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A Genetic Algorithm Optimization Model for Stability of an Inclined Cutoff with Soil-Embedded Depth

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Abstract: A coupled artificial neural network model with a genetic algorithm optimization model is developed for a practical case of a single cutoff. The proposed cutoff is of a soil-embedded vertical part with an inclined extension. The model successfully found the optimum dimensions of the vertical and inclined parts, the optimum angle of inclination, and the optimum length of protection downstream of the cutoff for a factor of safety of 3 against piping. Two thousand one hundred cases are modeled first using Geo-studio software to find the required length of downstream protection against piping for different lengths of the vertical, inclined lengths of the cutoff, its angle of inclination, soil layer depth, and degree of anisotropy. Then the created data set was used to develop an Artificial Neural Network (ANN) model for finding the length of protection required. The ANN model showed high performance with a determination coefficient of (0.922). The genetic algorithm model needs a minimum number of randomly generated populations of 100000 and three crossover iterations to produce a stable optimum solution. Running the model for different practical cases showed that the optimum angle variation was low and fluctuated around 30o. This low angle variation was due to its lower effect on the downstream soil protection length compared to the other decision variables. At the same time, the other dimensions varied with input variables, such as the depth of the soil layer, the seepage driving head, and the degree of isotropy. For a degree of anisotropy (ratio of vertical to horizontal hydraulic gradient) less than 0.5, the results showed no need for protection against piping; hence it is recommended to use minimum dimensions for such a case. The coupled model can easily obtain the optimum dimensions for any given input. Importance analysis showed that the optimum length of the downstream protection was highly affected by the vertical and inclined length of the cutoff, while it was less affected by the angle of inclination. Correlation analysis supported the importance analysis.

نموذج الأمثلية لإستقرار حاجب مكون من جزء شاقولي مدفون بالتربة وجزء مائل

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الخلاصة

تم تطوير نموذج مدمج بين الشبكة العصبية الصناعية ونموذج تحسين الخوارزمية الجينية لحالة عملية لحاجب منفرد. الحاجب المقترح متكون من جزء شاقولي مدفون في التربة وجزء مائل. نجح النموذج في إيجاد الأبعاد المثلى للأجزاء الشاقولية والمائلة والزاوية المثلى للميل وطول الحماية المطلوبة لتربة مؤخرة الحاجب الأمثل وذلك باستخدام عامل أمان قدره 3 ضد ظاهرة الغليان لجعل الكلفة أقل ما يمكن. تم بناء النموذج لقاعدة بيانات متكون من 2100 حالة التي حصلت عليها باستخدام برنامج Geo-studio لإيجاد طول المطلوب للحماية المؤخرة ضد ظاهرة الغليان، لقيم مختلفة من الأطوال الشاقولية والأطوال المائلة وزاوية الميلان للحاجب وعمق طبقة ودرجة تباين خواص التربة، بعد ذلك تم استخدام قاعدة البيانات هذه لبناء نموذج الشبكات العصبية الصناعية لإيجاد طول الحماية المطلوبة. يظهر نموذج ANN درجة عالية من الأداء مع معامل تحديد (0.922 يحتاج نموذج الخوارزمية الجينية إلى حد أدنى لعدد الحلول المولدة عشوائيًا من 100000 وعدد المحاولات المطلوبة هو 3 لإنتاج حل أمثل مستقر. يوضح تشغيل النموذج لحالات عملية مختلفة أن التباين الأمثل للزاوية منخفض ومتقلب حول 30 درجة. يرجع هذا التباين المنخفض للزاوية إلى تأثيرها المنخفض على طول حماية التربة في اتجاه مجرى النهر مقارنة بمتغيرات التحكم الأخرى. في نفس الوقت، تختلف الأبعاد الأخرى باختلاف متغيرات الإدخال مثل عمق طبقة التربة وشحنة الماء ونسبة معامل النفاذية. أظهرت النتائج بأنه في حالة نسبة معامل النفاذية الشاقولي والأفقي أقل من (0.5) فلا يوجد حاجة لحماية مؤخر الحاجب. لذلك نوصي باستخدام الحد الأدنى من الأبعاد لمثل هذه الحالة. باستطاعة النموذج المدمج الحصول بسهولة على الأبعاد المثلى لأي معطيات معينة. بيّن تحليل الاهمية وتحليل الارطبات، بأن طول الحماية الأمثل للتربة في مؤخرة الحاجب يتأثر بشكل كبير بالطول الشاقولي والمائل للحاجب بينما زاوية الميل ذات تأثير قليل.

الكلمات الدالة: نموذج ANN، نموذج التحسين، الخوارزمية الجينية، الحاجب المائل، الشاقول المدفون، Geo-studio.

1.INTRODUCTION

For hydraulic structures, foundation design cutoffs and sheet piles are usually used to increase the safety factor against prevailing failures. One of the most common failures is the failure of the downstream soil due to piping. To increase the safety factor against this failure, downstream protection is usually used in addition to other facilities such as cutoffs. Much research has been done analyzing the effect of the upstream and downstream cutoffs on the required protection length. Other research has developed optimization models to find the optimum design for these facilities (upstream cutoff length, downstream cutoff length, and protection length) with the constraints satisfying the required safeties factor against both uplift and piping [1, 3, 7, 12]. Al-Suhili and Karim (2014) [2] developed a Genetic Algorithm model coupled with an Artificial Neural Network model to find the optimal values of upstream and downstream cutoff lengths, foundation length, and downstream protection length required for a hydraulic structure [1]. Other research investigated the effect of an inclined sheet pile on the piping phenomenon. Alnealy and Alghazali (2015) [1] analyzed the seepage under hydraulic structures using a "slide program". The results presented were the uplift pressure variation along the structure's base and the exit gradient at the toe of the structure. These variations were shown for different cutoff angles; for two cases of upstream and downstream cutoff locations, the soil beneath the structure was either one layer or two layers. They observed that the best angles for the upstream and downstream cutoffs were 45 and 120, respectively [2]. Hassan (2017) used a genetic algorithm technique integrated with a numerical model (finite element method) to compute the optimal cutoff location and angle of inclination for barrages constructed on homogenous anisotropic soil foundations. The results indicated that the optimum depth of upstream cutoff to the width of foundation n ratio was 0.4, and the optimum angle range was (59^o, 68^o) [3]. Mansuri et al. (2014) studied the effect of the location and angle of the cutoff wall on uplift pressure in a diversion dam. They concluded that as the cutoff wall location approached the downstream side with an increasing inclination angle, the reduction in total uplift force decreased [4]. Ijam (1994) developed an analytical solution for the exit gradient variation downstream of a horizontal foundation dam with an inclined cutoff at the downstream side resting on a homogeneous, isotropic soil of infinite depth. The author concluded that using an inclined cutoff would increase the factor of safety against uplift and piping [5]. Ijam (2011) modified this solution to cover the same configuration, except that the cutoff locations can be at any point along the dam foundation. Similar results were obtained in the above-cited work [6]. Al-Saadi et al. (2011) investigated the effect of cutoff inclination angle on the exit gradient and uplift pressure head under hydraulic structure using (ANSYS11.0). They concluded that a downstream cutoff inclined to the right side by less than 120^o was beneficial for increasing the factor of safety against piping

[7]. Esmat (2011) used (Geo-Studio 2007, SEEP/W) software to analyze the effect of the cutoff wall angle of inclination on uplift, seepage flow, and piping. Results showed that the angle that minimized the seepage flow was about 60°, while that minimized the uplift pressure ranged from 120° to 135° and that for the piping ranged from 45° to 75° [8]. Obead (2013) used (FORTRAN 90) to investigate the inclined cutoff position and inclination influence. Results showed that as the location of the inclined cutoff approached the downstream side, the required inclination angle for minimizing the seepage flow should be increased [9]. Armanuos (2021) used FEM to investigate the effectiveness of inclined double-cutoff walls under hydraulic structures. The results showed that increasing the inclination angle of the downstream cutoff wall had a major impact on the exit gradient reduction. In addition, they concluded that the use of cutoff walls in the upstream and downstream ended with right angles and equal depths significantly reduced the seepage discharge more than any other configurations [10]. Alsenousi and Mohamed (2008) used a two-dimensional finite element model for analyzing seepage flow below a dam with an inclined cutoff located anywhere along the dam base. The results agreed with Ijam's (2011) conclusions regarding the benefits of locating the inclined sheet pile at the toe of the dam and the inclination angle towards the downstream [11]. Al-Suhili et al. (2017) conducted an experimental study to verify the results of the SEEP/W software for seepage analysis under hydraulic structures with upstream and downstream inclined cutoffs. A genetic algorithm model coupled with the ANN model was used as an optimization tool to find the optimum lengths and inclinations for any hydraulic structure configurations [12]. Al-Suhili (2009) used conformal mapping to obtain an analytical solution for the exit gradient variation along the downstream side of an inclined sheet pile [13]. Hassan (2018) applied an optimization model using the finite element method coupled with the genetic algorithm technique to find the optimal cutoff location and angle of inclination for barrages constructed on homogenous anisotropic soil foundations. The results showed that these optimal distance variables were affected by the anisotropic degree [14]. The novelty of the current work is related to the geometry of the hydraulic structures under study. None of the cited related research regarding inclined cutoffs' effect on seepage has investigated an inclined cutoff with an embedded vertical part for traditional seepage analysis and the optimum design of the cutoff dimensions and inclinations. The practical implementation of an inclined cutoff is to have a vertical embedded followed by the inclined part. This structure is usually used when constructing an inclined cutoff or sheet pile. This study aims to investigate the case of an inclined sheet pile with an embedded vertical part. More specifically, determine the effect of the cutoff dimensions and inclination variations on the exit gradient and hence on the optimum dimensions and inclination of the cutoff. Starting with a simple sheet pile will open the gate for future research on a complete hydraulic structure with incline cutoffs constructed with an embedded part. This study will extend observing of the effect of the embedded part length, inclined part length, and angle of inclination to obtain the optimum design for these parameters and the length of the downstream protection required.

2. METHODOLOGY

Fig. 1 shows the physical configuration of the problem under study. The following are the definitions of the terms used. L is the length of downstream protection for a given factor of safety against piping, which is related to the exit gradient and the critical exit gradient, H is the difference of head between upstream and downstream water levels, D is the depth of impervious layer, d is the length of the vertical embedded part of the cutoff, S is the length of the inclined part of the cutoff, θ is the angle of inclination, and kr is the hydraulic conductivity ratio (ky/kx). Fig. 2 shows a flowchart of the used methodology, as follows:

1. Developing a database that includes the input variables (D, H, d, S, θ, and Kr) and the corresponding output variable L for a factor of safety of 3 against piping (Fs = $\frac{i_{cr}}{i_{exit}} \geq 3$, i_{cr} is the critical exit gradient, and i is the hydraulic exit gradient). The software used is Geo-Studio 2018, SEEP/W.
2. Use dimensional analysis to cast the variables into dimensionless pi-terms.
3. Develop an ANN model to find the output pi-term variables (L/H) as a function of the input pi-term variables (S/H, D/H, d/H, Kr, and θ).
4. Formulate an optimization model to find the optimum design variables (decision variables, L, S, d, and θ) for any given set of input variables (H, D, and Kr).
5. Develop a coupled ANN-Genetic algorithm model to solve the optimization model developed above.

Some of the above steps require clarifications, such as the ANN and GA optimization models. The ANN theoretical basis is well-known; however, the explanation presented herein will focus on the application. Similarly, an explanation will be given for the Genetic Algorithm solution of the optimization problem.

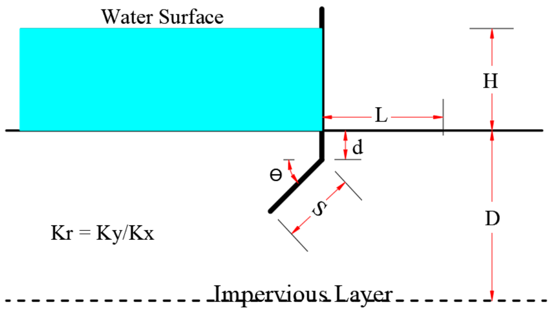

Fig.1 Physical Configuration of the Problem.

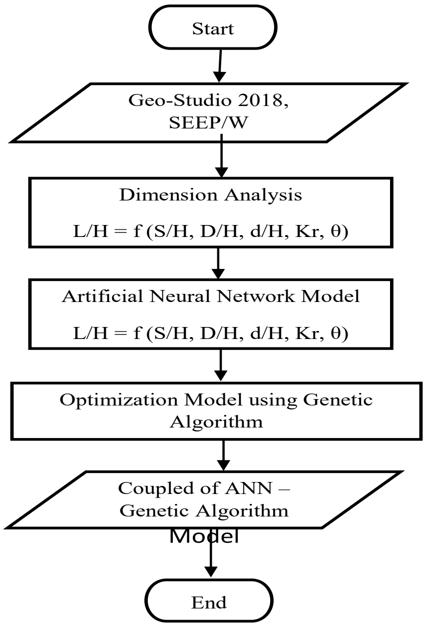

Fig.2 Methodology Flowchart.

2.1. *Artificial Neural Network Model*

The artificial neural network models are black-box data, dependable models. In this research, the ANN model was used with the physical judgment of the phenomenon. Since the exit gradient was physically a function of the soil strata properties and the geometrical dimensions of the incline cutoff, the ANN model was cast herein to follow this physical concept. The application of this software also allowed the selection of the data divided into a training set, testing set, and validation (holdout) set

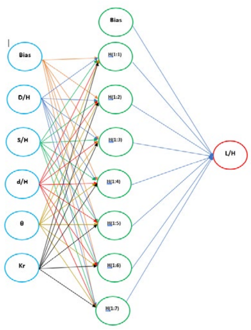

Fig.3. Architecture of the Artificial Neural Network Model.

The general equations for the ANN model are shown below, as presented by Al-Suhili and Ghafour (2013) [15]

$\mathbf{Zin}_{(\mathbf{px1})} = V_o bias_{(px1)} + V^T{}_{(nxp)} * X_{(nx1)}$ **(1)**

$\mathbf{Z}_{(\mathbf{px1})} = \tanh (Zin_{(px1)})$ **(2)**

$\mathbf{yin}_{(\mathbf{mx1})} = W_o bias_{(mx1)} + W^T{}_{(pxm)} * Z_{(px1}$ **(3)**

$\mathbf{y}_{(\mathbf{mx1})} = yin_{(mx1)}$ **(4)**

$\mathbf{L} = y_1 * sd_L + Mean_L$ **(5)**

where n is the number of input variables (nodes) in the input layer, P is the number of nodes in the hidden layer, and m is the number of nodes (variables) in the output layer. The activation functions of the hidden and the output layers are the hyperbolic tangents and the identity, respectively. ***X*** is the standardized input variables vector (D/H, S/H, d/H, θ, Kr), y is the standardized output variables vector (L/H), and L is the anti-standardized variable

2.2.a.OptimizationModel Formulation

The dimensions and inclination of the inclined cutoff (d, S, and θ) and the required length of protection against downstream piping (L) are all affected by the maximum expected difference in head between the upstream and downstream sides of the hydraulic structure (H), the depth of impervious layer D, and the soil strata properties (kx and ky). The most critical failure for such a structure may be the 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 exit gradient failures(piping). The controlling process is done by selecting the dimensions of S, d, θ, and L for a given (H), (D), and (Kr). It is better to select optimum dimensions; the following formulation of such a problem could be introduced.

$$\text{Min.} \quad f(x) = C_1S + C_2d + C_3L \qquad \textbf{(6)}$$

where f(x) is the cost function that should be minimized. C_1, C_2, and C_3 are the relative cost of each dimension. These values should be set relatively from available location-wise cost databases for such types of constructions. These costs are usually available in known databases in advanced countries, while for developed countries, they can be set using practical cost experience and construction market prices. Since these costs are relative, they should be assigned such that they sum to unity. This function is subject to the following constraint:

$$Fs = \frac{i_{cr}}{i_{exit}} \geq 3 \qquad \textbf{(7)}$$

where Fs is the factor of safety against piping, with a minimum selected value of 3, as recommended by many authors [1, 12, 16]. i_{cr} is the critical exit gradient $= \frac{Gs-1}{1+e}$, where Gs and e are the soil's specific gravity and void ratio. However, for most soils, i_{cr} is approximately (1), which is the hydraulic gradient at the downstream soil bed, where the seeped water exits the soil body, at which it will create soil boiling, i.e., piping failure. i_{exit} is the computed exit gradient at the downstream side of the cutoffs due to the soil properties and cutoff dimensions and inclination.

The other constraints are:

$$\left.\begin{cases} d + S^{*}\sin\theta < D \\ d_{min} \leq d \leq d_{max} \\ S_{min} \leq S \leq S_{max} \\ \theta_{min} \leq \theta \leq \theta_{max} \end{cases}\right\} \quad \textbf{(8)}$$

where d_{min}, d_{max}, S_{min}, S_{max}, θ_{min}, and θ_{max} are user-selected limits of the minimum and maximum vertical and inclined cutoff dimensions and angle of inclination.

2.2.b. The Genetic Algorithm Model Solution

For the formalized optimization model solution shown above, the genetic algorithm solution methodology followed the steps below:

1. Randomly generate Np (number of population). Each solution was represented by the following chromosome, which had four genes, as the decision variables were four, as shown below.

L/H	S/H	d/H	θ

2. Apply Eq. (9) to ensure each generated variable is feasible and satisfies the related constraints.

$$x^{*} = x * (Xmax - Xmin) + Xmin \quad \textbf{(9)}$$

3. Apply the crossover process such that every two parents from the randomly generated population produced two offspring, as shown in Fig. 4 . The variables A, B, C, D, E, F, G, and H are the corresponding x* values shown as letters to explain the crossover process (swapping).

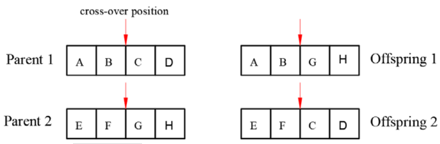

Fig.4 Crossover Process.

4. Evaluate the fitness function (the objective function) for each solution in the population and the offspring societies combined in one society (2*Np) using the developed ANN model. All the solutions were sorted in ascending order, and the last Np solutions were removed. The remaining Np solutions were used for the next iteration.

5. As the number of iterations was decided and implemented, the last three best solutions of the final iteration were used for a mutation process (if needed) to reach the most optimal solution.

It is worth mentioning that many factors of the genetic solution process were subjected to sensitivity analysis to find the best values for the problem under study, i.e., the Np value that gave a stable solution, the crossover position, 1, 2 or 3, and the percent of crossover and the percent of mutation.

3.RESULTS AND DISCUSSION

3.1.Result of the Geo-Studio

In order to create a database that could be used to develop the ANN model, (2100) different cases of the proposed phenomenon were analyzed using the Geo-studio model. For each case, different S, d, H, D, θ, and Kr values were selected. The results were used to estimate the required length (L) of the protection of the soil downstream of the cutoff, which satisfied the constraints of factors of safety against piping failure of (3) using equations (7) and (8), respectively. The results of the (2100) cases and the corresponding input values were cast in dimensionless variables (D/H, S/H, d/H, θ, and Kr) as the inputs and (L/H) as the output. This use of these dimensionless variables allowed the generalization of the developed model. Even though these results were proposed to be only a database for the ANN model, some results would be illustrated to prove reasonable variation. However, the validity of the Geo-Studio modeling of seepage was well verified by (1) by comparing the head values obtained from the software to the corresponding heads obtained from measurements of physical models. The validation was done for complicated geometrical configurations, such as a dam with two vertical cutoffs. In order to ensure validation for inclined cutoffs, the Geo-Studio results were highly verified by Al-Suhili et al. [12], as they used a similar complicated configuration to (1), except inclined cutoffs, rather than vertical ones. Figs. 5 (a) and (b) show the geo-studio results for the isotropic case, i.e., the soil had the same hydraulic conductivity in all directions (Kx=Ky). The y-axis is the exit gradient expressed in the Geo-Studio software, while the x-axis is the distance from the downstream cutoff edge. The variation of the exit gradient in Fig. 5 (b) looks reasonable, as all the exit gradient values are less than 1 and give a non-linear decreasing variation with distance along the downstream side of the cutoff. Also, the exit gradient approached a limiting almost constant value as distance increased. These observations comply with the physical behavior. Figs. 6 (a) and (b) show the geo-studio results for a case of anisotropic soil ($Kx \neq Ky$). The results shown agree with the expected physical behavior The validation was done for complicated geometrical configurations, such as a dam with two vertical cutoffs. In order to ensure validation for inclined cutoffs, the Geo-Studio results were highly verified by Al-Suhili et al.

[12], as they used a similar complicated configuration to (1), except inclined cutoffs, rather than vertical ones. Figs. 5 (a) and (b) show the geo-studio results for the isotropic case, i.e., the soil had the same hydraulic conductivity in all directions (Kx=Ky). The y-axis is the exit gradient expressed in the Geo-Studio software, while the x-axis is the distance from the downstream cutoff edge. The variation of the exit gradient in Fig. 5 (b) looks reasonable, as all the exit gradient values are less than 1 and give a non-linear decreasing variation with distance along the downstream side of the cutoff. Also, the exit gradient approached a limiting almost constant value as distance increased. These observations comply with the physical behavior.

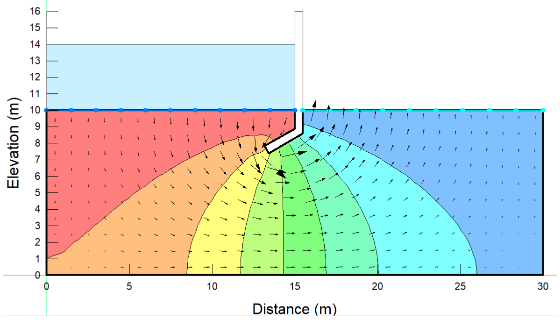

Fig.5a. Geo-Studio Analysis Flow Field Result for the Isotropic Case.

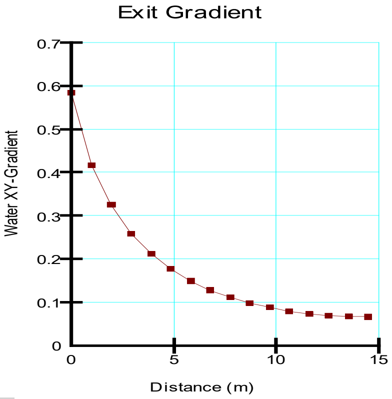

Fig.5b. Geo-Studio Results for Exit Gradient Variation Downstream of the Sheet Pile for the Isotropic Case.

Figs. 6 (a) and (b) show the geo-studio results for a case of anisotropic soil ($Kx \neq Ky$). The results shown agree with the expected physical behavior. The variation of the exit gradient in Fig. 5 (b) looks reasonable, as all the exit gradient values are less than 1 and give a non-linear decreasing variation with distance along the downstream side of the cutoff. Also, the exit gradient approached a limiting almost constant value as distance increased. These observations comply with the physical behavior. Figs. 6 (a) and (b) show the geo-studio results for a case of anisotropic soil ($Kx \neq Ky$). The results shown agree with the expected physical behavior.

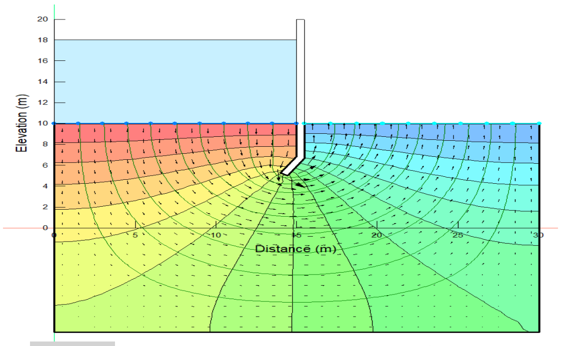

Fig.6a. The Geo-Studio analysis flow field result for the anisotropic case

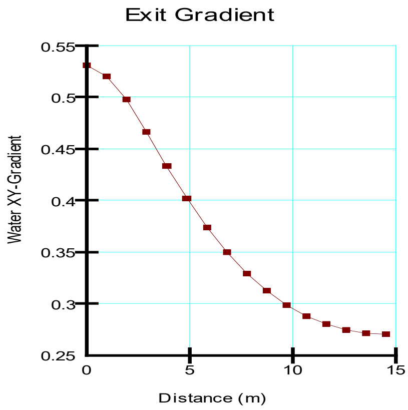

Fig.6b. Geo-studio Results for Exit Gradient Variation Downstream of the Sheet Pile for Anisotropic Case

3.2. Result of the ANN Model

The input variables for the ANN modeling should be standardized to remove each variable's effect on the order of magnitude. Hence, each variable's means and standard deviation values in the database were considered part of the ANN model parameters (Table 1).

Table 1. The Max. and Min. Values of The Input and Output Variables of the ANN Model.

Variables	N	Minimum	Maximum	Mean	Std. Deviation
D / H	2100	0.83	5.00	2.25	1.25
S / H	2100	0.08	0.75	0.29	0.19
d / H	2100	0.08	0.75	0.30	0.20
L / H	2100	0.00	2.20	0.96	0.58
θ	2100	0.00	180.00	90.04	58.93
Kr	2100	0.25	1.00	0.63	0.28
Valid N (listwise)	2100				

The application of the SPSS software on the database showed that 78.7% (1653 cases) were selected for training, 16.8% (353 cases) for testing, and 4.5% (94 cases) for validation. The required number of the hidden nodes in the hidden layer was found to be p =7, as n =5 and m =1. The ANN model matrices were found to be as follows

$$wobias_{(1x1)} = -0.553 \quad \mathbf{(10)}$$

$$X_{(5x1)} = \begin{bmatrix} D/H \\ S/H \\ d/H \\ \theta \\ kr \end{bmatrix} \qquad \mathbf{(11)}$$

$$\text{Vobias}_{(7x1)} = \begin{bmatrix} -1.679 \\ -0.190 \\ -3.372 \\ -0.485 \\ -1.326 \\ -0.330 \\ -0.269 \end{bmatrix} \quad \textbf{(12)}$$

$$\text{Vobias}_{(7x1)} = \begin{bmatrix} -1.778 & -0.200 & -0.325 & 0.134 & 0.544 & 0.160 & 0.183 \\ -0.712 & 0.724 & 2.109 & 0.749 & -0.319 & -0.360 & -0.060 \\ -0.437 & -0.831 & 4.122 & 1.768 & -0.809 & -0.556 & 0.144 \\ 0.122 & 0.269 & 0.207 & -0.500 & 0.294 & 0.217 & -0.337 \\ -0.441 & -0.690 & 0.308 & -0.472 & -1.458 & -0.447 & -0.209 \end{bmatrix} \quad \textbf{(13)}$$

$$W_{(7x1)} = \begin{bmatrix} -0.674 \\ 1.157 \\ -0.874 \\ 0.376 \\ 0.271 \\ -2.170 \\ 0.053 \end{bmatrix} \quad \textbf{(14)}$$

Interpretation of the ANN model results showed that the software had adjusted the selected percentages of the training set from 70% to 78.7%, for the testing set from 20% to 16.8%, and for the validation from 10% to 4.5%. This software modification was performed due to the selection of the option of random data set for training, testing, and validation, which will make the software selection more accurate than the user selection. The optimum number of hidden nodes in the hidden layer was selected by the software as 7 from the tried hidden nodes number between 1 and 50 nodes. The determination coefficient of the model showed that the model performance was very well, as it can explain 92.2% of the variance of the phenomenon.

3.3. Result of The Coupled Genetic Algorithm ANN Model

A Matlab code was written for the genetic algorithm solution of the formulated optimization model. As explained above, this method requires finding the objective function of many solutions many times throughout the process. For this purpose, the developed ANN model was coupled with the genetic algorithm model. To apply the genetic algorithm model using this code, some parameters need to be set, such as (d_{min} = 0, d_{max} = 2 m, S_{min} = 0, S_{max} = 4 m, θ_{min} = 30°, θ_{max} = 150°, C1= C2 = 0.25, and C3 = 0.5). Other parameters should be found using sensitivity analysis as follows:

3.3.1. The Number of Population (Np)

As the genetic algorithm solution starts with generating Np random solutions, arbitrary selection of a small Np value will result in different optimum solutions in each run, which creates the problem of robustness. For this reason, it is essential to determine the minimum Np value that assures a stable solution, i.e., gives the same optimum solution in each run. Table 2 below shows a sensitivity analysis for Np to achieve this goal. Table 2 shows that an Np value of 1500 was required to obtain a stable optimum objective function. For Np=10, there was a considerable difference in the optimum solution (minimum objective function) between the three runs. As Np further increased, those differences got smaller; however, they got equal when Np increased to 1500.

Table 2. Sensitivity Analysis of Np for A Stable Solution

Np	Run 1	Run 2	Run 3
10	4.1761	4.2724	4.1119
50	4.1512	4.0952	4.0985
200	4.0890	4.0922	4.0821
800	4.1000	4.0717	4.1000
1000	4.0722	4.0721	4.1000
1200	4.1000	4.1000	4.0809
1500	4.1000	4.1000	4.1000

However, this Np value gave an unstable optimum solution, i.e., the same decision output variables (S, d, θ, and L) for the same inputs for different runs. For these reasons, different runs were made, increasing the Np value to 100000, the minimum found Np value that gave a stable optimum solution.

3.3.2 The Number of Iterations (Ni)

As explained above, in the genetic algorithm solution, the crossover process should be iterated in order to get a stable optimum solution. It was found that for Np =1500, the required number of iterations was equal to two. Hence, three iterations were used to ensure a stable solution, and this number of iterations was acceptable for an Np = 100000.

3.3.3 Effect of Input Variables on Decision Variables and Objective Function

The input variables for the problem under study were D, H, and Kr. The genetic algorithm model developed was used to investigate the effect of variations of these input variables on the optimum solution and the objective function. These effects were investigated using dimensionless forms of the input variables, such as D/H and Kr. Figs. (7, 8) show the effect of D/H on the optimum solution for isotropic soil media. To illustrate the effect of H and D, Fig. 7 was obtained by setting H = 8 m and changing the D values, while Fig. 8 was obtained by setting H = 2m and allowing D to change as before.

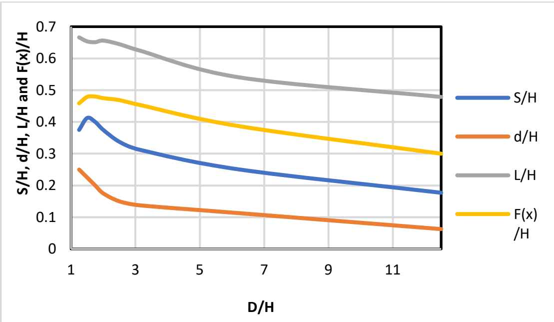

Fig.7. Variation of Decision Variables and Objective Functions with D/H, H = 8 m and Kr = 1 (Isotropic Case).

Fig. 7 shows a slight declining slope of all the variables with the increase of D/H. However, S/H and F(x) showed a slight increase at the low value of D/H, then followed the declined slope, as mentioned above. Fig. 8 shows similar behavior, except that the value increase at low D/H values was observed for S/H, F(x), and L/H. The two figures indicate that the optimum L/H value was less or equal to 0.5, and as H increased, the L/H values increased. Increasing the H value may increase the L/H but still far below one. To investigate the effect of this variation for an anisotropic case, Fig. 9 was obtained by setting the same values as Fig. 7, except that Kr was changed to 0.75 instead of 1. A comparison between Fig.7 and Fig. 9 shows that for the isotropic case, the d/H decreased while the S/H increased. To obtain the effect of anisotropy more thoroughly, the variation of the decision variables and objective function with Kr was investigated. to investigate the effect of this variation for the anisotropic case, Fig. 9 was obtained by setting the same values as Fig. 7, except that Kr was changed to 0.75 instead of 1. Comparing Figs. (7, 9) show that the d/H decreased while the S/H increased for the isotropic case. In Figs. (7, 8, 9), the angle of inclination of the sheet pile was not shown. The reason is that the results of θ showed a very narrow range (30.01°, 30.78°). For this reason, the optimum inclination angle was 30° for a wide range of inputs. This variation is shown in Figs. (10, 11), where H changed from 8m to 12m. The Kr values varied from 0.5 to 1, as the calculation showed that the S/H and d/H were approximately zero for smaller Kr values, which is reasonable since, for low Kr values, the vertical permeability was much lower than the horizontal one, which decreased the hydraulic vertical gradient. Fig. 10 shows that for Kr between 0.5 and 0.6, the required L/H was greater than one. As Kr changed from 0.6 to 0.7, a steep decrease in the L/H value was obtained, which stayed almost constant for Kr between 0.7 and 1. As H increased to 12 m (Fig. 11), the L/H value showed similar behavior, except as Kr increased from 0.7 to 1, the L/H value decreased. The objective function variation was relatively low, slightly decreasing as Kr increased, as shown in Figs. (10, 11). The S/H and d/H variation with Kr was the same for both figures. S/H and d/H were zero for Kr = 0.5, sharply increased as Kr increased from 0.5 to 0.7, then almost constant as Kr increased further to 1. The above discussions show important effects on the objective function and decision variables. Fixing some variables while changing others does not give the global ideal about the relative effects of the input variables on the optimum design. For this purpose, an importance analysis was done to first show the effect of each ANN input variable on the output L/H.

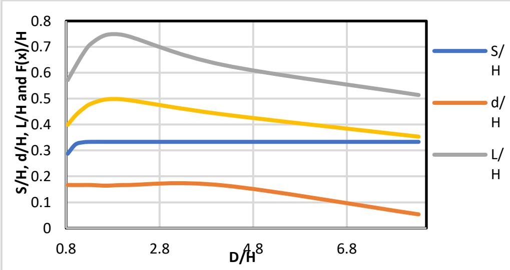

Fig. 8. Variation of Decision Variables and Objective Functions with D/H, H = 12 m and Kr = 1 (Isotropic Case).

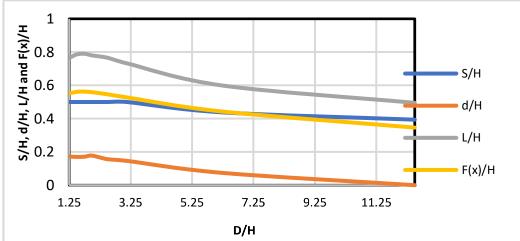

Fig.9 Variation of Decision Variables and Objective Functions with D/H, H = 8 m and Kr = 0.75 (Anisotropic Case).

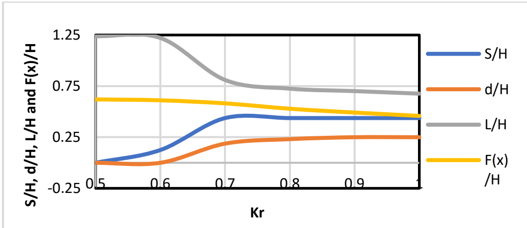

Fig.10. Variation of Decision Variables and Objective Functions with Kr, H = 8 m and D =10 m (Anisotropic Case)

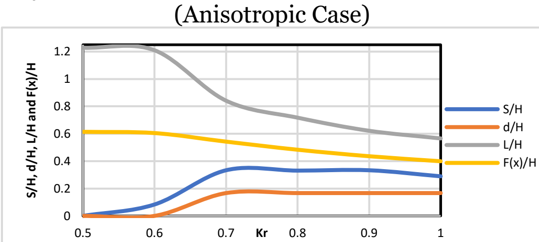

Fig.11 Variation of Decision Variables and Objective Functions with Kr, H =12 m and D=10 m (Anisotropic case

Table 3 Independent Variable Importance.

variable	Importance	Normalized Importance
D/H	0.121	31.2%
S/H	0.251	64.8%
d/H	0.387	100.0%
θ	0.057	14.7%
Kr	0.184	47.6%

Table 3 shows that the variables' relative importance to L/H were in descending order (d/H, S/H, Kr, D/H, and θ) with the following numerical relative importance (100%, 64.8%, 47.6%, 31.2, and 14.7), respectively. As Kr and D/H were not decision variables, then the other three decision variables should be focused on.

The d/H had the highest effect, which relatively means the vertical embedment of the cutoff, followed by the S/H, which means the inclined length of the cutoff. In contrast, the angle of inclination of the cutoff had the lowest effect and a high difference from the S/H value by almost 50%. Table 4 shows the correlation matrix between the decision variables of the optimum solutions. The correlation of d/H and S/H was significantly high (at 0.01 level of significance) and negative. As these two variables increased, they decreased the required L/H, which complies with the logical physics of the phenomenon. The correlation between L/H and angle of inclination was significant at (0.05 level of significance); however, the correlation was much lower than that with d/H and S/H, which was positive and a lower direct variation with less effect of θ. The correlation between d/H and S/H was highly significant and positive, which means both increased or decreased together for an optimum solution. The optimum angle of inclination with d/H and S/H was insignificant.

Table 4 Correlation Matrix Between Decision Variables for the Optimum Solution.

Variables	L/H	d/H	S/H	θ
L/H	1	-0.683	-0.604	0.054
d/H	-0.683	1	0.546	0.02
S/H	-0.604	0.546	1	0.03
θ	0.054	0.02	0.03	1

4.CONCLUSIONS

An ANN-GA optimization model was developed to find the optimum dimensions and inclination for an inclined cutoff with an embedded vertical part followed by an inclined part. The auxiliary variables were the difference in head between the downstream and upstream sides, the depth of the soil layer, and the degree of the anisotropy of the soil. The research was limited to finite soil layer depth and one soil layer, i.e., no soil stratification.

The findings of the present research are summarized as follows:

1. The developed ANN model prediction performance was found to be 92.2%, which was considered a high prediction level. This model was considered practically validated as it used the database developed by SEEP/W, as the results of this software were verified with experimental results.
2. The couple ANN-Genetic Algorithm model was capable of producing a stable objective function with a minimum value of an initial population of 1500.
3. The initial population size of 1500 should be increased to 100000 to get a stable decision variable of the optimum solution.
4. The number of iterations required for the genetic algorithm model to give a stable optimum solution was 3.
5. The optimum solutions (S/H, d/H, L/H, and F(x)) with D/H generally decreased with a mild slope for relatively low H values. However, for relatively high H values, an increase in L/H and F(x) was found for small D/H values, followed by decreased variation.
6. The optimum angle of inclination showed very little variation with the range of (30.01° to 30.78°). This observed narrow range for the angle of inclination was due to its low effect on the length of downstream protection compared to the other variables, as shown in the importance analysis.
7. The effect of anisotropy showed that for low Kr values less than 0.5, there was no requirement for protection against piping. When Kr was between 0.5 and 0.6, the required protection was (L/H > 1). As Kr increased from (0.6 to 0.7), a steep decrease in the required (L/H) was obtained. No signification values were found for the (L/H) value as Kr changed from (0.7 to 1).
8. The importance analysis showed that the effects of the independent variables on the required length of protection for optimum solution were as follows in descending order of importance (d/H, S/H, Kr, D/H, and θ), with the following numerical relative importance (100%, 64.8%, 47.6%, 31.2%, and 14.7%), respectively.
9. The correlation analysis showed that d/H and S/H significantly affected the optimum L/H value and showed inverse variation. This analysis showed that the angle of inclination had a low effect on the optimum L/H value and had direct variation. The optimum angle of inclination with d/H and S/H was insignificant.
10. There was no specific unique, controlling optimum solution that covered most of the cases with different input variables, such as the depth of the soil layer, the seepage driving head difference, and the degree of anisotropy, which reflects the importance of developing such a model that can be easily programmed in a simple MatLab code or any simple software.

<u>The following are recommended for future extension of the present work:</u>

1. The model developed in the present investigation assumed one soil layer where the cutoff was embedded. The same methodology could be used to develop a model for layered soil, which requires adding other variables related to these layers, such as the number of layers with each layer depth and hydraulic conductivities.
2. As all the variables involved in the phenomenon were certain except the degree of anisotropy, a study is recommended to address the effect of uncertainty of this variable on the optimum solution.

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