Number 2 Volume 20 February 2014 Journal of Engineering

Optimal Dimensions of Small Hydraulic Structure Cutoffs Using Coupled Genetic Algorithm and ANN Model

Dr.Prof.Rafa Hashim Al-Suhaili
Prof., Civil Eng. Dept., College of Eng.,
University of Baghdad, Iraq
Email:rafaalsuhili@yahoo.com

Rizgar Ahmed Karim
Asst. Lec., Dam and W. R. Eng. Dept.,
Faculty of Eng., University of Sulaimani, Iraq
Rizgar_Karim@yahoo.com

ABSTRACT

A genetic algorithm model coupled with artificial neural network model was developed to find the optimal values of upstream, downstream cutoff lengths, length of floor and length of downstream protection required for a hydraulic structure. These were obtained for a given maximum difference head, depth of impervious layer and degree of anisotropy. The objective function to be minimized was the cost function with relative cost coefficients for the different dimensions obtained. Constraints used were those that satisfy a factor of safety of *2* against uplift pressure failure and *3* against piping failure.

Different cases reaching 1200 were modeled and analyzed using geo-studio modeling, with different values of input variables. The soil was considered homogeneous anisotropic. For each case, the length of protection (L) and the volume of the superstructure (V) required to satisfy the factors of safety mentioned above were calculated. These data were used to obtain an artificial neural network model for estimating (L) and (V) for a given length of upstream cutoff (S1), length of downstream cutoff (S2), head difference (H), length of floor (B), depth of impervious layer (D) and degree of anisotropy (kx/ky).

A MatLAB code was written to perform a genetic algorithm optimization modeling using the obtained ANN model .The obtained optimum solution for some selected cases were compared with the Geo-studio modeling to find the length of protection required in the downstream side and volume required for superstructure. Values estimated were found comparable to the obtained values from the Genetic Algorithm model.

Key words: optimization, genetic algorithm, artificial neural networks, geo-Studio, uplift pressure, exit gradient, factor of safety.

الأبعاد المثالية لحواجب منشأ هيدروليكي صغير بأستخدام مدمج خوارزميةً وراثيةً ونموذجَ شبكة عصبية اصطناعية

الأستاذ الدكتور رافع هاشم السهيلي
استاذ، قسم الهندسة المدنية، كلية الهندسة
جامعة بغداد، العراق

رزكار أحمد كريم
مدرس مساعد، قسم هندسة السدود و الموارد المائية
كلية الهندسة، جامعة السليمانية، العراق

الخلاصة

تم في هذا البحث بناء نموذج الأمثلية باستخدام تقنية جينات الوراثة و تقنية الشبكات العصبية الصناعية لايجاد الأبعاد المثلى للقواطع الاساس في كل من المقدم و المؤخر و كذلك طول الارضية الاساس و طول الحماية المطلوبة في المؤخر في المنشات الهيدروليكية. تم ايجاد هذه الابعاد لقيم معطات لكل من اعلى فرق للشحنة بين مقدم و مؤخر المنشاء، و لعمق طبقة صماء

و درجة التباين في قيم خواص التربة مع الاتجاه. دالة الهدف التي تم ايجاد القيم الصغرى لها هي دالة الكلفة بمعاملات كلفة نسبية. اما المحددات المستخدمة في النموذج فهي معاملات الامان ضد ضغط الاصعاد و غليان التربة بقيم 2، 3 على التوالي.

تم نمذجة عدة حالات وصل الى 1200حالة باستخدام برنامج Geo-studio. في هذه النمذجة تم اعتبار التربة متجانسة و ذات تباين مع الاتجاه. لكل حالة تم حساب طول الحماية L و حجم المنشاء V المطلوبة لتحقيق معاملات الامان المشار اليها أعلاه. تم استخدام البيانات الخاصة بالحالات اعلاه لبناء نموذج شبكات العصبية لحساب L و V لقيم معطات من عمق القاطع في المقدم (S1)، عمق القاطع في المؤخر(S2) و فرق الشحنة بين المقدم و المؤخر(H)، طول الارضية(B) ، عمق طبقة الصماء (D) و درجة التباين(kx/ky) مع الاتجاه في خواص التربة.
تم كتابة برنامج Matlab لنموذج الجينات الوراثية يستخدم نموذج شبكات العصبية المشار اليه اعلاه. باستخدام هذا النموذج تم ايجاد الحل الامثل لبعض الحالات المختارة و تم مقارنتها بالنتائج المناظرة التي تم الحصول عليها باستخدام برنامج Geo-studio كانت نتائج النموذجين متقاربة.

الكلمات الرئيسية: الأمثلية، الخوارزمية الجينية، الشبكات العصبية الاصطناعية، جيو-ستوديو، الضغط الاصعاد، غليان التربة، معامل الأمان.

1. INTRODUCTION

The most critical aspects that the designer of hydraulic structures should take into account are the failures due to uplift pressure and / or piping phenomenon at the toe of the structure. Proper factors of safety should be adopted for both aspects.

In order to provide the required factors of safety against both uplift pressure and piping due to exit gradient, the designers usually provide cutoffs at the upstream and the downstream sides of the foundation of the hydraulic structures. The upstream cutoffs in general decreases the uplift pressure and exit gradient. However, they reduce the uplift pressure in a rate more than that for the exit gradient. In order to control the exit gradient, a downstream cutoff should be provided, which has direct effect on the exit gradient. The designer should decide the depth of both cutoffs so as to achieve the required factors of safety.

In order to have an additional control of piping downstream of the structure, designers provide a downstream protection just after the toe of the foundation with a suitable length decided to provide the factor of safety against exit gradient piping. This protection is usually provided as an apron or a carefully designed filter, **Al-Suhaili, 2009.**

The designer faces the difficulty of deciding the optimum depths required to control both uplift pressure and piping failure. The decision variables are the minimum depth required of both upstream and downstream cutoffs, weight of the superstructure required and length of the downstream filter required.

Many researchers, **Al-Suhaili et al.,1988,Al-Suhaili,2009, Al-Fatlawy,2007, Khassaf et al.,2009, Al Dury,1986, Ismail and Aziz,2005, Ghobadian and Khodaei,2009, Shadravan et al.,2004 , Griffiths and Fenton,1993 and1998, and Haszpra et al.,2000,** had studied the effect of upstream or downstream cutoffs either on uplift pressure on the foundation of the structure or on the variation of exit gradient downstream of the structure. The results were usually provided in a form of dimensionless curves that can help in the design process.

Recently with the availability of a new era of models that have been developed such as Artificial Neural Network models and Genetic Algorithm models, these techniques provide models for designing hydraulic structures instead of the dimensionless curves used before.

The objective of this research is to develop a model to help designers in finding the optimum dimensions of a hydraulic structure foundation using a coupled Artificial Neural Network (ANN) model and Genetic Algorithm (GA) techniques.

Al- Duri, 1986, had investigated the protection at the downstream of hydraulic structures. **Al-Suhaili et al. 1988,** had investigated exit gradient variation downstream of hydraulic structures, using the solution of Laplace equation by Schwrz-Christoffel conformal mapping. **Ilyinsky and Kacimov, 1992,** had investigated an analytical estimation of ground-water flow around cutoff walls and into interceptor trenches, developing analytical solutions for different cases using Schwarz-Christoffel transformation. **Griffiths and Fenton, 1993,** had investigated the seepage beneath water retaining structures found on spatially random soil. **Griffiths and Fenton, 1998,** had investigated a probabilistic analysis of exit gradients due to steady seepage. **Haszpra et al. 2000,** had investigated seepage around structures built into flood levees. **Manna et al., 2003,** had investigated the groundwater flow beneath a sheet pile analyzed using six-node triangular finite element method. **Shadravan et al., 2004,** had investigated the cutoff wall analysis and design of Karkheh storage dam. **Ismail and Aziz, 2005,** had investigated the seepage analysis of Tushka spillway barrages with stability analysis. **Al-Fatlawy, 2007,** had investigated the seepage analysis through soil foundation under dams. **Mukhopadhyay, 2008,** had investigated the seepage analysis through foundation using a finite element model and flownet Seepage analysis. **Moellmann, et al., 2008,** had investigated a probabilistic finite element analysis of embankment stability under transient seepage conditions. **Khassaf et al. 2009,** had investigated seepage analysis underneath Diyala weir foundation. **Al-Suhaili, 2009,** had investigated an analytical solution for exit gradient variation downstream of inclined sheet pile. **Ghobadian and Khodaeik, 2009,** had investigated the effects of cutoff walls and drains on the uplift pressure and exit gradient under hydraulic structures to prevent piping phenomena. **Goel and Pillai, 2010,** had investigated the variation of exit gradient downstream of weirs on permeable foundations. None of the above researches had used a coupled model of Genetic Algorithm with ANN model; hence in this research such model was used.

2. THE OPTIMIZATION MODEL FORMULATION

As previously mentioned, the most critical design of a hydraulic structure is the foundation design. The required for the design are the length of floor (B), depth of upstream cutoff (S1), depth of downstream cutoff (S2), length of protection at the downstream side against exit gradient (L) and the uplift pressure or due to erosion of the downstream side, when the hydraulic gradient exceeds the critical exit gradient. The designer can control these failures by providing the recommended factors of safety against both uplift pressure and exit gradient failures. The controlling process was done by selecting the dimensions of S1, S2, B, and L for a given (H), (D) and (kx/ky). It is better to select optimum dimensions; the following objective function of such a problem could be introduced.

the volume of superstructure (V) for a given head difference (H), depth of impervious layer (D) and given soil properties underneath the structure, horizontal permeability kx, and vertical permeability ky. **Fig. 1** shows these dimensions.

The values of (S1, S2, L, and V) are affected by the maximum expected difference in head between the upstream and downstream sides of the hydraulic structure (H) and the soil strata properties (kx and ky). The most critical failures that may occur for such structures are either due to

$$\text{Min.} \quad f(x) = C1S1+C2S2+C3V+C4L+C5B \tag{1}$$

Where: f(x) is the cost function that should be minimized.

C1, C2, C3, C4 and C5 are the relative cost of each dimension.

This function is subjected to:

$$\text{F.o.s}_{\text{uplift}} = \frac{\gamma c V}{uplift\ force} \geq 2 \tag{2}$$

Where: $\text{F.o.s}_{\text{uplift}}$ is the factor of safety against uplift pressure,

V: volume of concrete of the superstructure, (L^3)

γc: Concrete weight density, (F/L^3)

and the uplift force is estimated by integrating the uplift pressure curve along the base of the structure. The other constraint is:

$$\frac{icr}{i} \geq 3 \tag{3}$$

Where: *icr* is the critical exit gradient and ≅ 1,

i is the computed exit gradient at the downstream side of the structure.

Further constraints could be imposed on the selected dimensions such as:

$$\left\{ \begin{array}{l} S1_{min.} \leq S1 \leq S1_{max.} \\ S2_{min.} \leq S2 \leq S2_{max.} \\ B_{min.} \leq B \leq B_{max.} \end{array} \right\} \tag{4}$$

3. GEO-STUDIO MODEL

The problem under-study explained in the previous section, is represented in the Geo-studio program (GEOSTUDIO.2004.V6.02-LND). This program was applied for 1200 case. For each case the program solves the seepage equation of the steady-state flow and anisotropic homogeneous soil using the finite element technique. From the results of the head distribution in the nodes, the required volume of concrete (V) and the required length of the downstream protection (L) are estimated such that the constraints of **Eqs. (2) and (3)** were achieved respectively.

Fig. 2 shows the structure for one of the cases with the discretization process. The elements used are square and rectangular as shown, with four nodes at the corners. This figure shows also the system of both element and node numbering.

Fig. 3 shows the distribution of the exit gradient along the downstream side of the structure. The required length of protection can be estimated using this curve and **Eq. (3).**

Table 1 shows the results of some cases analyzed using the Geo-studio models.

4.ARTIFICIAL NEURAL NETWORK (ANN) MODEL.

The results of L and V for the 1200 cases were used for building an ANN model capable of estimating L and V as output variables using S1, S2, H, B, D and kx/ky as input variables.

In order to obtain this model, the SPSS software (Statistical Procedure for Social Science, version 19.0) was used. For application of this software, six nodes were selected for the input layer which represents the input variables (S1, S2, H, B, D and kx/ky). Two nodes were selected for the output layer which represents the output variables (L and V). One hidden layer was selected for simplicity. To build the ANN model, many running trials were performed, in each one the software parameters were changed as follows:

- Selection the division of the data into training, testing, and validation sets.
- Also the selection of the division method either blocked, stripped, or random.
- Testing the proper number of nodes in the hidden layer.
- Changing the learning rate and momentum factor.

The selection of the best ANN model was achieved according to the smallest error and the highest correlation coefficient of the predicted and observed outputs.

The applied data to the software were the 1200 cases used in the Geo-Studio program. **Table 2** represents the best data division and **Fig. 4** shows the architecture of the ANN network.

Table 3 shows the bias and weight matrices for the input and hidden layers.

Figs. 7- a and 7-b show the comparison between predicted and observed values of L and V respectively.

The results of the ANN model indicated high correlation coefficients between the observed and predicted values of L and V as r_L= 98.3% and r_V= 99.4% respectively. **Table 6** shows the comparison of the values of L and V estimated using both Geo-studio and ANN models, which indicates the capability of the ANN model to produce acceptable results.

5- OPTIMIZATION USING GENETIC ALGORITHM (GA) MODEL

The steps are used in the Genetic Algorithm models are shown in the appendix:

A MatLAB code was written for the Genetic Algorithm model using the Algorithm shown above. In order to apply this model values for the Genetic Algorithm, parameters were selected as np = 100, pc = 0.8, pm = 0.2, ML = 0.1, S1min = 0.5m, S1max = 4m, S2min = 0.5m, S2max = 4m, Bmin = H, Bmax = 2.5H.

Sensitivity analysis was also done for each parameter in order to find the effect of each one on the results obtained by the model. It was found that pc, pm and ML had little effect on the solution, and the above selected values give stable solution. Different values of np = 10, 20, 30, 40, 60, 80, 100 were tested and np = 100 gave the stable solution, and upon increasing this value above 100, the same solution was obtained. With these selected values, the number of iteration where the software reached the stable solution was found to be 2.

It is also worth to mention that the algorithm of genetic model solution is robust, i.e., in each run the results exhibit some changes among the output results for the same input values. This is true because the solution starts with random generation of S1, S2 and B, moreover the crossing-over and mutation selection is also randomly selected, and in each run different random matrices of those variables was generated. However, for each case the values of S1, S2 and B that give the least value of f(x) should be selected, however, the difference between f(x) values is small.

In order to compare the values of the obtained optimum solution using the Genetic Algorithm model, with the values obtained using Geo-studio model three cases were used as shown **in Tables 7, 8 and 9.**

Table 7 shows the results of using the Genetic Algorithm model for case (A). The second run solution was selected, since it gives the minimum f(x) value. The obtained value of S1=3.97m, S2=0.86m and B=5.02m were then approximated by S1=4.0m, S2=0.90m and B=5.0m respectively to be used in a simulation of this case in Geo-studio analysis for checking. This approximation was done to make the discretization process in the Geo-Studio modeling easy.

Table 8 shows the results of the use of Genetic Algorithm model for case (B) where H was increased to 10m and kx/ky to 4. The fifth run was selected, since it gives the minimum f(x) value. The obtained value of S1=3.58m, S2=0.61m and B=10.13m were then approximated to S1=3.60m, S2=0.60m and B=10.0m respectively to be used in a simulation in Geo-studio analysis for checking.

Table 9 shows the results of the use of Genetic Algorithm model for case (C) increasing kx/ky to 8. The third run solution was selected, since it gives the minimum f(x) value. The obtained value of S1=2.5687m, S2=0.82m and B=10.1396m were then approximated by S1=2.50m, S2=0.80m and B=10.0m respectively to be used in a simulation in Geo-studio analysis for checking.

These cases were re-analyzed using the Geo-studio model to find whether the obtained values of L and V by the Genetic Algorithm is compared with these obtained by the Geo-studio solution for the same approximated values of S1, S2 and B, and for the selected H, D and kx/ky values. The comparison is shown in **Table 10** which shows good agreement.

6. CONCLUSIONS

From the present work, the following conclusions could be obtained:

1) The obtained artificial neural network model, using depth of upstream cutoff (S1), depth of downstream cutoff (S2), head differences (H), length of floor required (B), depth of impervious layer (D) and degree of anisotropy(kr = kx/ky) to obtain values of the length of protection in the downstream side (L) and volume required for superstructure (V), that satisfies the related constraints of safety factors, is efficient with correlation coefficients 98.3% and 99.4% respectively. The required number of hidden nodes was 13 with one hidden layer.

2) The genetic algorithm model indicates that the values of probability of crossing-over, probability of mutation and mutation level have little effect on the obtained optimal solutions for the problem studied. Moreover, the generated population size that gave the stable solution is not less than 100 and the required number of iterations to reach this stable solution is 2.

3) The optimum solution obtained using the genetic algorithm model is robust, i.e, each run gave different solutions, and however, a slight difference was obtained for the decision variables for most of the solutions. Hence, the designer should select the solution that gives the minimum objective function {f(x)}.

4) The optimum solution obtained using the genetic algorithm model for upstream cutoff length (S1), downstream cutoff length (S2) and length of floor required for hydraulic structure (B) with the corresponding L and V values were compared with the L and V values obtained using geo-studio models and found to be comparable.

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APPENDIX: GENETIC PROGRAM STEPS

1) Structure data input:
   - Enter the maximum expected difference in head between upstream and downstream sides (H in meters),
   - Enter limits of floor length (B maximum in meters),
   - Enter limits of floor length (B minimum in meters),
   - Enter limits of maximum upstream cutoff length (S1max. in meter) < depth of impervious layer (D),
   - Enter limits of minimum upstream cutoff length (S1min.in meter),
   - Enter limits of maximum downstream cutoff length (S2max. in meter),
   - Enter limits of minimum downstream cutoff length (S2min. in meter), and
   - Enter value of impervious layer depth (D in meter)
   - Enter kr = kx / ky ratio of horizontal to vertical permeability.

2) Genetic Algorithm / population, cross-over, mutation parameters:
   - Enter number of population solutions to be generated (np),
   - Enter cross-over probability (pc),
   - Enter mutation probability (pm),
   - Enter mutation level (ML), and

- Enter number of iterations to be performing (ni).

3) Genetic Algorithm objective function parameter input:
   - Minimize $f(x) = C1S1+C2S2+C3V+C4L+C5B$, (5)
   - Enter (C1) as the percent cost for S1,
   - Enter (C2) as the percent cost for S2,
   - Enter (C3) as the percent cost for V,
   - Enter (C4) as the percent cost for L, and
   - Enter (C5) as the percent cost for B.

4) Generate (np) random S1 values between $S1_{max}$ and $S1_{min}$

$$S1_{min} \leq S1 \leq S1_{max}$$

5) Generate (np) random S2 values between $S2_{max}$ and $S2_{min}$

$$S2_{min} \leq S2 \leq S2_{max}$$

6) Generate (np) random B values between B_{max} and B_{min}

$$B_{min} \leq B \leq B_{max}$$

7) Find number of couples to be cross-over (NOCC)

$$NOCC = \left| \frac{np * pc}{2} \right| \quad (6)$$

8) Generate a matrix (randomly) between (1 and np) with (8*NOCC) elements.

9) Make cross-over, odd element with the near even element.

10) Make new populations,

$$New\ Population = (np + 8*NOCC) \quad (7)$$

11) Find S1, S2 and B for a mentioned new population, find the values of (Land V) from the ANN program and then calculate the value of f(x) from equation (4.1).

12) Sort values in ascending order and kill (remove) the last (8*NOCC) cases.

13) Find number of persons to be muted (NOPM),

$$NOPM = pm * np \quad (8)$$

14) Generate a matrix randomly (number of 1 to np) with elements (NOPM * number of input variables)

15) Make mutation accordingly; find NOPM persons using (± ML).

16) Add to population in step (11) or

[np +NOPM(+ML) + NOPM(-ML)]

17) Find f(x) for them, sort in ascending order, and kill (remove) last (2*NOPM) cases.

18) Go to make another iteration, go back to step (8).

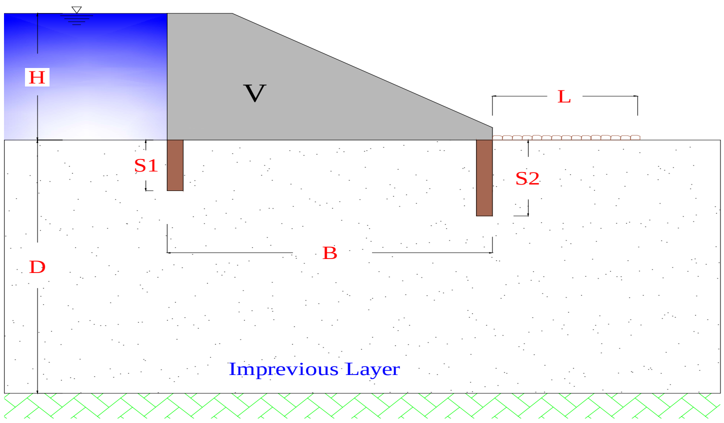

Figure 1. Schematic representation of the problem under study.

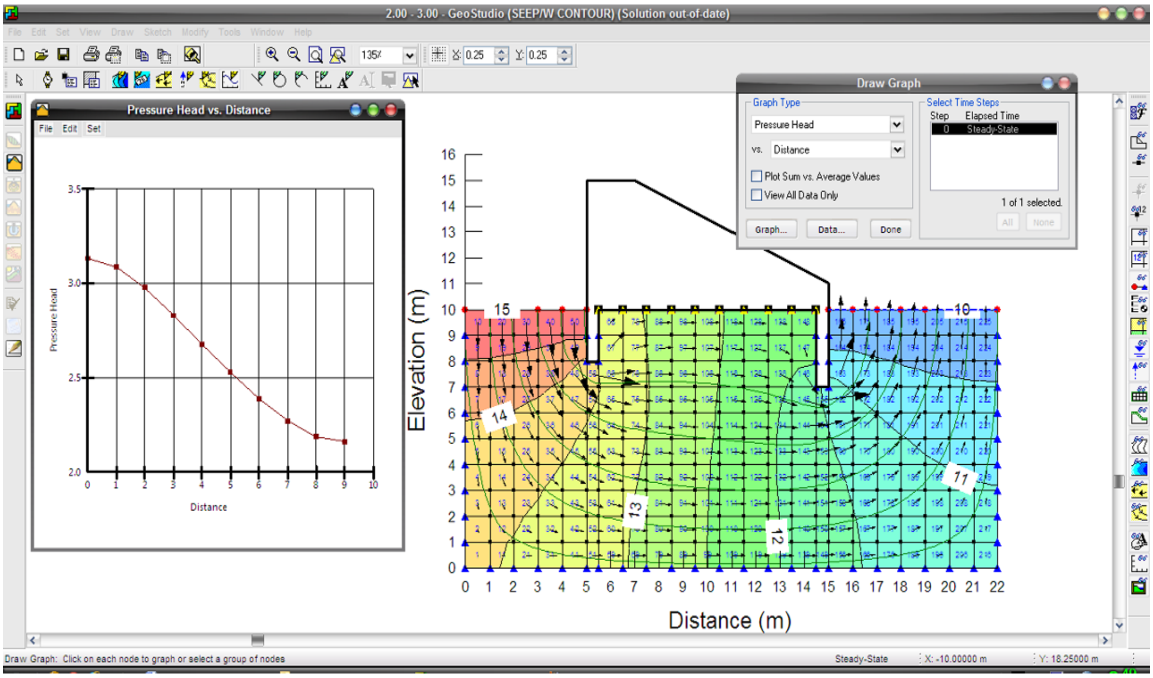

Figure 2. Uplift pressure distribution beneath the Structure, flow lines and equipotential lines.

(Note: on the left figure, x=0 refers to the upstream point of the structure foundation on the right figure**)**

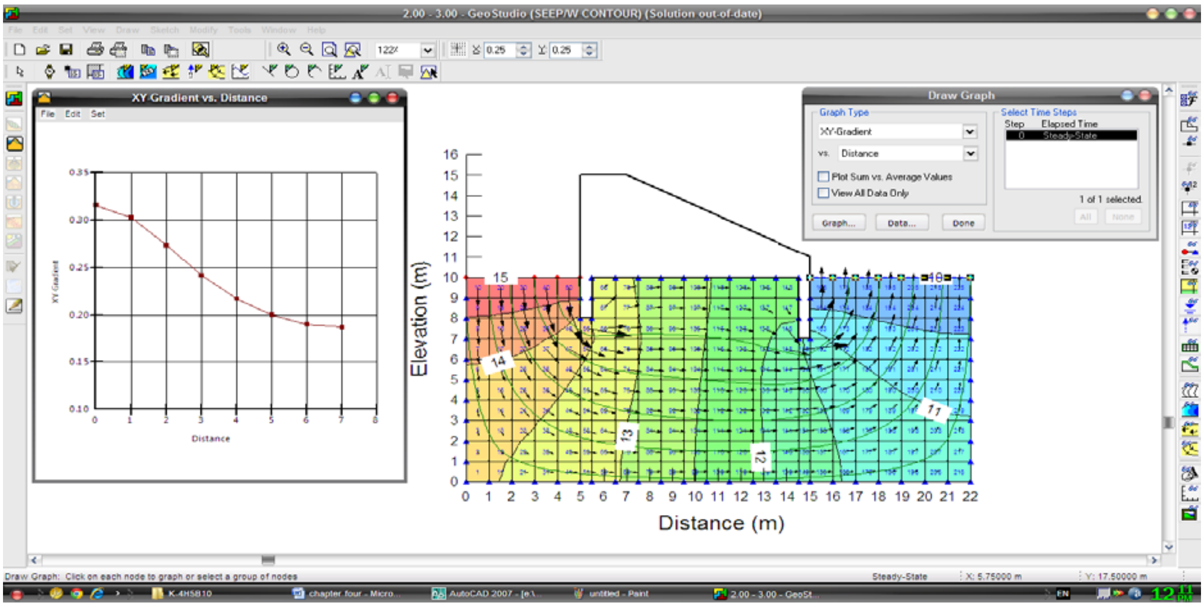

Figure 3. Distribution of the exit gradient along the downstream side.

(Note: on the left figure, x=0 refers to the downstream point of the structure foundation on the right figure)

Table 1. Results obtained for L and V using the Geo-studio models.

S1 (m)	S2 (m)	L (m)	V (m^3)
1	1	2.65	105.701
1	1.5	2.72	116.696
1	2	2.66	125.408
1	2.5	2.46	134.658
1	3	2.11	142.067
1	3.5	1.23	149.912
1	4	0.00	156.281
1.5	1	2.40	97.891
1.5	1.5	2.48	108.809
1.5	2	2.41	117.593
1.5	3	1.76	134.736
1.5	3.5	0.39	142.972
1.5	4	0.00	149.701
2	0.5	1.98	82.774
2	1	2.18	92.711
2	1.5	2.26	103.441
2	2	2.18	112.177
2	2.5	1.92	121.698
2	3	1.42	129.495
2	3.5	0.00	137.967
2	4	0.00	144.931

Table 2. Data division selected for the ANN model.

Item		N	%Total output
Sample	Training	960	80%
	Testing	180	15.0%
	Holdout	60	5.0%
Valid		1200	100%
Excluded		0	
Total		1200	

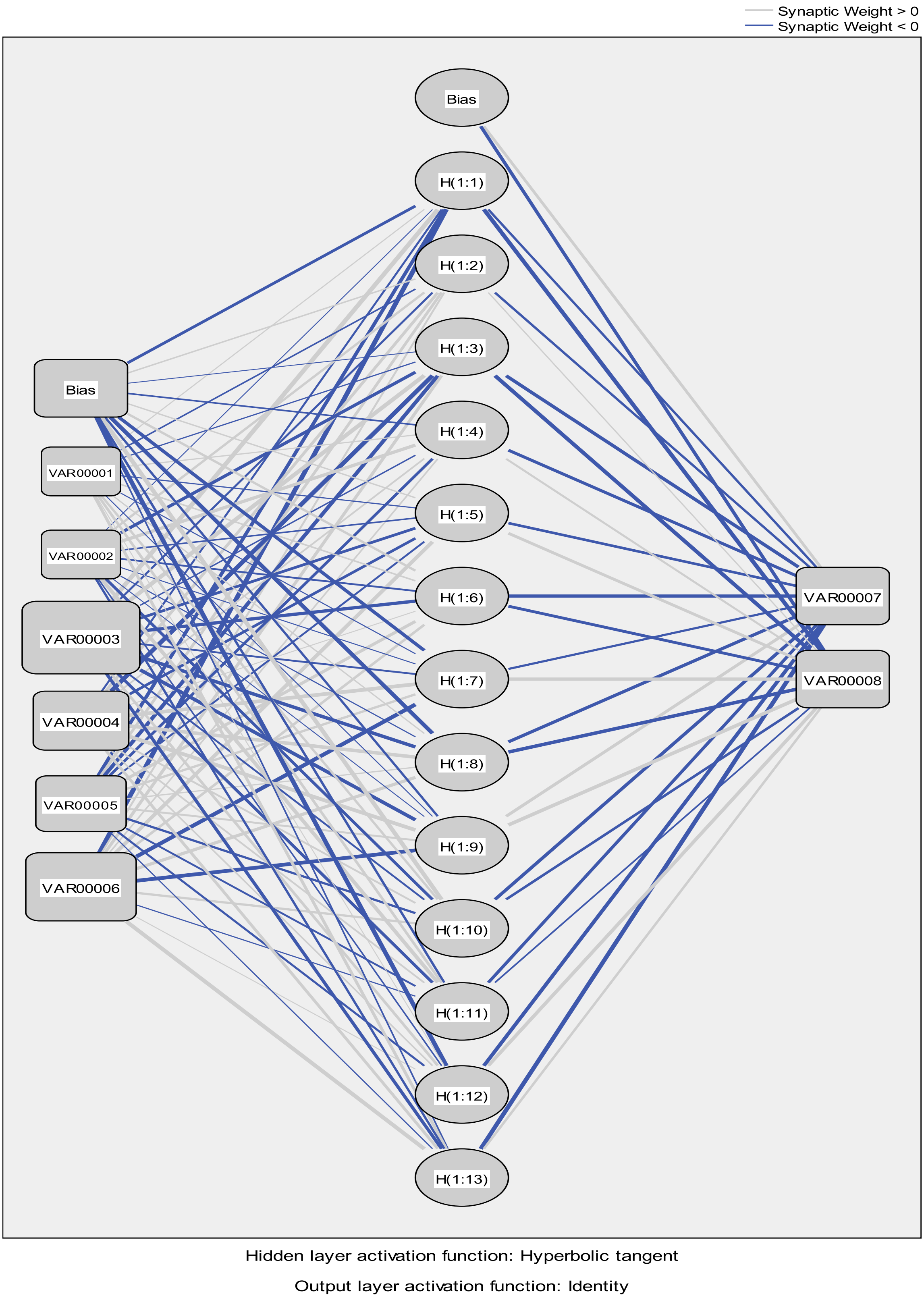

Figure 4. Architecture of the artificial neural network model.

Table 3. Bias and weight matrices for the ANN model.

Predictor		Predicted														
		Hidden Layer 1													Output Layer	
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (1:9)	H (10:1)	H (1:11)	H (1:12)	H (13:1)	VAR007	VAR008
Input Layer	(Bias)	-0.556	0.098	-0.009	0.127	0.084	0.295	-0.945	-1.794	-0.196	1.984	-0.216	-2.078	-0.067		
	VAR0001	0.033	-0.101	-0.052	0.064	-0.044	0.112	-0.029	0.062	-0.017	0.219	0.317	0.004	0.414		
	VAR0002	-0.005	0.256	-0.914	1.134	-0.102	-0.158	-0.028	-0.038	-0.006	-0.511	1.103	-0.066	-0.179		
	VAR0003	3.265	-0.157	2.824	-0.072	-0.577	-1.310	-0.160	-1.571	-1.462	-0.135	-0.542	0.373	-0.613		
	VAR0004	-0.132	0.442	-4.170	0.122	-0.474	0.028	2.961	1.930	2.154	0.155	0.126	0.093	0.437		
	VAR0005	-0.815	0.399	-1.271	-0.409	-0.150	0.756	0.365	0.065	0.180	-0.279	-0.156	-0.176	-0.034		
	VAR0006	-5.794	0.131	0.537	0.089	1.297	0.373	-2.889	1.057	-3.650	0.342	-0.038	0.024	2.018		
Hidden Layer	(Bias)														0.406	-0.711
	H (1:1)														-0.227	-1.699
	H (1:2)														-0.241	0.039
	H (1:3)														-1.063	-1.614
	H (1:4)														-0.799	0.166
	H (1:5)														-0.513	0.619
	H (1:6)														-1.211	-0.742
	H (1:7)														-0.271	1.447
	H (1:8)														-0.949	-1.621
	H (1:9)														0.636	1.576
	H (1:10)														-0.882	-0.389
	H (1:11)														-0.604	-0.102
	H (1:12)														-1.103	0.916
	H (1:13)														-2.068	0.238

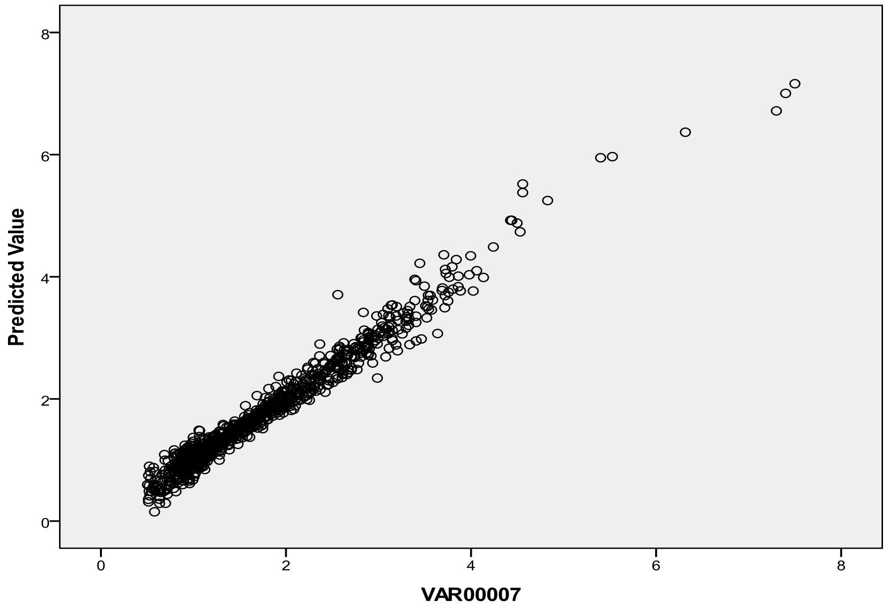

Figure 7- a. Comparison between predicted and observed values of (l).

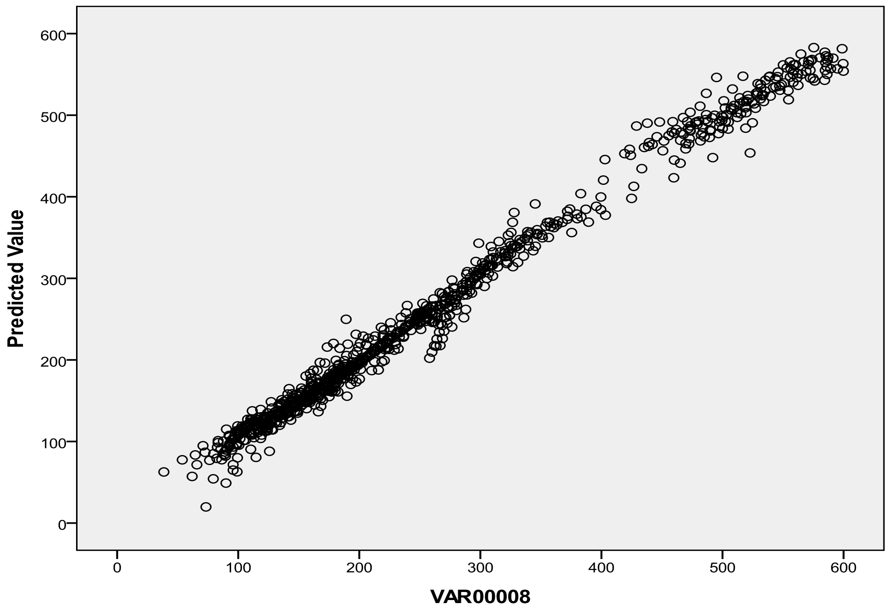

Figure 7- b. Comparison between predicted and observed values of (v) using the ANN model.

Table 6. Comparison of (L and V) values using Geo-studio and ANN Model.

S1	S2	H	B	D	kx/ky	Calculated L value using Geo-studio	Calculated V value using Geo-studio	Estimated L value using ANN model	Estimated V value using ANN model	% difference for L value	% difference for V value
1.50	2.50	5	5	10	1	2.867	133.238	2.836	138.876	1.08	-4.23
3.00	3.00	6.25	5	10	2	1.498	152.259	1.57	158.722	-4.79	-4.24
3.00	1.50	8	5	10	4	2.953	509.584	2.976	510.245	-0.78	-0.12
3.50	2.50	8	5	10	4	3.044	551.282	3.160	537.973	-3.82	2.41
2.50	2.50	12.5	5	10	8	1.19	145.94	1.175	146.53	1.28	-0.41
2.00	1.50	5	7.5	10	1	1.997	157.43	2.08	160.836	-4.28	-2.16
4.00	1.00	10	7.5	10	2	2.4	247.939	2.379	256.261	0.87	-3.35
1.50	2.50	10	7.5	10	2	3.755	332.517	3.706	340.982	1.32	-2.54
1.50	2.00	10	7.5	10	4	1.895	325.049	1.903	329.873	-0.42	-1.48
1.50	2.00	12.5	7.5	10	8	1.17	266.24	1.12	264.57	4.15	0.63
2.75	1.50	5	10	10	1	1.41	188.15	1.36	181.91	3.37	3.32
2.00	0.50	5.00	10.0	10	1	1.36	175.79	1.368	174.367	-0.59	0.81
4.00	2.00	15	10	10	4	2.46	471.00	2.476	490.375	-0.65	-4.11
2.50	1.50	15	10	10	4	2.58	493.52	2.66	498.24	-3.07	-0.96
2.00	3.00	30	10	10	8	1.413	141.755	1.350	136.985	4.44	3.36
4.00	2.50	30	10	10	8	1.22	117.834	1.253	124.391	-2.72	-5.56
3.00	2.00	7.5	12.5	10	1	2.48	373.93	2.509	383.94	-1.17	-2.68
3.00	1.00	10	12.5	10	2	1.826	465.25	1.886	468.02	-3.29	-0.60
1.00	2.00	10	12.5	10	4	1.12	547.143	1.19	533.47	-6.23	2.5
2.00	2.50	20	12.5	10	8	1.14	292.8	1.08	293.81	5.07	-0.34

Table 7. Optimum solution obtained using Genetic Algorithm model for case (A).

H = 5 m, D = 10 m, kx/ky = 1

Optimum solution obtained using Genetic Algorithm model						
Run No.	S1 (m)	S2 (m)	B (m)	L (m)	V (m^3)	F(x)
1	3.5	0.908	5.57	1.88	106.93	23.79
2	3.97	0.8601	5.0267	1.8128	81.6163	18.7174
3	3.645	1.47	5.0	2.087	100.28	22.54
4	3.56	0.598	5.344	1.78	94.48	21.182
5	3.5	0.71	5.7	1.78	102.88	22.95

Table 8. Optimum Solution obtained using Genetic Algorithm model for case (B).

H = 10 m, D = 10 m, kx/ky = 4:

Optimum solution obtained using Genetic Algorithm model						
Run No.	S1 (m)	S2 (m)	B (m)	L (m)	V (m^3)	F(x)
1	3.77	1.52	10.6	0.83	359.12	75.35
2	3.71	0.53	10.18	0.77	338.4	70.87
3	3.55	1.58	11.22	0.78	379.35	79.47
4	3.65	1.44	10.50	0.85	356.44	74.77
5	3.58	0.61	10.13	0.79	338.42	70.84

Table 9. Optimum solution obtained using Genetic Algorithm model for case (C).

H = 10 m, D = 10 m, kx/ky = 8:

Optimum solution obtained using Genetic Algorithm model						
Run No.	S1 (m)	S2 (m)	B (m)	L (m)	V (m^3)	F(x)
1	1.6492	0.7161	10.7606	1.00	476.8957	98.2226
2	1.2946	0.6998	10.0684	0.694	476.9712	97.9759
3	2.5687	0.8212	10.1396	0.6626	474.7486	97.8914
4	1.6708	0.5426	10.9744	0.6508	477.16.83	98.2470
5	3.40	0.8176	10.4655	0.6290	473.7681	97.9640

Table 10. Comparison of estimated (L and V) values for the three cases selected.

Case No.	Given Values			Estimated Values							% difference for L value	% difference for V value
				Genetic Algorithm Optimization					Geo-Studio Model			
	H (m)	D (m)	Kx/ky	S1 (m)	S2 (m)	B (m)	L (m)	V (m^3)	L (m)	V (m^3)		
A	5	10	1	4	0.9	5	1.81	81.616	1.79	82.233	-1.11	0.75
B	10	10	4	3.6	0.60	10	0.89	338.42	0.91	357.08	2.19	-5.23
C	10	10	8	2.6	0.80	10	0.66	474.74	0.70	469.86	-5.83	1.04