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Optimization of Levee's Setback; A New GA Approach

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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. Over the years, risk-based design and optimization methods have proven to be useful tools to obtain economic design of protection systems. 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 have 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. The primary objective of this paper is to introduce a new GA formulation in application to flood defense systems. The problem addressed here is about optimization of levee setback. It has been demonstrated that GAs provide robust and acceptable solutions to the levees setback optimization problem along presented formulation.

Keywords: Optimization, Levee, Setback, GA, Classified Population, Genetic Operators

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 [1]. His study indicates that floods contribute to 58% of total death and 33% of economic losses. 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.

Over the years, risk-based design and optimization methods have proven to be useful tools to obtain a balanced level of protection. These methods have been explicitly accounted for in the design of various flood defense systems, such as storm sewer system (Yen and Ang, 1971, Yen et al, 1976, Yen and Jun, 1984), levees (Tung and Mays, 1981), dams and spillways (Tang and Yen, 1993), and storm surge protection work (Vrijling, 1993). Cheng et al. (1993) demonstrated how to apply the reliability analysis method to calculate the risk reduction associated with freeboard in dam design [2].

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. 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, Lund, 2002, Shafiei et al., 2005).

GAs have so far had very 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)). Shafiei et al. used genetic algorithms for optimization of levees setback along certain probability of crossover and mutation operators and also investigated sensitivity analysis to genetic operators in the same problem [10]. The objective of this paper is to explore a new GA formulation in application to flood levee systems. The problem addressed here is about levee setback along the reaches of a river. In this paper the main object has been to present a new approach for GAs as a practical tool in levee design optimization.

2 Optimal Tradeoff of Levee Setback and Height

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.

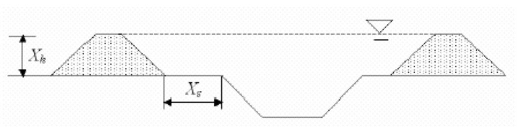

Fig. 1: Levee Height and Setback

A static model is formulated to maximize the benefit of flood levee construction, considering levee construction cost and resultant protected land value benefit due to levees. 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

B/C( ) =ratio between benefit and cost

X_s =designed levee setback

X_h =designed levee height

C(0) =Construction cost of a levee of height X_h

B(0) =benefit of land value

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 (e.g., a trapezoid cross-section).The first order condition for maximizing the expected total benefit of flood control is that the first 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

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

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 [12].

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:

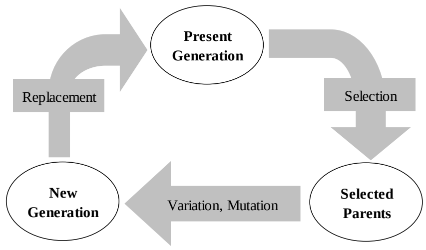

Fig. 2: Schematic Diagram of Evolution Cycle

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 [4].
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 [14]) 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 [8]).
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 substrings 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 (environment) which is appropriate to conditions of problem.
2. Present the possible solutions (phenotype) as real value (genotype or chromosome). All the optimization parameters should be placed somewhere inside chromosome. The chromosome is defined by individual genes.
3. Generate a random population of specific size. The population size affects the efficiency and performance of GA. GA does poorly for very small size of populations and very large population size impacts performance of the algorithm. For typical applications, the suggested range is between 10-160 chromosomes.
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, the most popular one is called proportional selection method which will be discussed.
5. Select a population of chromosomes of the same size of initial population for mating, by a random selection method. There are some selection algorithms like tournament selection and roulette-wheel selection which are discussed later.
6. Apply crossover operation on selected pairs if they have been chosen for crossover (based on probability of 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. Real-value chromosomes have been also used with success by various authors (e.g., Oliveira and Loucks 1997). 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 [4]), 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.

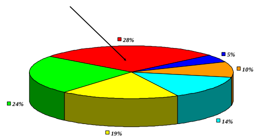

Fig. 3: Roulette Wheel Selection

There are also other selection techniques such as constant selection differential, drawback and tournament. Goldberg and Deb (1990) have compared various selection schemes, and indicated a preference for the tournament selection scheme.

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) describes the following methods of crossover (I) one-point crossover; (2) two- point crossover and (3) uniform crossover [4].

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.

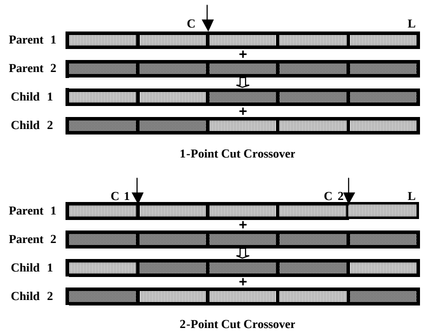

Fig. 4: Crossover Approaches

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 (Michalewicz 1992). 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.

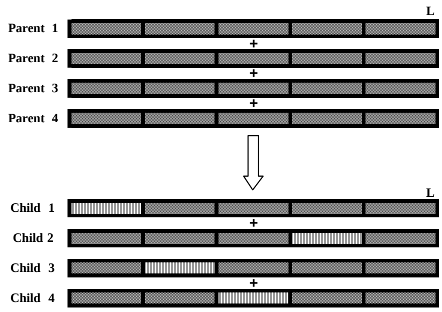

Fig. 5: Uniform Mutation

4 Methodology

In this paper, the methodology can be expressed as following steps:

1. Applying HEC-HMS to conduct hydrologic analysis. The resulting peak flows of 25-year and 100-year hydrograph is to extract from the outputs of the model.
2. Using digital topographic maps of study area to make the required DEM of study area and defining cross-sections.
3. Applying steady uniform flow for hydraulic modeling along the river. The design discharge for optimizing the setbacks of levees of study area was selected as the peak flow of hydrograph with return period of 100 year. For accomplishing hydraulic 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 part of analysis is done to enable the hydraulic simulator to participate in the iterative process of optimization.
4. Economic analysis and optimization using 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.

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 using levee fill volume and its unit cost. 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.

In this paper, a new structure of real-value formulation of GA is applied and the corresponding solutions would be extracted. In this new structure, called classified population, the population size is 80. After initial simulation and corresponding calculation of fitness, in selection step, first the chromosome with highest fitness is forced to be selected for new generation and then, other chromosomes will be selected through roulette-wheel selection method till the size of new population overcomes a quarter of initial population. Then, 1-point cut crossover will be applied through selected chromosomes and another quarter of new population is made of changed chromosomes. Finally, mutation operator is going to be applied based on the probability of mutation through the first half of new generation and remained half of new generation will be produced thorough this process. This process is repeated until the termination criteria met. The diagram of new structure to GA is shown below:

Fig. 5: Schematic Diagram of GA Formulation

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.

Fig. 6: Ajichai River and Basin

Bank-full discharge corresponding to an event with the 4-percent chance of exceedance (25-year) is 400 cubic meters per second and the 1-percent chance of exceedance (100-year) event is 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 a new approach for producing new generations. Figures 7 to 9 show obtained results for presented GA formulation.

The objective function values through 10 runs are shown in figure 7. Minimum, average and maximum of objective function values through the generations and finally the standard deviation and coefficient of variation's fluctuation are illustrated in figure 8 and 9, respectively.

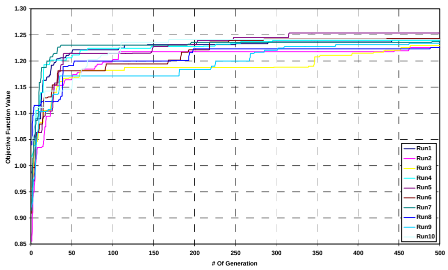

Fig. 7: Objective Function Value (2-point cut Crossover and 1 Gene per Chromosome Mutation)

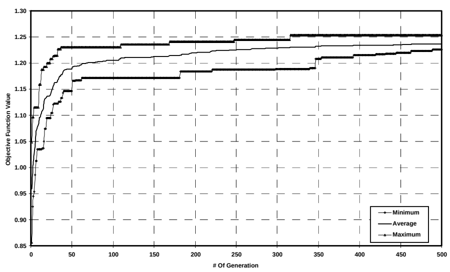

Fig. 8: Minimum,Average and Maximum of Objective Function Value (2-point cut Crossover and 1 Gene per Chromosome Mutation)

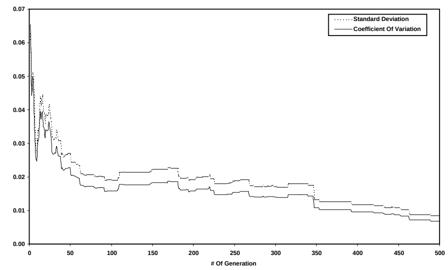

Fig. 9: Std. Deviation and Coeff. of Variation of Objective Function Value (2-point cut Crossover and 1 Gene per Chromosome Mutation)

The longitudinal profile of river is also schematically shown in figure 10 including ground, levees base and top elevations and water which are obtained from optimization process.

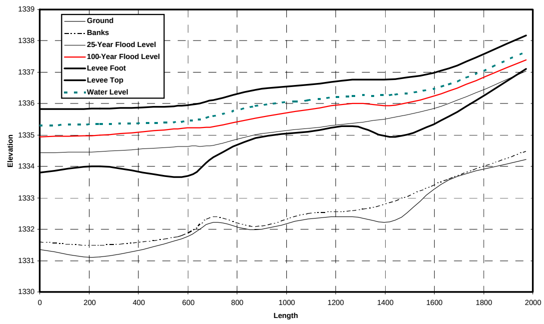

Fig. 10: Longitudinal Profile of Ajichai Study Reach

In this paper, 1.253 is obtained through new formulation. Table 1 includes levee foot elevation and water level in sections of study river.

Table 1: Levees Elevations and Water Levels in Sections of River

Obtained Ratio of B /C		1.253
Section	Levee Foot Elevation	Water Level
1	1333.8	1335.3
2	1334	1335.4
3	1333.4	1335.4
4	1334.3	1335.5
5	1334.9	1335.6
6	1335.1	1335.8
7	1335.4	1336.0
8	1334.3	1335.9
9	1335.6	1336.5
10	1337.1	1337.5

7 Conclusion

It has been demonstrated that GAs provide robust and acceptable solutions to the levees setback optimization problem. It is included that in real-value representation scheme, incorporating roulette wheel selection, elitism, 2-point cut crossover and uniform mutation with low probability through a new approach for producing new generations will operate efficiently and produce better results.

The results achieved indicate that there is potential for the application of presented GA formulation 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.

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