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Best GA Operators Probabilities in Optimizing Levee's Setback

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Abstract: Floods are one of the major natural disasters that often threaten human lives and cause significant economic losses around the world. The history of mankind is filled with the stories of our struggles with floods to protect human races and to sustain the progression of our civilizations. Flood defense systems are designed and constructed to protect low-lying areas against flooding. Engineering design often is at the final stage for finding technical means to best accomplish the project goals. Conceptually, in the cost of the protection system, the most important factor in designing flood defense systems, should be in balance with the value of the protected area. Over the years, risk-based design and optimization methods have proven to be useful tools to obtain a balanced level of protection. The most common economic framework for floodplain management is minimization of expected annual damages and flood management expenses, structural and nonstructural flood control options. Levee systems have been built for flood protection in numerous rivers, lakes and coasts in the world over the long human history. Early flood levees usually were designed with scant quantitative analysis, relying primarily on occasional observations of flood stages and empirical judgments on required project scales. Economic design of a levee system for flood protection involves balancing costs of levee building (height), the losses of land value sacrificed for floodway expansion (setback) and flood damages from inadequate channel capacity. The application of GAs to water resources problems has been increased in recent years. The study of genetic algorithms (GAs) originated, and has developed into a powerful optimization approach. GAs have so far had very little applications in flood defense systems optimization. In this paper several different approaches to GA formulation are considered, along with a range of sensitivity analysis. The object has been to present GAs as a practical tool in levee design optimization and to examine the potential of different GA formulations for solving the problem. It has been demonstrated that GAs provide robust and acceptable solutions to the levees setback optimization problem. The results obtained indicate that there is potential for application of GAs to levees optimization problems, where the objective function is nonlinear and other optimization techniques may be difficult to apply and find the global optimum.

Keywords: Optimization, Levee, Setback, Genetic Algorithm, Selection, Crossover, Mutation

1 Introduction

Floods are one of the major natural disasters that often threaten human lives and cause significant economic losses around the world. The history of mankind is filled with the stories of our struggles with floods to protect human races and to sustain the progression of our civilizations. Even with centuries of experiences on flood defense and tremendous amount of progresses have been achieved, flood still appears to enjoy being the main enemy of public in the category of natural disaster. Berz (2000) recently compares flood disasters with earthquakes, storms and other forms of nature disasters in the world. The study indicates that floods contribute to 58% of total death and 33% of economic losses [1]. Great majority of flood, related death and economic losses occurred in developing countries.

Flood defense systems are designed and constructed to protect low-lying areas against flooding. Decision for a flood defense system are multi-dimensional which involve a set of goals and constraints arising from political, economical and engineering aspects. Engineering design often is at the final stage for finding technical means to best accomplish the project goals. Over the years engineering design concepts have been evolved as the science and technology in dealing with flood issues progress and improve.

The application of GAs to water resources problems is not deniable. Wang (1991) applied a

GA to the calibration of a conceptual rainfall-runoff model. Similar work has been reported by Franchini (1996), who used a GA in combination with sequential quadratic programming to calibrate a conceptual rainfall-runoff model. There have been also several applications of GAs to pipe net work problems. Goldberg (1987), Murphy et al. (1993), Davidson and Goulter (1995) and Dandy et al (1996) used a simple and also improved GA for pipeline, pipe network and water supply network optimization. In ground-water pollution problems, Ritzel al. (l994) and McKinney and Lin (1994) have been made good experiences.

Levee systems have been built for flood protection in numerous rivers, lakes and coasts in the world over the long human history. Early flood levees usually were designed with scant quantitative analysis, relying primarily on occasional observations of flood stages and empirical judgments on required project scales. The achievements in experimental and theoretical hydraulics since the 18th century, rational estimation of storm discharge in the mid 19th century and the emerging of early economic-engineering analysis (Humphreys, 1861) made possible the “modern sense” designs of flood levees. In recent decades, several studies have addressed the economic aspects of flood levee design, usually with benefit-cost analysis and optimization techniques (Tung and Mays, 1981, Wurbs, 1983).

GAs have so far had little applications in flood defense systems optimization. Excellent introductions to GAs are given by Goldberg (1989) and by Michalewicz (1992) and several recent papers give summaries of the essentials (e.g. Oliveira and Loucks, 1997 and Savic and Walters, 1997). Shafiei et al. used genetic algorithms for optimization of levees setback along certain probability of crossover and mutation operators [11]. In this paper, several different probabilities of genetic operators in GA formulation are considered, along with a range of sensitivity analysis in the same problem of setback optimization. In this paper. The object has been to present GAs as a practical tool in levee design optimization and to examine the potential of different GA formulations for solving the problem.

2 Economic Design of Flood Defense Systems

Flood defense systems are designed and constructed to protect low-lying areas against flooding. The objective in economic design of a hydraulic structure is to minimize the sum of capital investment cost, the expected flood damage costs and operation and maintenance costs.

Economic design of a levee system for flood protection involves balancing construction costs of levee, the losses of land value sacrificed for floodway expansion (Setback) and flood damages from inadequate channel capacity. The most common economic objective for floodplain management is minimization of expected annual damages and flood management expenses. Under static conditions, the flood frequency distribution is stationary and economic factors, such as the value of damage to properties, construction cost, and floodplain land values, are constant.

2.1 Data Requirements in Economic Design of Flood Defense Systems

The information needed for this process can be categorized into four types.

- Hydrologic/Physiographical Data
- Hydraulic Data
- Structural Data
- Economic Data

2.2 Optimal Tradeoff of Levee Setback and Height

A static model is formulated to minimize the sum of expected flood damage, considering levee construction cost and resultant land value loss due to floodway occupancy. This simple model allows preliminary quantitative examination of the tradeoff between optimal setback and optimal height in designing a new levee. The objective function is:

$$Max\frac{B}{C}(Xs, Xh) = \frac{B(Xs, Xh)}{C(Xs)} \tag{1}$$

Where X_s and X_h are designed levee setback and height respectively. B and C also identify the benefit and cost of levee system.

The land value benefit function B( ) depends not only on levee setback but also on levee height because the bottom width of levee cross-section may change with levee height. Considering partial derivatives of $B/C(X_s,X_h)$, with respect to X_s and X_h equal zero,

$$\frac{\partial(B/c)}{Xs} = 0 \tag{2}$$

$$\frac{\partial(B/c)}{Xh} = 0 \tag{3}$$

Given a levee overtopping flow Q(Xs,Xh), we have

$$\frac{\partial Q}{\partial Xh} / \frac{\partial Q}{\partial Xs} = \frac{\partial (C+B)}{\partial Xh} / \frac{\partial B}{\partial Xs} \qquad (4)$$

Equation (4) holds for the optimal levee height and setback. The optimal levee height and setback can be found by numerically solving combined equations (2) and (3) and verifying that a minimum has been found, even though the expected total cost function in Equation (1) is not convex [13].

3 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:

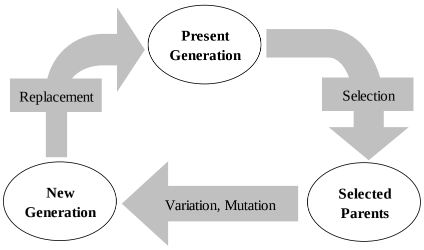

Fig. 1: Schematic Diagram of Evolution Cycle

A GA is a search algorithm based upon the mechanics of natural selection, derived from the theory of natural evolution. GAs simulate mechanisms of population genetics and natural rules of survival in pursuit of the ideas of adaptation, indeed this has led to a vocabulary borrowed from natural genetics [3].

Goldberg (1989) identifies the following as the significant differences between GA and more traditional optimization methods:

- GAs work with a coding of the parameter set, not with the parameters themselves.
- GA search from a population of points, not a single point
- GAs use objective function information, not derivatives or other uxillary knowledge
- GAs use probabilistic transition rules not deterministic rules

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 he problem. In early GAs (Goldberg and Kuo 1987, Wang 1991) these strings were comprised of binary bits. In binary representation. the bits may encode integers, real numbers, sets or whatever else is appropriate to the problem. Real-value coding is now proving more effective in many problems than binary coding (e.g.. Oliveira and Loucks 1997).

Coding components of possible solutions into a chromosome is the first part of a GA formulation. Each chromosome is a potential solution and is comprised of a series of sub-strings or genes, representing components or variables that either form or can be used to evaluate the objective function of the problem. The fitness of a chromosome as a candidate solution to a problem is an expression of the value of the objective function represented by it. It is also a function of the problem constraints and may be modified through the introduction of penalties when constraints are not satisfied.

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 of other chromosomes of high 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 and will be discussed.

3.1 Genetic Algorithm Process

Canonical form of GA approach can be summarized as:

1. Define the objective function which is appropriate to conditions of problem.

2. Present the possible solutions (phenotype) as real value (genotype or chromosome). 3. Generate a random population of specific size. The population size affects the efficiency and performance of GA.

4. Evaluate the fitness of every solution over the objective function. There are many methods to evaluate fitness and assign a real number to each chromosome.

5. Select a population of chromosomes of the same size of initial population for mating, by a random selection method.
6. Apply crossover operation on selected pairs if they have been chosen for crossover. 7. Replace the parent population with new generation.
8. Applying mutation operator based on the probability of mutation. At this point the process of producing a pair of offspring from two selected parents is finished.
9. Go through steps 4 to 8 until the termination criteria met.

3.2 Representation Schemes

Traditionally GAs have used binary coding, in which a chromosome is represented by a string of binary bits that can, encode integers, real numbers, or anything else appropriate to a problem. In a real-value representation, individual genes of a chromosome are initially allocated values randomly within feasible limits of the variable represented, with a sufficiently large population of chromosomes adequate representation will be achieved. There is a significant advantage in not wasting computer time on decoding for objective function evaluation, although a more careful approach to mutation is required. In real-value coding there is no discretization of the decision variable space. This is another advantage of this approach.

3.2.1 Selection Approaches

Selection is the procedure by which chromosomes are chosen for participation in the reproduction process. A popular approach has been fitness proportionate selection (Goldberg 1989), in which the probability P of an individual k being selected is given by:

$$p_k = \frac{f_k}{\sum f_j} \tag{5}$$

where f is fitness of individuals along the population.
Various rank selection schemes are in use (Michalewict 1992) that tend to ensure that good chromosomes have higher chances of being selected for the next generation. Ranking schemes operate by sorting the population on the basis of fitness values and then assigning a probability of selection based upon the rank. The roulette wheel approach is one of ranking schemes of selection.

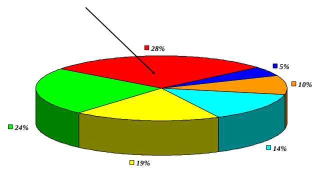

Fig. 2: Roulette Wheel Selection

A constant selection differential is thus maintained between the best and the worst individuals in the population. A drawback is that information on the relative fitness of the individuals is not used. Goldberg and Deb (1990) have compared various selection schemes, and indicated a preference for the tournament selection scheme. In tournament selection a group of individuals are chosen at random from the population, and the individual with the highest fitness is selected for inclusion in the next generation. The procedure is repeated until the appropriate number of individual are selected for the new generation. The approach had originally been developed with groups of two individuals and was called binary tournament selection, but larger groups lead to greater diversity and a smoother progression to a solution. Tournament selection was used by some authors in the ground-water monitoring problem.

3.2.2 Crossover Approaches

The general theory behind the crossover operation is that, by exchanging important building blocks between two strings that perform well, the GA attempts to create new strings that preserve the best material from two parent strings. The number of strings in which material is exchanged is controlled by the crossover probability forming part of the parametric data. Goldberg (1989) and Michalewicz (1992) describe the following methods of crossover (1) one-point crossover; (2) two- point crossover and (3) uniform crossover [3] , [6].
Crossover occurs between two selected chromosomes with some specified probability. In one-point crossover, a crossover point is selected at random at some point C in the chromosome length L and two new individuals are created by swapping all genes between positions C and L. In two-point crossover, genetic material between two positions chosen at random along the length of the chromosomes, C1 and C2, is exchanged. Uniform crossover operates on individual genes of the selected chromosomes, rather than on blocks of genetic maternal, and each gene is considered in turn for crossover or exchange.

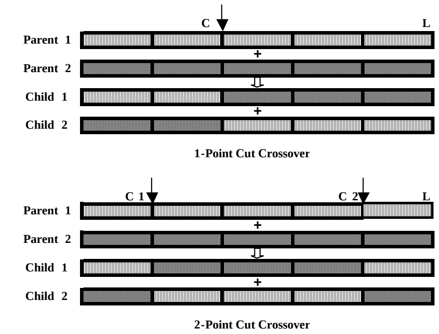

Fig. 3: Crossover Approaches

3.2.3 Mutation Approaches

Mutation is an important process that permits new genetic material to be introduced to a population. A mutation probability is specified that permits random mutations to be made to individual genes. The two basic approaches to mutation for teal-value representations are uniform ruination and non-uniform mutation [6]. Uniform mutation permits the value of a gene to be mutated randomly within its feasible range of values; possibly resulting in significant modification of otherwise good solutions. Modified uniform mutation permits modification of a gene by a specified amount, which may be either positive or negative. In non-uniform mutation, the amount by which genes are mutated can be reduced as a run progresses, and can therefore help in the later generations to fine tune the solutions. This operator is particularly suited to problems where high precision is required.

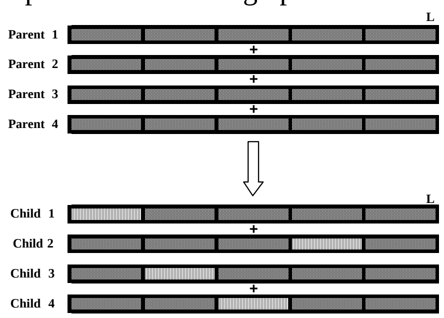

Fig. 4: Uniform Mutation

4 Methodology

4.1 Hydrologic Analysis

In this paper, the HEC-HMS was applied to fulfill hydrologic analysis. The Corps' HEC-HMS is a Windows-based program with significant improvements over its predecessor. The resulting peak flows of 25-year and 100-year hydrograph is to extract from the outputs of the model.

4.2 Geometry Model

In this paper, the digital topographic maps of study area were used to make the required DEM of study area and the cross-sections were defined and extracted to use in next steps.

4.3 Hydraulic modeling

In this paper, the steady uniform current is applied along the river. The design discharge for optimizing the setback of levees of study area was selected as the peak flow of hydrograph with return period of 100 year.

For accomplishing hydraulic modeling and analysis in this study, HEC-RAS model, HEC-RAS version 3.0.1, as developed by the Hydrologic Engineering Center, U.S. Army Corps of Engineers, was used as a basis model to verify water surface profiles based on the flood discharges which are excluded from a visual basic code determining water level of each section. This code make the calculations having the characteristics of the cross-sections such as ground points elevations and maning value and also discharge of current with unit of cubic meter per second. This part of analysis is done to make the hydraulic simulator able to participate in the iterative process of optimization.

4.4 Economic Analysis And Optimization

In this stage, we continue to use a visual basic code written to analyze the cost and benefit of flood defense system and determine the optimum levees setback with the maximum economic benefits. Genetic algorithm is applied to achieve best solution. Substituting the hydrologic and hydraulic study outputs in the optimization analysis and refining the construction cost estimate based on developing knowledge of cost-sensitive features such as water level, we make it possible to determine the optimum design.

4.4.1 Genetic Algorithm Formulation

Since the objective function is based on maximizing ratio between benefit and cost of flood levees, levee height in each section should be the decision variable on which the GA is based. Construction cost is calculated by using volume of constructed levee and unit cost of it. Benefit is calculated from the value of protected land due to constructed hydraulic structure (Levee). With 10 sections and one levee height, there are thus 10 discrete variables to be represented in the GA. Each of these may be considered to be a gene. Elevation values are to be considered as non-integer quantities with precision of 0.1 meter. This is toward defining the problem and is not a limitation for GAs.

An alternative approach to formulation of the GA is to use a representation appropriate to the components of the problem. Here, Real-value chromosomes have been used with success where individual genes of a chromosome are initiated by randomly within feasible zone. With a sufficiently large population good representation will be achieved.

The schematic diagram of steps accomplished during the optimization process using genetic algorithm is shown below:

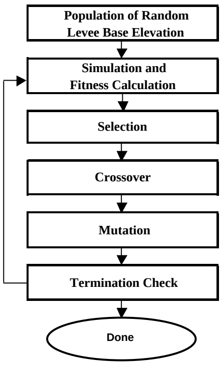

Fig. 4: Schematic Diagram of GA Formulation

For generating a random population, the population size is 80 chromosomes for making the sensitivity analysis and 400 chromosomes for final optimization analysis.

Proportional selection method is used here to evaluate the fitness of every solution over the objective function. In selection step, roulette wheel approach is applied to select population of chromosomes of the same size of initial population. In the crossover step, 1-point cut crossover is applied on selected pairs based on probability of crossover. The probabilities of 0.2, 0.4 and 0.6 were applied. In this approach, after replacing the parent population with new generation, these changed chromosomes have not to be selected again for further crossover. Having finished crossover along the population, it is necessary to apply mutation operator based on the probability of mutation. The probabilities of 0.005, 0.01 and 0.02 were used in this step. This process is repeated until the termination criteria met.

5 Study Area

The Ajichai Watershed is located in Tabriz. It flows from the southern part of the Sabalan Mountain in a westerly direction across the urbanized Herris and Sarab County and through the city of Tabriz to its confluence with the Uroumieh Lake.

The Ajichai River natural valley flood plain averages about 600 meters wide while the main channel averages about 50 meters wide through the study reach.

The Ajichai catchment elevation ranges from 1458 m to 3883 m above sea level and the annual average precipitation is approximately 300 mm.

Fig. 5: Ajichai River and Basin

Bank-full discharge corresponding to an event with the 4-percent chance of exceedance (25-year) is about 400 cubic meters per second and the 1-percent chance of exceedance (100-year) event is about 700 cubic meters per second. The average bed slope through the project reach is on the order of 20 centimeters per 100 meters.

A subset area was selected along the river with a length of 2 kilometers and used as study area during the hydraulic and optimization process. Such a subset is just large enough to represent the river and the surrounding surfaces so that the computing time is reduced to minimum in the optimization algorithm.

6 Results

As discussed above, consideration of GA formulation has been given to real-value coding with some probabilities of crossover and mutation. Performance of each different operator probabilities is discussed below.

6.1 Sensitivity analysis

A series of sensitivity analyses were carried out to establish appropriate parameter settings under real-value coding and alternative operators. In many practical problems, GA results are found to be sensitive to crossover and mutation probabilities. This is because genetic material lost at the stag of a run, through either crossover or mutation, may be needed to improve fitness. Sensitivity to crossover and mutation probability is discussed below for real-value coding scheme in GA formulation

6.1.1 Sensitivity to Crossover and Mutation Approaches

In this study, sensitivity to crossover and mutation probability was carried out using a population size of 80. The roulette wheel selection approach was adopted with 1-point cut crossover with probabilities from 0.2 to 0.6, and a uniform mutation operator with probability of 0.005 to 0.02 were considered through runs with a fixed length of 500 generation. Fig. 6 and 7 show the sensitivity of the achieved fitness to crossover probability for each of the schemes considered. Fitness is expressed as maximum and average values of objective function, as the ratio between benefit and cost of levee problem.

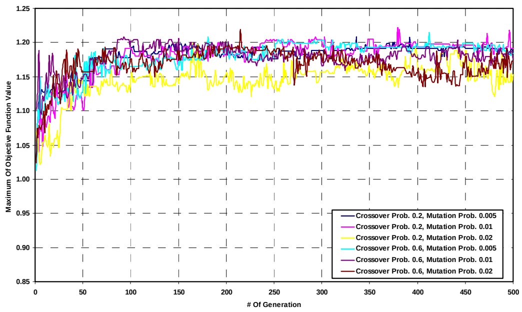

Fig. 6: sensitivity to crossover and mutation probability, maximum of objective function values (Standard GA)

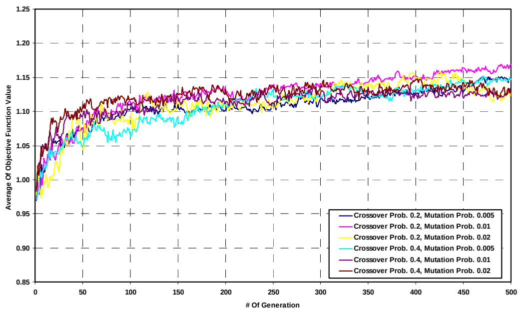

Fig. 7: sensitivity to crossover and mutation probability, average of objective function values (Standard GA)

Table 1 include the information such as minimum, average and maximum of obtained results through different operators of crossover and mutation.

Table 1: sensitivity analysis information in standard GA

Crossover Prob.	Mutation Prob.	Minimum	Average	Maximum	Standard Deviation	Coefficient Of Variation
0.2	0.005	1.077	1.148	1.188	0.035	0.030
0.2	0.01	1.146	1.169	1.192	0.015	0.013
0.2	0.02	1.109	1.127	1.153	0.019	0.017
0.4	0.005	1.103	1.146	1.188	0.032	0.028
0.4	0.01	1.057	1.126	1.163	0.032	0.028
0.4	0.02	1.097	1.130	1.158	0.019	0.017
0.6	0.005	1.081	1.136	1.185	0.032	0.028
0.6	0.01	1.125	1.154	1.175	0.015	0.013
0.6	0.02	1.072	1.125	1.173	0.025	0.022

The results demonstrate clearly that GAs are robust, with reasonable results being obtained by 1-point cut crossover with probability of 0.2 and mutation probability of 0.01. As it is seen, by this structure, it would be possible to obtain better results than previous works (Shafiei et al., 2005).

7 Conclusion

It has been demonstrated that GAs provide robust and acceptable solutions to the levees setback optimization problem. Several possible formulations have been considered, along with their sensitivity to various parameters. It is included that in real-value representation scheme, incorporating roulette wheel selection, elitism, 1-point cut crossover and uniform mutation with low probability will operate most efficiently and produce the best results.

Developing formulation of GA having different probabilities of operators, crossover probability of 0.2 and mutation probability of 0.01 are appropriate for the problem presented here. For the levee problem, a more precise solution can be achieved within 4000 generations with a population of 400.

The results achieved indicate that there is potential for the application of GAs to large rivers levees optimization problems, where the objective function is complex and other techniques are difficult to apply.

The approach is easily applied to complex systems. A GA will generate several solutions that are very close to the optimum, and this gives added flexibility to an operator of a complex flood defense system.

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