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UNCERTAINTY CHARACTERIZATION IN THE DESIGN OF HYDRAULIC STRUCTURES PROFILES USING GENETIC ALGORITHM AND FUZZY LOGIC

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Abstract: *Most of the hydraulic structures are founded on alluvial planes of India. Hydraulic structures such as weirs or barrages are integral parts of diversion head works. However, there is no fixed procedure to design the basic barrage parameters. The depth of sheet piles, the length and thickness of floor may be treated as basic barrage parameters. The variation in seepage head affects the downstream sheet pile depth, overall length of impervious floor, and thickness of impervious floor. The exit gradient, which is considered the most appropriate criterion to ensure safety against piping on permeable foundations, exhibits non linear variation in floor length with variation in depth of down stream sheet pile. These facts complicate the problem and increase the non linearity of the problem. However, an optimization problem may be formulated to obtain the optimum structural dimensions that minimize the cost as well as satisfy the exit gradient criteria. The optimization problem for determining an optimal section for the weirs or barrages consists of minimizing the construction cost, earth work, cost of sheet piling, length of impervious floor etc. Nonlinear optimization formulation (NLOF) with subsurface flow embedded as constraint in the optimization formulation is solved by Genetic algorithm (GA). The results obtained in this study indicate that considerable cost savings can be achieved when the proposed NLOF is solved using GA. Uncertainty in design, and hence cost from uncertain safe exit gradient, a hydrogeologic parameter, are quantified using fuzzy numbers. Results show linear correlation between uncertainty in overall cost and uncertainty in safe exit gradient value. The limited evaluation show potential applicability of the proposed methodology.*

Keywords: *nonlinear optimization formulation; genetic algorithm; hydraulic structures; barrage design; fuzzy numbers.*

INTRODUCTION

Hydraulic structures such as weirs and barrages are costly water resources projects. A safe and optimal design of hydraulic structures is always being a challenge to water resource researchers. The hydraulic structure such as barrages on alluvial soils is subjected to subsurface seepage. The seepage head causing the seepage vary with variation in flows. Design of hydraulic structures should also insure safety against seepage induced failure of the hydraulic structures.

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The variation in seepage head affects the downstream sheet pile depth, overall length of impervious floor, and thickness of impervious floor. The exit gradient, which is considered the most appropriate criterion to ensure safety against seepage induced piping (Khosla, 1932; Khosla, et al., 1936; Varshney and Gupta, 1988; Asawa, 2005) on permeable foundations, exhibits non linear variation in floor length with variation in depth of down stream sheet pile. These facts complicate the problem and increase the non linearity of the problem. However, an optimization problem may be formulated to obtain the optimum structural dimensions that minimize the cost as well as satisfy the safe exit gradient criteria.

The optimization problem for determining an optimal section for the weirs or barrages consists of minimizing the construction cost, earth work, cost of sheet piling, and length of impervious floor (Garg et al., 2002; Singh, 2007). Earlier work (Garg et al., 2002) discussed the optimal design of barrage profile for single deterministic value of seepage head. This study first solve the of nonlinear optimization formulation problem (NLOP) using genetic algorithm (GA) which gives optimal dimensions of the barrage profile that minimizes unit cost of concrete work, and earthwork and searches the barrage dimension satisfying the exit gradient criteria. The work is then extended to characterize uncertainty in design due to uncertainty in measured value of exit gradient, an important hydrogeologic parameter. Uncertainty in design, and hence cost from uncertain safe exit gradient value are quantified using fuzzy numbers.

SUBSURFACE FLOW

The general seepage equation under a barrage profile may be written as:

$$\frac{\partial^2 h}{\partial x^2}+\frac{\partial^2 h}{\partial y^2}+\frac{\partial^2 h}{\partial z^2}=0 \qquad (1)$$

This is well known Laplace equation for seepage of water through porous media. This equation implicitly assumes that (i) the soil is homogeneous and isotropic; (ii) the voids are completely filled with water; (iii) no consolidation or expansion of soil takes place;and (iv) flow is steady and obeys Darcy’s law.

For 2-dimensional flow, the seepage equation (1) may be written as:

$$\frac{\partial^2 h}{\partial x^2}+\frac{\partial^2 h}{\partial y^2}=0 \qquad (2)$$

The need to provide adequate resistance to seepage flow represented by equation (1) both under and around a hydraulic structure may be an important determinant of its geometry (Skutch, 1997).The boundary between hydraulic structural surface and foundation soil represents a potential plane of failure.

Stability under a given hydraulic head could in theory be achieved by an almost limitless combination of vertical and horizontal contact surfaces below the structure provided that the total length of the resultant seepage path were adequately long for that head (Skutch, 1997; Leliavsky, 1979). In practical terms, the designer must decide on an appropriate balance between the length of the horizontal and vertical elements.

Lane's (1935) Weighted Creep Theory, and Khosla's Method of Independent Variables, is most commonly adopted (Varshney *et al*, 1988) methods. Present work utilized Khosla's Method of independent variables (Asawa, 2005) to simulate the subsurface behavior in the optimization formulation.

Method of independent variables is based on Schwarz-Christoffel transformation to solve the Laplace equation (1) which represents seepage through the subsurface media under a hydraulic structure. A composite structure is split up into a number of simple standard forms each of which has a known solution. The uplift pressures at key points corresponding to each elementary form are calculated on the assumption that each form exists independently. Finally, corrections are to be applied for thickness of floor, and interference effects of piles on each others.

An explicit check is for the stability of the hydraulic structure for soil at the exit is devised by Khosla (Khosla et al., 1936). The exit gradient for the simple profile as in Fig. 1 is given by as follows:

$$G_E = \frac{H}{d_2}\frac{1}{\pi\sqrt{\lambda}} \qquad (3)$$

where $\lambda = \frac{1}{2}[1+\sqrt{1+\alpha^2}]$; $\alpha = \frac{L}{d_2}$; L is total length of the floor; and H is the seepage head.

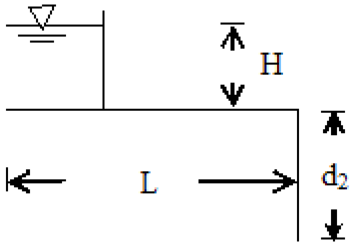

Fig.1. Schematic of parameters used in exit gradient

Equation (3) gives G_E equal to infinity for no sheet pile at the downstream side of the floor. Therefore, it is necessary that a vertical cutoff (sheet pile) be provided at the downstream end of the floor. To prevent piping, the exit gradient is kept well below the critical values which depend upon the type of soil.

The present work uses GA based optimization formulation incorporating uplift pressure and exit gradient in the optimization model to fix depth of sheet piles and length and thickness of floor. The optimization solution thus ensures safe structure with economy.

OPTIMAL DESIGN FORMULATION

Optimization Model

Minimize $C(L, d_1, d_d) = c_1(f_1) + c_2(f_2) + c_3(f_3) + c_4(f_4) + c_5(f_5)$ (4)

Subject to $SEG \geq \frac{H}{d_d \pi \sqrt{\lambda}}$ (5)

$L^l \leq L \leq L^u$ (6)

$d_1^{\ l} \leq d_1 \leq d_1^{\ u}$ (7)

$d_d^{\ l} \leq d_d \leq d_d^{\ u}$ (8)

$L, d_1, d_d \geq 0$ (9)

where $C(L, d_1, d_d)$ is objective function represents total cost of barrage per unit width (Rs/m), and is function of floor length (L), upstream sheet pile depth (d_1) and downstream sheet pile depth (d_d); f_1 is total volume of concrete in the floor per unit width for a given barrage profile and c_1 is cost of concrete floor (Rs/m^3); f_2 is the depth of upstream sheet pile below the concrete floor and c_2 is the cost of upstream sheet pile including driving (Rs/m^2); f_3 is the depth of downstream sheet pile below the concrete floor and c_3 is the cost of downstream sheet pile including driving (Rs/m^2); f_4 is the volume of soil excavated per unit width for laying concrete floor and c_4 is cost of excavation including dewatering (Rs/m^3); f_5 is the volume of soil required in filling per unit width and c_5 is cost of earth filling (Rs/m^3); SEG is safe exit gradient for a given soil formation on which the hydraulic structure is constructed and is function of downstream depth and the length of the floor; $\lambda = \frac{1}{2}[1+\sqrt{1+\alpha^2}]$; $\alpha = \frac{L}{d_d}$; L is total length of the floor; H is the seepage head ; d_1 is the upstream sheet pile depth; d_2 is downstream sheet pile depth; L^l, $d_1^{\ 1}$, and $d_d^{\ 1}$ is lower bound on L, d_1 and d_d respectively**;** L^u, $d_1^{\ u}$, $d_d^{\ u}$ are upper bound on L, d_1 and d_d respectively. The constraint equation (5) may be written as follows after substituting the value of λ:

$$L - d_d\left(\{2(\frac{H}{d_2\pi(SGE)})^2 - 1\}^2 - 1\right)^{1/2} \geq 0 \qquad (10)$$

In the optimization formulation, for a give barrage profile and seepage head H, f_1 is computed by estimating thickness at different key locations of the floor using Khosla's method of independent variables and hence nonlinear function of length of floor (L), upstream sheet pile depth (d_1) and downstream sheet pile depth (d_2). Similarly f_4, and f_5 is nonlinear. The constraint represented by equation (10) is also nonlinear function of length of the floor and downstream sheet pile depth

(d_2). Thus both objective function and constraint are nonlinear; make the problem in the category of nonlinear optimization program (NLOP) formulation, which are inherently complex.

Characterizing Model Functional Parameters

For a given geometry of a barrage and seepage head H, the optimization model functional parameters f_1, f_2, f_3, f_4 and f_5 are characterized for the barrage profile shown in Fig. 2. Intermediate sheet-piles are not effective in reducing the uplift pressures and only add to the cost of in reducing the uplift pressures and only add to the cost of the barrage (Garg et al., 2002). In present work, no intermediate sheet piles are considered.

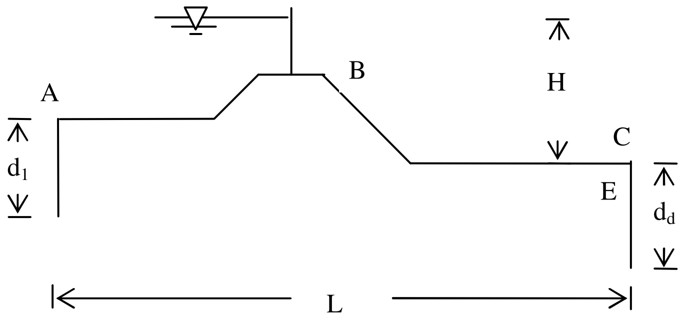

Fig 2. Schematic of barrage parameters utilized in performance evaluation.

Optimization Procedure Using Genetic Algorithm

GA was originally proposed by Holland (Holland, 1975) and further developed by Goldberg (Goldberg, 1989). It is based on the principles of genetics and natural selection.GA's are applicable to a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear (Haestad 2003). The GA search starts from a population of many points, rather than starting from just one point. This parallelism means that the search will not become trapped on local optima (Singh and Datta, 2006).

The optimization model represented by equations (4)-(10) and the functional parameters embedded in the optimization model are solved using Genetic Algorithm on MATLAB platform. The basic steps employed in solution procedure may be presented as follows:

(i) Specification of parameters (decision variables) and hydrogeologic parameters (seepage head, and exit gradient) of problem domain in optimization formulation.
(ii) Representation of solution space by string of chromosomes of specified lengths where each individual (chromosomes) correspond to a parameter.
(iii) Randomly generate initial population of potential values of parameters in forms of strings.
(iv) Decode each individual into decimal valued parameter

(v) Simulate seepage flow with decoded parameters to characterize f_1, f_2, f_3, f_4, and f_5 to evaluate objective function satisfying constraints.
(vi) Assign fitness value of each individual of population using objective function information.
(vii) Stop if termination criteria satisfied, otherwise select and met the individual with high fitness value. More fit individual end up with more copies of themselves
(viii) Perform cross-over operation on the selected parent population
(ix) Perform mutation operation as in cross over operation with low probability
(x) Obtain new population after cross-over and mutation
(xi) Go to step (iv)

In crossover, the offspring or children from the parents in the mating pool is determined. Mutation is performed with very low probability equal or close to the inverse of population size (DeJong, 1975). Such a low probability is helpful in keeping diversity in the population, and prevents the convergence of GA to local minima. The present work employed a real coded genetic algorithm (Passino, 2005), and implemented on MATLAB platform. The termination criteria is assumed to be satisfied when the population converges i.e. the average fitness of the population matches with the best fitness of the population and/or there is a little improvement in fitness with increase in number of generations.

Table 1. Physical parameters values of barrage profile by conventional method utilized for performance evaluation as shown in Fig. 2.

Physical parameters	Values (meters)
*L	105.37
H	7.12
*d_1	5.45
*d_2	5.9

* Decision variables to be optimized

Representation

A solution vector **x** (L, d_1, d_2) for the barrage profile, shown in Fig. 2 whose parameters are shown in Table 1, can be represented as a real parameter vector. A chromosome is a string of “genes” that can take on different “alleles” that are encoded with number systems in a computer. A gene is a “digit location” that can take on different values from a number system (i.e., different types of alleles). For instance, in a base-2 number system, alleles come from the set {0, 1}, while in a base-10 number system, alleles come from the set {0, 1, 2, 3, 4, 5, 6, 7, 8, 9}. Depending on the chosen number system, may need to encode and decode. In this study base-10 number representation is being used for coding.

UNCERTAINTY CHARACTERIZATION IN THE OPTIMIZATION MODEL

Real-world problems, especially those that involve natural systems, such as soil and water, are complex and composed of many non-deterministic components having non-linear coupling. In dealing with such systems, one has to face a high degree of uncertainty and tolerate imprecision. There is a high degree of local soil variability, and imprecision in the determination of soil parameters. Statistical techniques have been traditionally used to deal with parametric variation in model inputs, but these require substantial hydrogeologic explorations data for estimates of probability distributions. In the presence of limited, inaccurate or imprecise information, simulation with fuzzy numbers represents an alternative tool to handle parametric uncertainty. Fuzzy sets offer an alternate and simple way to address uncertainties even for limited exploration data sets. In the present work, the optimal design is first obtained assuming a deterministic value of hydrogelogic parameter, safe exit gradient, in optimization model. Uncertainty in safe exit gradient is then characterized using fuzzy numbers. The fuzzified NLOF is then solved using GA.

Sources of Uncertainty

Uncertainty in general comes in two forms: aleatory (stochastic, random natural variability or noncognitive) and epistemic (cognitive or subjective) (Hofer et al., 2002). Such distinctions in uncertainty are most often identified in risk assessment and reliability engineering (Helton et al., 2004; Helton and Oberkampf, 2004; Oberkampf et al., 2004). Recently, Srinivasan et al. (2007) identified these uncertainties in hydrogeological applications. Aleatory uncertainty refers to uncertainty that cannot be reduced by more exhaustive measurements or by a better model. Epistemic uncertainty, on the other hand, refers to uncertainty that can be reduced (Ross et al., 2009).

Approaches to Treatment of Uncertainties

Despite these apparent distinctions in uncertainty, probability theory alone has traditionally been used to characterize both forms of uncertainty in engineering applications (Apostolakis, 1990; Helton et al., 2004). While it is commonly accepted that probability theory is ideal for the characterization of aleatory uncertainty (Ganoulis, 1996), the facility with which probability theory effectively captures epistemic uncertainty has been called into question (O'Hagan and Oakley, 2004), especially given the introduction of a number of alternative methods of epistemic uncertainty characterization (Choquet, 1954; Zadeh, 1965, 1978; Shafer, 1976).

Klir (1995) has presented uncertainty representation in the context of different domains of applicability. Among them, probabilistic approaches (e.g. Monte Carlo Simulation) are quite common and have been commonly used in the treatment and processing of uncertainty for solution of system modeling (Schuhmacher et al., 2001). When it was recognized that probability theory is capable of representing only one of the several distinct types of uncertainty, new theories for treating uncertainty emerged. One of the milestones in the evolution of these new uncertainty theories is the seminal paper by Lofti A. Zadeh (1965). He proposed a new mathematical tool in his paper and called this new mathematical tool "fuzzy sets." He proposed the concept of fuzzy algorithms in 1968 (Zadeh, 1968), and together with Bellman, proposed a new approach for decision-making in fuzzy environments in 1970 (Bellman & Zadeh, 1970).

Fuzzy set theory has been recently applied in various fields for uncertainty quantification (Cho et al., 2002; Hanss, 2002; Kentel & Aral, 2004; Mauris et al., 2001).

A fuzzy number's membership function can be of arbitrary shape, either derived from (limited) experimental data or expert knowledge of the model parameters. The triangular shape is widely used for reasons of simplicity: when the exact parameter distribution is not known, it doesn't make sense to assign a more complex-shaped function. In practical applications simple linear functions, such as triangular ones are preferable due to their computational efficiency (Khrisnapuram, 1998).The membership functions are possibilistic distribution functions that denote if an input is possible ($\mu_A = 1$), impossible ($\mu_A = 0$) or something in between. The α -sublevel technique (Hanss & Willner, 1999) consists of subdividing the membership range of a fuzzy number into α -sublevels at membership levels $\mu_j = j/m$, for $j = 0, 1, ...m$. This allows to numerically represent the fuzzy number by a set of $m + 1$ intervals $[a^{(j)}, b^{(j)}]$. Fig. 3 shows a triangular fuzzy number, subdivided into intervals using m = 6.

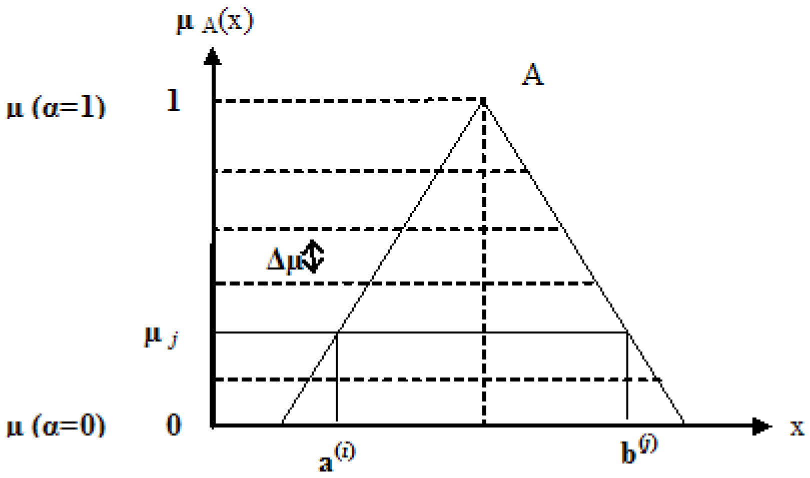

Fig. 3. The α-cut technique to numerically represent a fuzzy number

Membership functions define the degree of participation of an observable element in the set, not the desirability or the value of the information. The membership function is cut horizontally at a finite number of α -levels between 0 and 1 (Fig. 3). For each α -level of the parameter, the model is run to determine the minimum and maximum possible values of the output. This information is then directly used to construct the corresponding membership function of the output which is used as a measure of uncertainty. If the output is monotonic with respect to the dependent fuzzy variable/s, the process is rather simple since only two simulations will be enough for each α-level (one for each boundary). Otherwise, optimization routines have to be carried out to determine the minimum and maximum values of the output for each α-level.

The transformation method presented by Hanss, (2002) uses a fuzzy alpha-cut (FAC) approach based on interval arithmetic. The uncertain response reconstructed from a set of deterministic responses, combining the extrema of each interval in every possible way unlike the FAC technique where only a particular level of membership (α -level) values for uncertain parameters are used for simulation.

Uncertainty in Hydrogeologic Parameters

Traditionally, a deterministic procedure is employed to obtain design values for hydrogeologic parameters such as exit gradient, by calculating the average of values obtained from several tests. However, it is known that the results of both in-situ or laboratory tests may be influenced by several factors. The latter tests can be affected by factors such as mechanical disturbance in the soil samples, in the process of extraction and remolding; by changes in the samples during storage, and so forth. In-situ tests can also be affected by mechanical interferences, inadequate execution, and so on. Therefore, it can be intuitively understood that there is a high degree of local soil variability, and imprecision in the determination of the design values of soil parameters. Large variations in the values of exit gradient and hence in cost may be expected due to these uncertainties.

Fuzzy modeling of uncertainty for hydrogeologic parameters such as exit gradient and seepage head is based on Zadeh's extension principle (Zadeh, 1968) and transformation method (Hanss, 2002). In this study only exit gradient is considered to be imprecise. Input exit gradient, as imprecise parameter, is represented by fuzzy numbers. The resulting output i.e. minimum cost obtained by the optimization model is also fuzzy numbers characterized by their membership functions. The reduced TM (Hanss, 2002) is used in the present study. The measure of uncertainty used is the ratio of the 0.1-level support to the value of which the membership function is equal to 1 (Abebe et al., 2000).

RESULTS AND DISCUSSION

Earlier (mid 19th century), weirs and barrages have been designed and constructed in India on the basis of experience using the technology available at that period of time. Some of them were based on Bligh's creep theory, which proved to be unsafe and uneconomical. Comparison of the parameters of these structures with the proposed approach is, thus, not justified. Therefore, a typical barrage profile, a spillway portion of a barrage, is chosen for illustrating the proposed approach as shown in Fig. 2. The barrage profile shown in Fig. 2 and parameters values given Table 1 is solved employing the methodology presented in this work.

The barrage profile is first designed by the conventional method based on Khosla's 2-D seepage analysis, in which the depth of sheet-piles is limited from scour considerations and the floor length is established to achieve a permissible exit gradient. The barrage profile is then optimized using the proposed approach with the same relative prices of materials used in the conventional method. In the optimization approach the depth of sheet-piles determined from scour considerations is taken as a lower bound (3.0 m), and the upper bound is set from practical considerations and limited to 12.0 m. In present work, for performance evaluations, value of cost of concreting, c_1, is taken as Rs. 986.0/m^3; cost of sheet-piling including driving, c_1, is taken as Rs. 1510.0/m^2; cost of excavation and dewatering, c_3, is taken as Rs. 35.60/m^3; cost of earth filling, c_4, ia taken as Rs. 11.0/m^3; and minimum thickness of floor is 1.0 m by conventional method. The results are compared in Table 2.

Table 2. Results of GA and conventional method with safe exit gradient equal to 1/8 and minimum thickness of floor as 1m

Design Method	U/S sheet pile, d_1(m)	D/S sheet pile, d_2(m)	Floor length, L (m)	Cost (Rs/m)	Cost Reduction by GA (%)
Conventional Method	5.45	5.90	105.37	133605.0	16.73
GA	3	9.2	61.02	111250.0	

These results reveal that the optimization approach favors the depth of the downstream sheet pile to be deeper than that required from scour considerations. It also resulted in a smaller floor length and overall lower cost. It has shown a savings in the barrage cost ranging from 16.73 percent.

Uncertainty in Prediction of Cost due to Uncertain Exit Gradient

Here, the exit gradient is assumed to vary from 0.15 to 0.20 with central value of 0.175 (1/6) in triangular fuzzy numbers representation. The result of variation in cost is corresponding different degree of membership for exit gradient shown in Fig.4. The measure of uncertainty is found to be 14 percent. Since, left and right spread from central value of exit gradient is almost 14 percent, it can be concluded that uncertainty in cost has linear correlation with uncertainty in exit gradient.

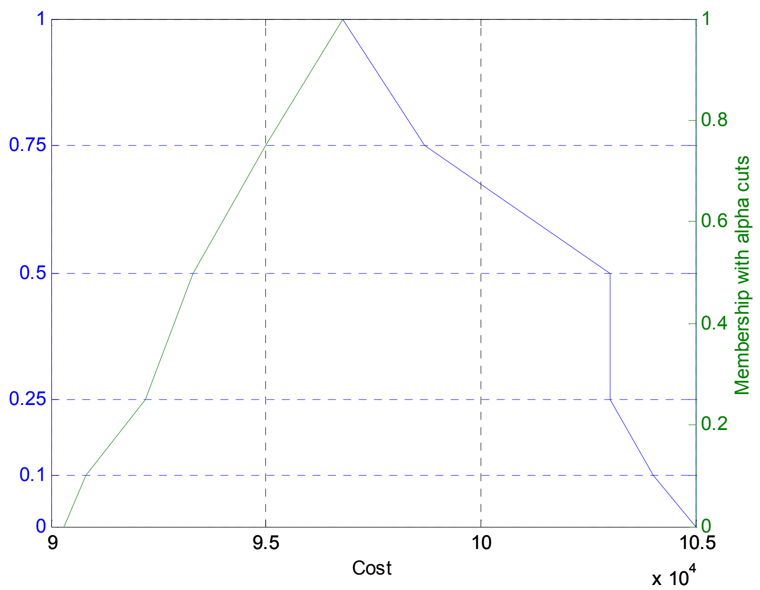

Fig.4. Costs variations corresponding to different α-cuts of exit gradient

CONSLUSIONS

Optimization model solution essentially provides the basic barrage parameters such as depth of sheet-piles/cutoffs and length and thickness of floor, and reduces the over all costs. The GA based optimization model is embedded with the subsurface flow simulation to solve the nonlinear objective function of minimizing cost subject to nonlinear constraints. The applicability of the model has been illustrated with an example. The optimization approach is capable of evolving an optimal design of a barrage, which otherwise is difficult using the conventional approach.

The limited performance evaluation results show the potential applicability of the GA based methodology for optimizing the barrage profiles dimensions to obtain optimal costs. The present work also demonstrates the fuzzy based framework for uncertainty characterization in optimal cost for imprecise hydrogeologic parameter, exit gradient. The uncertainty in cost is found to be directly proportional to uncertainty in exit gradient. The GA based optimization approach is equally valid for optimal design of other major hydraulic structures, such as canal drops and regulators.

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