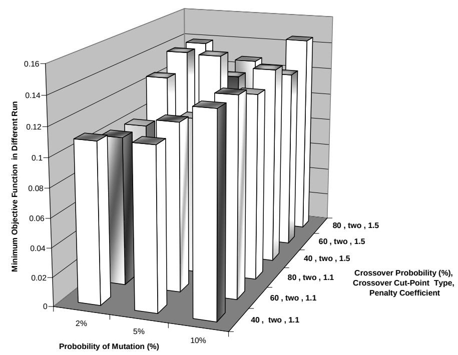


Figure11: Minimum of Final Objective Function Values Obtained Over 10 Runs in Two-Point Cut Crossover

CONCLUSION

A fuzzy waste load allocation model is developed in the present study to incorporate uncertainties due to randomness and vagueness in simulation-optimization model for water quality management. This water quality problem is formulated as a fuzzy multi-objective optimization which goals of pollution control agency and the dischargers are expressed with appropriate membership functions. The model is applied to a hypothetical river system to illustrate the fuzzy optimization modeling in water quality management. In fuzzy optimization model, we use Genetic Algorithm as an optimization tool which was linked with water quality simulation model, QUAL2E. Generally, water quality management characterized by various types of uncertainties due to randomness associated with various components of a river system such as river flow, effluent flow, temperature, source of pollutant, water quality parameter and other variables. Using these forms of uncertainties with fuzzy optimization will provide proper solutions in water quality management. Further more, in waste load allocation problems; the waste treatment cost is an important factor in decision making process. But because of vagueness, lack of adequate data and nonlinearity of cost function cause difficulties which we preclude to use cost function in optimization problem directly. In the fuzzy waste load allocation, the cost function is eliminated and goals of dischargers are expressed with appropriate membership functions. In the optimization model with GA, to handle the constraints, the penalty coefficient is used. The number of states which membership of state variables (dissolved oxygen deficit) is zero and the state variables are more than permissible level is exponent of penalty coefficient and cause the fitness function will be small. Generally, assigning appropriate value for penalty coefficient and appropriate shape for membership functions helps the decision makers to decide properly in water quality management. For this case, which is presented in this paper, we can use S-P model with linear membership function and solve the fuzzy optimization problem with linear programming, too. But use QUAL2E and GA, when we have nonlinear membership functions or coupled system with interactions between algae, phosphorous, nitrogen and dissolved oxygen is very useful.

***References*:**

[1] Brown, C. L., Barnwell, T. O., *The Enhanced Stream Water Quality Models QUAL2E and QUAL2E-UNCAS: DOCUMENTATION AND USER MANUAL*, Environmental Research Laboratory Office of Research and Development U.S. Environmental Protection Agency.

[2] Burn, D. H., Lence, B. J., *Comparison of Optimization Formulations For Waste Load Allocations*, Journal of Environmental Engineering, Vol. 118, No.4, 1992(ASCE).

[3] Burn, D. H., Yulianti, J. S., *Waste-Load Allocation Using Genetic Algorithms*. Journal of Water Resour. Pla., Vol.127, No.2, 2001, pp. 121-129.

[4] Chapra, S. D., *Surface Water Quality Modeling*. Mc GRAW- HILL COMPANIES, INC.

[5] Dandy, G. C., Simpson, A. R. and Murphy, L. J, *An improved genetic algorithm for pipe network optimization*, Water Resour. Res., Vol.32, No.2, 1996, pp. 449-458.

[6] Franchini, M., *Use of a genetic algorithm combined with a local search method for the automatic calibration of conceptual rainfall-runoff models*, Journal of Hydro. Sci., Vol.41, No.1, 1996, pp. 21-40.

[7] Goldberg, D. E. and K. Deb., *A Comparitive analysis of selection schemes used in genetic algorithms*, Foundation of genetic algorithms, Morgan Kaufman, San Mateo, Calif., 1989, pp. 69-93.

[8] Michalewics, Z., *Genetic algorithms + data structures = evolution programs*, Springer, New York, 1992.

[9]Mujumdar, P.P., Vemula, R.S., *Fuzzy waste load allocation model: simulation-optimization approach*, Journal of Computing in Civil Engineering, 2004, pp.120-131 (ASCE)

[10] Murphy, L. J., Simpson, A. R. and Dandy, C. G., *Design of a network using genetic algorithms*, Journal of Water, Vol.20, 1993, pp. 40-42.

[11] Oliviera, R. and Loucks, D. P., *Operating rules for multireservoir systems*, Journal of Water Resour. Res., Vol.33, No.4, 1997, pp. 1589–1603.

[12] Ritzel, B., Ebeart, J. W. and Ranjithan, S., *Use genetic algorithms to solve a multiple objective ground water pollution problem*, Journal of Water Resour. Res., Vol.30, No.5, 1994, pp. 1589-1603.

[13] Sasikumar, K., Mujumdar, P. P., *Fuzzy optimization model for water quality management of a river system*, Journal of Water Resour. Pla., Vol.124, No.2, 1998, pp. 79-87.

[14] Tang, W.H. and Yen, B.C. 1993. *Probabilistic inspection scheduling for dams, Reliability and Uncertainty Analyses in Hydraulic Design*, Edited by B.C. Yen and Y.K. Tung, 1993, pp. 107-122, ASCE, New York, NY.

[15] Wang, Q. J., *The genetic algorithm and its application to calibrating conceptual rainfall-runoff models*, Journal of Water Resour. Res., Vol.27, No.9, 1991, pp. 2467-2471.