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A Genetic Algorithm Optimization Model for the Gravity Dam Section under Seismic Excitation with Reservoir- Dam- Foundation Interactions

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Abstract: - A Genetic Algorithm optimization model was developed to find the optimum gravity dam section for dynamic loadings developed due to earthquakes excitations for a reservoir-dam-foundation system. The ANN model developed by Al-Suhaili et al. (2014), was used for estimating the developed stresses in the dam body and the developed hydrodynamic pressures, for a three groups of non-dimensional input variables concerning the dam section geometry, material properties and earthquake excitation properties. Some of these variables are inputs (non-decision) , while those concerning the dam section geometry are the decision variables. A MATLAB code was written for the developed model. Results show that the minimum size of population that should be generated randomly at the beginning in order to obtain a stable optimum solution is 30000. The effect of each of the non-decision variable on the optimum dimensions of the dam section was investigated. Different variables were found have different effects on the optimum solution.

I. INTRODUCTION

The dynamic behavior of a reservoir-dam-foundation system under dynamic earthquake loadings with consideration of interactions, between these three media, is of crucial importance to the dam safety analysis. An optimum dam section that satisfies the safety constraints with minimum area is the aim of the dam designer to ensure safety with minimum cost.

Simoes and Lapa (1994) used the maximum entropy formalism to obtain a Pareto solution indirectly by the unconstrained optimization of a scalar function. They posed the shape optimization of a concrete gravity dam as a multi objective optimization with goals of minimum volume of concrete, stresses and maximum safety against overturning and sliding. The earthquake response of gravity dam included dam reservoir and dam foundation interactions.They showed that the response to the vertical component of ground motion was especially significant for low height dams; it could even exceed the response to horizontal component.

A new hydraulic structure optimization method with a unified, easy operation and good optimizes effectiveness was developed by *Wu et al. (2008)*. For static loading conditions they solved the interface problem between exterior Particle Swarm Optimization (PSO) program of C language and ANSYS software and combined them to apply them to the shape optimization of concrete gravity dam. The results show that the PSO method can solve the difficulty to get differential coefficient and the weak ability to seek global optimization of traditional optimization methods. It improves the efficiency of optimization and can solve the optimization problem with discrete variables.

Lin et al. (2010) combined the genetic algorithms (GA) technique with the ANSYS Parametric Design Language in an effort to apply them to the shape optimization of the concrete gravity dam under static loading conditions. The results show that the new algorithm inherited the advantage of genetic algorithm in that it can search randomly instead of relying on the gradient information, and was also marked by a precision common in ANSYS. Also it was proved that the algorithm can not only improve computing speed, but also improve the accuracy of the algorithm by introducing the finite element method.

Khosravi and HeydariIn (2013) developed a procedure for modeling the geometry shape of concrete gravity dams considering dam-reservoir-foundation rock interaction with employing real values of the geometry variables. They established a 2D finite element model for the modal analysis of Concrete gravity dam-reservoir-foundation rock system with APDL language programming. The foundation rock was assumed to be mass less in which only the effects of foundation flexibility are considered and the inertia and damping effects of the foundation rock were neglected. They assumed that the foundation rock is extended to one and a half times the dam height in upstream, downstream and downward directions. The dam body was assumed to be homogeneous, isotropic and elastic properties for mass concrete. The foundation rock is idealized as a homogenous, isotropic media. The foundation model was constructed using solid elements arranged on semicircles having a radius one and a half times base of the dam. The impounded water was taken as in viscid and compressible fluid.

Investigating the previous researches, indicate the absence of a general optimization model for an optimum dam section, that minimize the massive dam concrete volume, while satisfying the constraints that do not violate the conditions of stresses developed in the dam body and factors of safety against overturning and sliding due to dynamic excitation with dam-reservoir-foundation interaction to be within the accepted limits. Hence, it is essential to develop a model that perform this task, in forms of non-dimensional input and output variables. The needed model is to be general, easy to apply for any concrete gravity dam, assigned an elevation given as input and decided according to the hydrological study.

II. THEORY OF GENETIC ALGORITHMS

Genetic Algorithms (GA) are direct, parallel, stochastic method for global search and optimization, which imitates the evolution of the living beings, described by Charles Darwin. GA is part of the group of Evolutionary Algorithms (EA). The evolutionary algorithms use the three main principles of the natural evolution: reproduction, natural selection and diversity of the species, maintained by the differences of each generation with the previous.

Genetic Algorithms work with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the desired solution. The best-suited individuals create the next generation, *Popov (2005)*.

The main components of GA are:

1-***Chromosomes:*** For the genetic algorithms, the chromosomes represent set of genes, which code the independent variables. Every chromosome represents a solution of the given problem. Individual and vector of variables will be used as other words for chromosomes. The genes could be boolean, integers, floating point or string variables, as well as any combination of the above. A set of different chromosomes (individuals) forms a generation. By means of evolutionary operators, like selection, recombination and mutation an offspring population is created.

2-***Selection:***In the nature, the selection of individuals is performed by survival of the fittest. The more one individual is adapted to the environment - the bigger are its chances to survive and create an offspring and thus transfer its genes to the next population. In EA the selection of the best individuals is based on an evaluation of fitness function or fitness functions. Examples for such fitness function are the sum of the square error between the wanted system response and the real one; the distance of the poles of the closed-loop system to the desired poles, etc. If the optimization problem is a minimization one, than individuals with small value of the fitness function will have bigger chances for recombination and respectively for generating offspring.

3-***Recombination:***The first step in the reproduction process is the recombination (cross-over). In it the genes of the parents are used to form an entirely new group of chromosomes. The typical recombination for the GA is an operation requiring two parents, but schemes with more parent area also possible. Two of the most widely used algorithms are Conventional (Scattered) Cross-over and Blending (Intermediate) Cross-over.

4- ***Mutation:***The newly created chromosomes by means of selection and cross-over population can be further subject to mutation. Mutation means, that some elements of the DNA are changed. Those changes are caused mainly by mistakes during the copy process of the parent's genes. In the terms of GA, mutation means random change of the value of a gene in the population. The chromosome, which gene will be changed and the gene itself are chosen by random as well.

III. OPTIMIZATION MODEL FORMULATION

The general schematic section geometry of a gravity dam is shown in Figure (1) below:
Where,
H: total dam height.
h_w: water height in the reservoir.
h_u: upstream dam face slope height.
h_d: downstream dam back slope height.
B: total dam base width.
b_u: upstream dam face slope width.
b_c: dam crest width.
b_d: downstream dam back slope width.

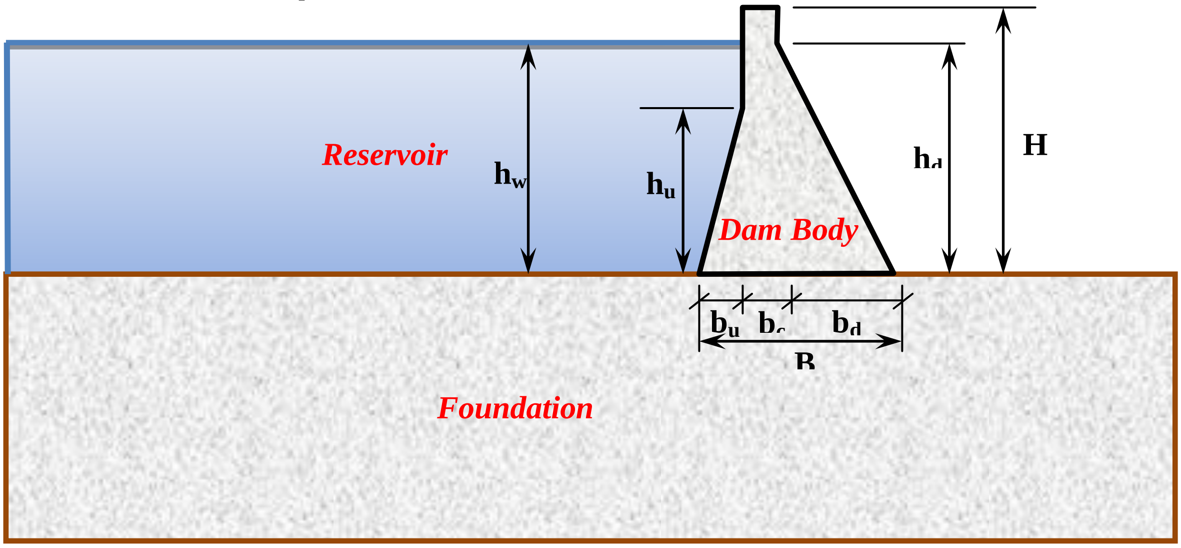

Figure 1: Schematic presentation of the dam-reservoir-foundation system analyzed dynamically using ANSYS.

The adopted objective function is to minimize the volume of dam,this implies the minimization of the dam section area, as given in Equation (1).

$$\text{Min } A\{[(b_u*h_u)/2] + (b_c*H) + [(b_d*h_d)/2]\} \quad (1)$$

This objective function given by Equation (1) is subject to a number of constraints. These constraints can be subdivided into input variables constraints, output variables constraints and overall stability constraints.

a) *Input Variables Constraints*:These constraints are set according to practical aspects and standards given by engineer manual of dam design, *Novak et.al.(2007), EM 1110-2-2200(1995), Chahar(2013)and USGS (2013)*:

$0.75 \leq B/H \leq 0.85$ (2)
$0.85 \leq h_w/H \leq 0.95$ (3)
$0.50 \leq h_u/H \leq 0.70$ (4)
$0.80 \leq h_d/H \leq 0.90$ (5)
$0.063 \leq b_u/B \leq 0.088$ (6)
$0.093 \leq b_c/B \leq 0.15$ (7)
$0.788 \leq b_d/B \leq 0.84$ (8)
$0.00 \leq a_x/g \leq 0.30$ (9)
$0.00 \leq a_y/g \leq 0.25$ (10)
$0.50 \leq w/w_n \leq 1.10$ (11)
$0.50 \leq E_s/E_c \leq 2.00$ (12)
$0.875 \leq \rho_s/\rho_c \leq 1.125$ (13)
$FOS_{ot} > 1.5$ (14)
$FOS_s > 1.5$ (15)

b) *Output Constraints*: The output constraints adopted are related to the criteria that the maximum developed shear, compressive and tensile stresses do not exceeds their respective allowable stresses, *ACI Code (2011)*:

$T/T_a < 1$ (16)

$S_{1t}/S_{ta} < 1$ (17)

$S_{1c}/S_{ca} < 1$ (18)

$S_{2t}/S_{ta} < 1$ (19)

$S_{2c}/S_{ca} < 1$ (20)

$S_{3t}/S_{ta} < 1$ (21)

$S_{3c}/S_{ca} < 1$ (22)

$Str/Str_u < 1$ (23)

c) *Overall Stability Constraints*: The overall stability of the dam section includes factors of safety against overturning and that against sliding.The overturning of the dam section takes place when the resultant force at any section cuts the base of the dam downstream of the toe. In this case the resultant moment at the toe becomes clockwise (or -ve). On the other hand, if the resultant cuts the base within the body of the dam, there will be no overturning. For stability requirements, the dam must be safe against overturning. The factor of safety against overturning is defined as the ratio of the righting moment (+ ve M_R) to the overturning moments (-ve M_0) about the toe.The factor of safety against overturning should not be less than 1.5 (FOS_{ot}> 1.5), *Punmia&Lal (2005)*. Equations (24) gives the factor of safety against overturning.

$$FOS_{ot} = \frac{Resistance\ Moment}{Overturning\ Moment} = \frac{\sum M_R}{\sum M_O} \quad (24)$$

Factor of safety against sliding is generally calculated by one of the following three methods; sliding resistance method, shear friction method and limit equilibrium method. The sliding resistance method calculates a coefficient of friction, (μ), by dividing the sum of horizontal forces parallel to the sliding plane by the sum of effective vertical forces normal to the sliding plane. The coefficient calculated in this way should be smaller than an allowable coefficient of friction (μ_{all}), *USACE (1981)*. As described in the US corps of engineering "Experience of the early dam designers had shown that shearing resistance of very competent foundation material need not to be investigated if the ratio of horizontal forces to vertical forces ($\Sigma H/\Sigma V$) is such that a reasonable safety factor against sliding results". The maximum ratio of ($\Sigma H/\Sigma V$) is set at 0.65 for static loading conditions and 0.85 for seismic conditions, *Iqbal (2012)*. Equations (25) gives the equation for the factor of safety against sliding which should not be less than 1.5 (FOS_s> 1.5).

$$FOS_s = \frac{\sum F_v}{\sum F_h} \quad (25)$$

IV. THE GENETIC ALGORITHM APPLICATION

The optimization model formulated above is used to obtain the optimum solution. The MATLAB programming language was used to write a program to apply the Genetic Algorithm technique to find the optimum section of the gravity dam for any set of non-decision input variables. Figure (2) shows the schematic of the Genetic Algorithm model flowchart. This model is solved using the genetic algorithm procedure explained in steps in section below.

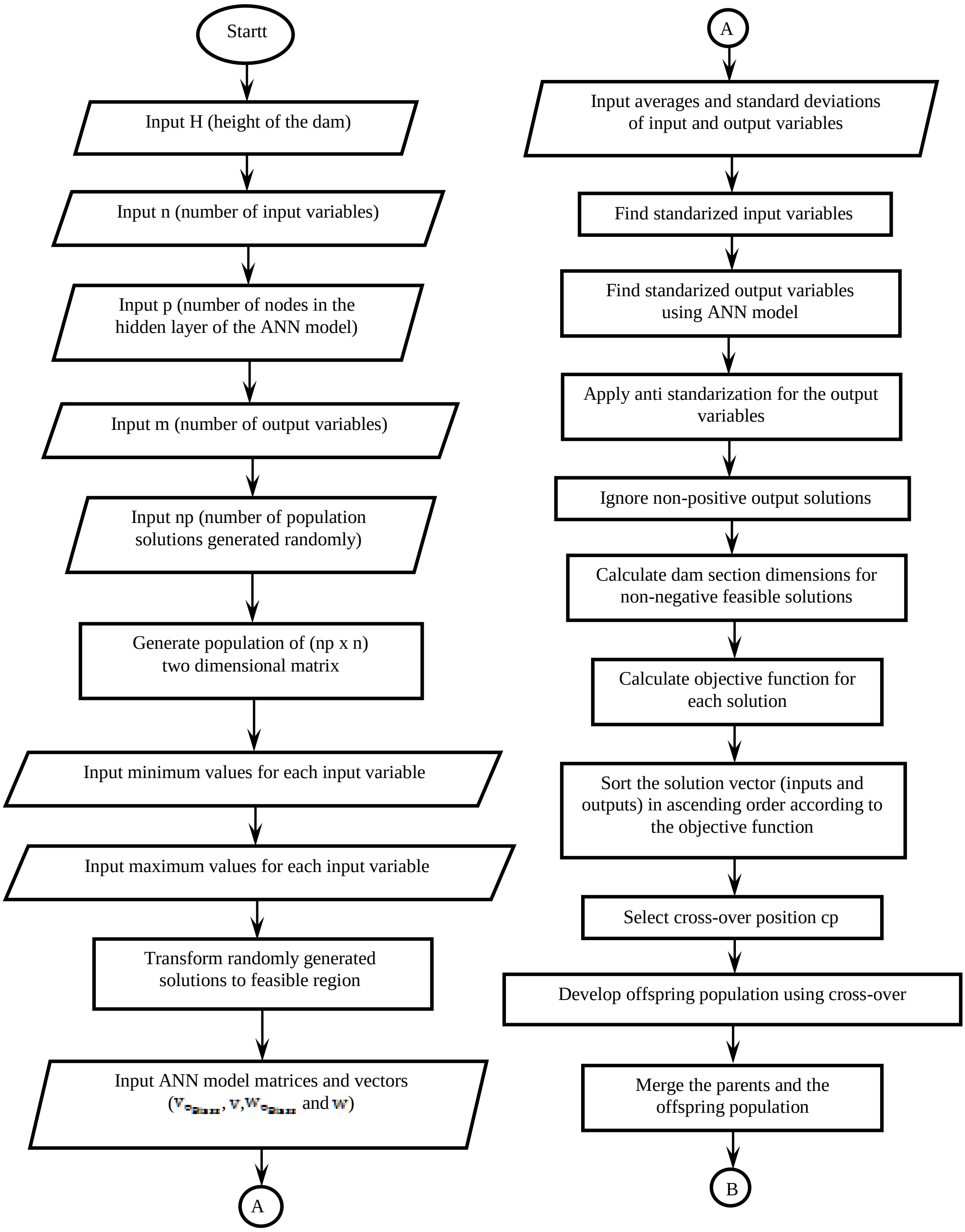

Figure 2: Schematic Genetic Algorithm model flowchart.

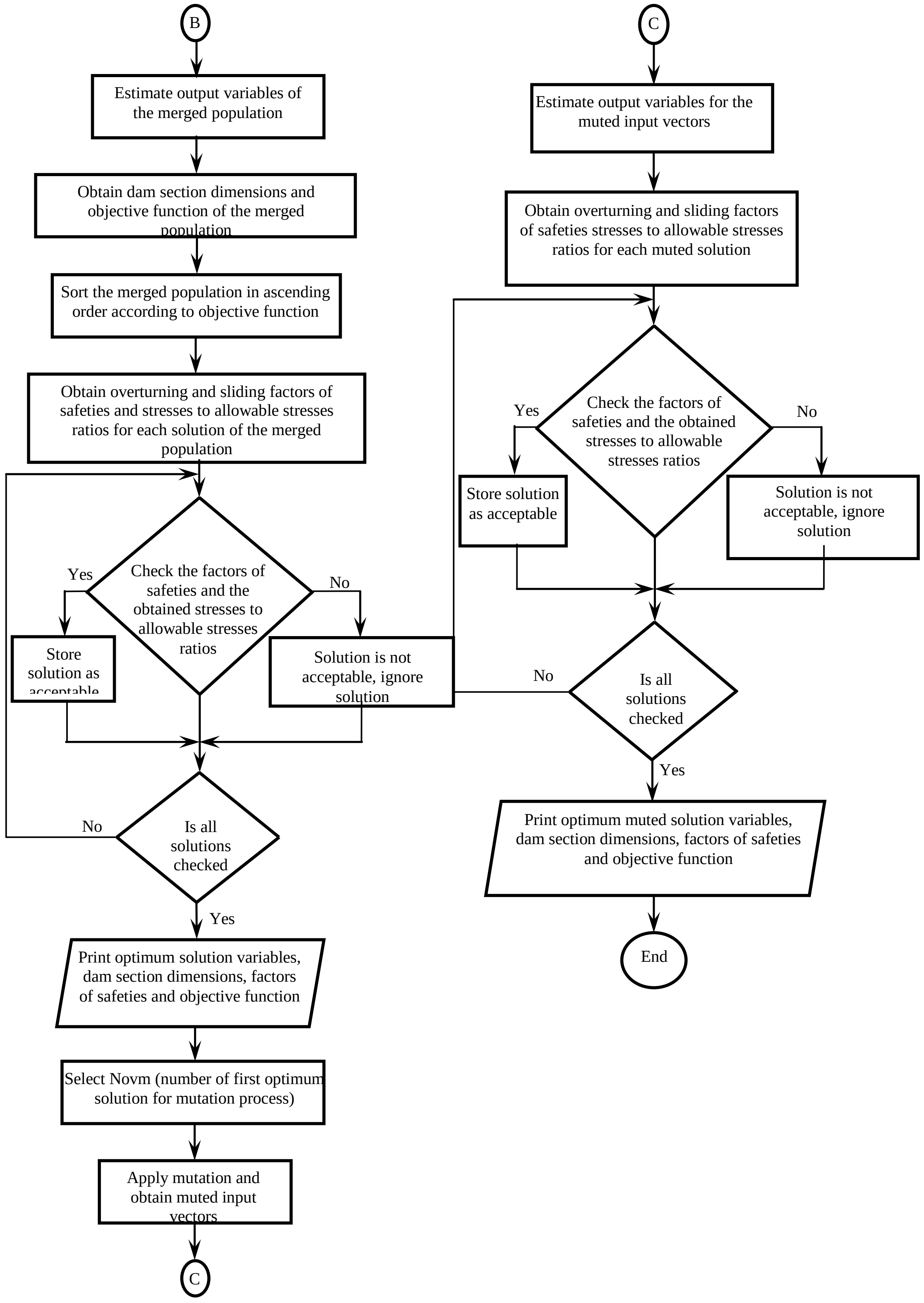

Figure 2: continued

V. OBTAINING STABLE OPTIMUM SOLUTION

Since the genetic optimization process includes the generation of a population of random solutions, the optimum solution obtained for a given input values will change for each run if the size of the population is relatively low. Hence, it is important to obtain the minimum required size of population that should be generated randomly at the first step to obtain a stable optimum solution, i.e., getting the same solution even though the run is repeated, for the same set of input data. This minimum size is depended on the phenomena for which the genetic algorithm model is applied, and the number of variables involved. Hence, this size is to be found by a trial and error procedure.

The Genetic Algorithm procedure used herein is explained in the following steps. Knowing that in this procedure the estimation of the output variables for a given set of input variables is required for a large number of randomly generated feasible solutions (chromosomes), or those resulted from the cross-over and mutation processes. For this purpose, the developed and verified ANN model by Al-Suhaili et al.(2014) is used as a direct method of estimation instead of the long process of modeling each case using the ANSYS software. The steps of the Genetic Algorithm procedure are those usually adopted in such models and as listed below and shown in a flowchart in the appendix:

1- Generate randomly an *np* (number of population) of feasible solutions with respect to the input variables constraints.
2- Estimation of the fitness function (objective function) of each set of input variables for feasible solutions with respect to output variables using the following steps:
a) Apply standardization process for the generated input variables.
b) Apply the developed ANN model to estimate the standardized output variables using the feed-forward process and model parameters.
c) Apply anti-standardization process to the output variables and check the feasibility of the output variables, ignoring the infeasible solution that violates Equations (14) to (23), (the output variables constraints).
d) Check the solution left in step (b) for feasibility of the overall stability, ignoring these solutions that violate the overall stability constraints, Equations (24) and (25).
3- Creation of mating pool with frequencies of each feasible solution obtained in step (2) above according to its fitness function.
4- Apply the cross-over process. The cross-over process adopted here in is the serial method that making cross-over with each two solution, serial (1 and 2, 3 and 4, and so on) which are considered as the parents that each couple produce a couple of offsprings. The cross over position (*cp*) can be change from (2 to 6) since the number of input variables containing the dam section geometry are (7). The probability of cross over (*pc*) can have different values, (*pc* = 100%, 90%,…..).
5- The output variables for the produced offspring population solutions was estimated using the procedure of step (2) and only those feasible solutions will be kept.
6- The population produced from the feasible solutions of offspring and those of parents will be mixed to generate a new feasible population.
7- The objective function (fitness function) will be obtained for each solution of the two mixed populations and sorted into ascending order, and only the first (*np*) solution will be kept for a next iteration of steps (2) to (7).
8- After completing the iterations for any number of iteration selected, the optimum solution will be the first one.
9- A further process of the Genetic Algorithm can be performed which is the mutation process. This can be done after the completion of the iterations by selecting for example the first (10) solutions. That means we have (90) variables to be muted. The usual mutation probability is (*pm* = 0.05), that means (4) numbers will be muted. The mutation process is to change their values by an amount called mutation level (*ml*), for example ±0.01. This level is set according to the order of magnitude of the variables. The (4) numbers selected for mutation is a random process that is to generate a four random number range from (1) to (90).

VI. ILLUSTRATION OF RESULTS

Since the genetic algorithm optimization method needs first the generation of (*np*) random solutions, it is needed to find the minimum required (*np*) value that gives a stable optimum solution, i.e., ignored differences in the objective function values for different runs with the same data input. This (*np*) value is dependent on the physical phenomenon that is under optimization, hence will be found by trial and error. A dam example is used for illustration of the model application, is of (100m) height subject to horizontal and vertical excitation equal to ($a_x/g = 0.25$) and ($a_y/g = 0.2$) respectively, with earthquake frequency to the natural frequency ratio equal ($w/w_n = 1.0$). The modulus of elasticity and density ratios are ($E_s/E_c = 0.8$) and ($\rho_s/\rho_c = 0.9$) respectively. Table (1) gives the objective function for the optimum solution for three different runs, and different values of the generated (*np*). The cross-over position was held constant at (*cp*) equal to four. It is obvious that as the (*np*) value increases the differences in the objective functions for the runs was decreased and the final (*np*) value that gives the stable solution is 30000. Hence, this value will be adopted in the further analysis.

Table 1: Effects of the number of the population (*np*) on the objective function.

np	***Objective Function, (Area -m^2-)***		
	Run 1	***Run 2***	***Run 3***
500	3900.048	4012.433	4056.273
1000	3816.635	3730.952	3899.299
3000	3826.213	3814.389	3720.883
5000	3757.099	3629.661	3725.686
8000	3728.983	3593.522	3650.425
10000	3596.001	3704.253	3662.584
15000	3529.465	3679.242	3607.222
20000	3529.760	3655.887	3487.915
25000	3559.387	3495.583	3633.377
30000	3591.269	3593.197	3590.797

As the decision variables for the optimization model are seven, hence the cross-over position effect on the optimum solution should be investigated. This value can be set as (2, 3, 4, 5 and 6). Table (2) shows the variation of the optimum objective function for these values of (*cp*), for the same example shown in Table (1), with (*np*) equal to 30000. As shown in this table the cross-over position equal to four gives minimum objective function, so it will be used in the optimization model to obtain the optimum dimensions.

Table 2: Effect of the cross over position (*cp*) of the G. A. on the objective function.

np	***cp***	***Objective Function Area (m^2)***
30000	2	3593.865
	3	3605.988
	4	3593.197
	5	3652.562
	6	3685.605

Table (3) shows the results of the optimum dimensions obtained from the optimization model for three different heights dams with various non-decision inputs.

Table 3: Optimum dimensions for three different dams using G.A. model.

Variable Type	***Variable Name***	***Case 1***	***Case 2***	***Case 3***
Non-Decision Inputs	H	50	100	150
	a_x/g	0.15	0.25	0.30
	a_y/g	0.10	0.20	0.15
	w/w_n	0.70	1.00	0.50
	E_s/E_c	0.50	0.80	1.50
	ρ_s/ρ_c	0.80	0.90	1.00
Optimum Outputs*	h_w	42.552	88.963	127.676
	B	38.420	76.180	113.555
	h_u	29.075	67.652	101.640
	h_d	40.897	85.287	130.946

Variable Type	Variable Name	Case 1	Case 2	Case 3
	b_u	2.511	4.939	7.519
	b_c	3.884	9.369	10.801
	b_d	32.025	61.871	95.234
	FOS_O	1.640	1.616	1.629
	FOS_S	1.533	1.521	1.541
	Obj. Fun.	885.554	3742.374	8237.590

*****All dimensions in meter.

Tables (4) to (9) shows the investigation of the effect of each non-decision variable on the optimum dimensions of the dam section, by using the same dam section with various decision variables at each time.

As shown in those tables the objective function (cross-section area) always is directly proportional to each non-decision variable. The dam base width to height ratio (B/H), the water height to dam height ratio (h_w/H) and the upstream slope height to dam height ratio (h_u/H) are inversely proportional to dam height only and directly proportional to other non-decision variables. The downstream slope height to dam height ratio (h_d/H) is wobbling with the increase of horizontal and vertical accelerations and foundation modulus of elasticity and inversely proportional to other non-decision variables. Also the upstream slope width to dam base width ratio (b_u/B) is inversely proportional to dam height only and directly proportional to other non-decision variables, while the downstream slope width to dam base width ratio (b_d/B) is directly proportional to dam height only and inversely proportional to other non-decision variables. Finally the crest width to dam base width ratio (b_c/B) is always directly proportional to each non-decision variable.

Table 4: Effect of dam heights.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	50	100	150
	a_x/g	0.10	0.10	0.10
	a_y/g	0.05	0.05	0.05
	w/w_n	0.50	0.50	0.50
	E_s/E_c	0.50	0.50	0.50
	ρ_s/ρ_c	0.88	0.88	0.88
Optimum Outputs*	h_w	42.686	85.064	127.672
	B	37.778	75.245	113.161
	h_u	33.832	55.770	101.131
	h_d	42.201	82.488	122.539
	b_u	2.712	4.775	7.382
	b_c	3.514	7.042	10.753
	b_d	31.551	63.427	95.026
	FOS_O	1.610	1.628	1.634
	FOS_S	1.508	1.520	1.523
	Obj. Fun.	887.343	3453.390	7808.357
Dimensionless Optimum Outputs	B/H	0.756	0.752	0.754
	h_w/H	0.854	0.851	0.851
	h_u/H	0.677	0.558	0.674
	h_d/H	0.844	0.825	0.817
	b_u/B	0.072	0.063	0.065
	b_c/B	0.093	0.094	0.095
	b_d/B	0.835	0.843	0.840

*All dimensions in meter.

Table 5: Effect of horizontal acceleration.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	100	100	100
	a_x/g	0.10	0.20	0.30
	a_y/g	0.05	0.05	0.05
	w/w_n	0.50	0.50	0.50
	E_s/E_c	0.50	0.50	0.50
	ρ_s/ρ_c	0.88	0.88	0.88
Optimum Outputs*	h_w	85.064	85.918	86.783
	B	75.245	79.063	76.228
	h_u	55.770	68.740	61.580
	h_d	82.488	80.505	84.927
	b_u	4.775	5.140	4.929
	b_c	7.042	7.630	7.314
	b_d	63.427	66.293	63.985
	FOS_O	1.628	1.658	1.618
	FOS_S	1.520	1.542	1.515
	Obj. Fun.	3453.390	3608.163	3600.152
Dimensionless Optimum Outputs	B/H	0.752	0.791	0.762
	h_w/H	0.851	0.859	0.868
	h_u/H	0.558	0.687	0.616
	h_d/H	0.825	0.805	0.849
	b_u/B	0.063	0.065	0.065
	b_c/B	0.094	0.097	0.096
	b_d/B	0.843	0.838	0.840

*All dimensions in meter.

Table 6: Effect of vertical acceleration.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	100	100	100
	a_x/g	0.10	0.10	0.10
	a_y/g	0.05	0.15	0.22
	w/w_n	0.50	0.50	0.50
	E_s/E_c	0.50	0.50	0.50
	ρ_s/ρ_c	0.88	0.88	0.88
Optimum Outputs*	h_w	85.064	86.033	87.809
	B	75.245	75.928	83.978
	h_u	55.770	68.115	69.524
	h_d	82.488	83.412	82.197
	b_u	4.775	5.228	5.331
	b_c	7.042	7.098	8.503
	b_d	63.427	63.602	70.145
	FOS_O	1.628	1.626	1.666
	FOS_S	1.520	1.521	1.549
	Obj. Fun.	3453.390	3540.417	3918.455
Dimensionless Optimum Outputs	B/H	0.752	0.759	0.840
	h_w/H	0.851	0.860	0.878
	h_u/H	0.558	0.681	0.695
	h_d/H	0.825	0.834	0.822
	b_u/B	0.063	0.069	0.064
	b_c/B	0.094	0.094	0.101
	b_d/B	0.843	0.838	0.835

*All dimensions in meter.

Table 7: Effect of acceleration frequency.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	100	100	100
	a_x/g	0.10	0.10	0.10
	a_y/g	0.05	0.05	0.05
	w/w_n	0.50	0.80	1.10
	E_s/E_c	0.50	0.50	0.50
	ρ_s/ρ_c	0.88	0.88	0.88
Optimum Outputs*	h_w	85.064	85.611	85.050
	B	75.245	76.039	75.246
	h_u	55.770	67.328	65.465
	h_d	82.488	81.608	80.099
	b_u	4.775	5.715	5.220
	b_c	7.042	7.368	8.935
	b_d	63.427	62.955	61.090
	FOS_O	1.628	1.628	1.649
	FOS_S	1.520	1.523	1.549
	Obj. Fun.	3453.390	3498.046	3511.066
Dimensionless Optimum Outputs	B/H	0.752	0.760	0.752
	h_w/H	0.851	0.856	0.851
	h_u/H	0.558	0.673	0.655
	h_d/H	0.825	0.816	0.801
	b_u/B	0.063	0.075	0.069
	b_c/B	0.094	0.097	0.119
	b_d/B	0.843	0.828	0.812

*All dimensions in meter.

Table 8: Effect of foundation elasticity.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	100	100	100
	a_x/g	0.10	0.10	0.10
	a_y/g	0.05	0.05	0.05
	w/w_n	0.50	0.50	0.50
	E_s/E_c	0.50	1.00	2.00
	ρ_s/ρ_c	0.88	0.88	0.88
Optimum Outputs*	h_w	85.064	85.339	85.541
	B	75.245	77.046	76.359
	h_u	55.770	68.034	58.302
	h_d	82.488	80.563	83.077
	b_u	4.775	5.198	6.070
	b_c	7.042	7.233	7.235
	b_d	63.427	64.616	63.053
	FOS_O	1.628	1.625	1.610
	FOS_S	1.520	1.503	1.512
	Obj. Fun	3453.390	3502.910	3519.614
Dimensionless Optimum Outputs	B/H	0.752	0.770	0.764
	h_w/H	0.851	0.853	0.855
	h_u/H	0.558	0.680	0.583
	h_d/H	0.825	0.806	0.831
	b_u/B	0.063	0.067	0.079
	b_c/B	0.094	0.094	0.095
	b_d/B	0.843	0.839	0.826

*All dimensions in meter.

Table 9: Effect of foundation mass density.

Variable Type	Variable Name	Case 1	Case 2	Case 3
Non-Decision Inputs	H	100	100	100
	a_x/g	0.10	0.10	0.10
	a_y/g	0.05	0.05	0.05
	w/w_n	0.50	0.50	0.50
	E_s/E_c	0.50	0.50	0.50
	ρ_s/ρ_c	0.88	1.00	1.13
Optimum Outputs*	h_w	85.064	85.058	86.295
	B	75.245	76.031	78.484
	h_u	55.770	67.972	59.829
	h_d	82.488	82.045	80.828
	b_u	4.775	5.085	5.409
	b_c	7.042	7.552	7.439
	b_d	63.427	63.394	65.636
	FOS_O	1.628	1.637	1.623
	FOS_S	1.520	1.529	1.502
	Obj. Fun.	3453.390	3528.633	3558.302
Dimensionless Optimum Outputs	B/H	0.752	0.760	0.785
	h_w/H	0.851	0.851	0.863
	h_u/H	0.558	0.680	0.600
	h_d/H	0.825	0.821	0.808
	b_u/B	0.063	0.067	0.069
	b_c/B	0.094	0.099	0.095
	b_d/B	0.843	0.834	0.836

*All dimensions in meter.

VII. CONCLUSIONS

From the research conducted herein, the following conclusion can be deduced:

1- The Genetic Algorithm optimization model cannot give stable optimum solution for the dam-reservoir-foundation system subject to dynamic loading ,unless a minimum number of initial populations generated are (30000).

2- A sensitivity analysis of the position of the cross-over process was performed to select the best cross-over position for the Genetic Algorithm optimum solution. The position of cross-over which gives the most optimum solution is (4), i.e. cross-over of (b_u/B, b_c/B and b_d/B).

3- It was found that the cross-over probability and mutation probability values have little effect on the optimization process.

4- The results show that the optimum solution (optimum dimensions) for the dam cross-section is to be highly affected by any change in the non-decision variables, direct or inverse proportionality were obtained with varying rates.

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