Studying the seepage phenomena under a concrete dam using SEEP/W and Artificial Neural Network models.

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Abstract. Seepage under hydraulic structures is considered to be a dangerous phenomenon which may cause the collapse of the structure over time if neglected. In this research, a SEEP/W model was developed to find the seepage rate and exit gradient under a concrete dam provided with two sheet piles. The independent variables were head difference; coefficient of soil permeability; and the spacing, lengths, and inclined angles of the sheet piles. The model was run for three different values of each independent variable. The results obtained from SEEP/W model were then used to create two neural artificial network (ANN) models (A and B) in which the output variables were the seepage rate (model A) and exit gradient (model B). The most appropriate structure, which gave minimum relative errors, was (7 3 1) nodes for both models. The results of the ANN models indicated that the variable with the most effect on seepage rate was the coefficient of soil permeability, with an importance ratio of about 76%, followed by the difference in the head (8%), the distance between piles (5.5%), length of downstream pile (5%), length of upstream pile (4%), and downstream and upstream inclined angles of the sheet piles, with ratios of about 1% and 0.5%. In terms of exit gradient, the most influential factor was the distance between piles at 35%, followed by the downstream inclination angle, length of downstream pile, head difference, length of upstream pile, inclined angle of upstream pile, and soil permeability with importance of about 23%, 19%, 14%, 7.5%, 1% and 0.5%, respectively. These results are in agreement with an analysis of the SEEP/W model.

Keywords: Seepage, Exit gradient, SEEP/W, sheet pile, Artificial Neural Network, Importance.

1.   Introduction

The most critical phenomenon to be taken into account when planning and designing dams is the seepage of water through and under the body of the dam. If seepage occurs without maintenance, after a period of time, the dam may well collapse, causing loss of life and property. The important quantities which must be estimated when studying this phenomenon include seepage quantity (flow rate), uplift pressure, and exit gradient [1]. The flow of water below the dam creates uplift pressure on its floor, and if the thickness of the floor is insufficient, its weight will be unable to resist this pressure, and the floor will become cracked, leading to a failure of the structure. Additionally, when the exit gradient at the toe of dam exceeds a critical value, the water will begin to remove soil particles from the foundation and carry them away with it, forming a hole under the dam known as a piping phenomenon, and causing the dam to collapse. There are several different ways to control the rate of seepage through the foundation of a dam, such as providing a sufficient length and thickness of structural flooring or adding a protective apron. Recently a new tool to reduce seepage has been developed using trenches that are drilled in the foundation of the dam and then filled with plastic concrete materials, which offers less permeability than normal concrete [2]. In other hand, to provide a safe exit velocity against the washout of soil particles, sheet piles can be provided at the upstream and downstream ends of the dam to increase the creep length of the water particles between the solid part of the hydraulic structure and the soil. Study and analysis of seepage problems can be made using analytical equations, experimental methods, simulated models, and numerical methods. Most researchers prefer to use numerical methods, however, especially since the recent enormous

developments in computer programs capable of solving differential equations by various methods such as finite element, finite difference, and finite volume.

SEEP/W software, which is a part of the Geo-Studio package, includes many applications and it is widely used by engineers to study and analyse seepage problems in dams. It is based mainly on the numerical finite element method. In recent decades, a new process of artificial intelligence technique called artificial neural networks (ANNs) has been widely adopted by researchers in the fields of dams and water resource engineering. As the relationships between the rate of seepage and its influencing factors are nonlinear, ANNs have become the most useful tool to model these complex phenomena, particularly when their rules are very difficult to identify or partially unknown [3].

Many researchers have studied the phenomenon of seepage in different types of dams by using both numerical methods and neural networks. Miao et al. (2011) developed a new neural network model known as the Genetic Algorithm to predict the flow rate of seepage in an earth dam in China; this model offered good agreement with the field data and better performance than classical ANNs models [4]. Tayfur et al. (2012) studied the difference between a finite element model and a multi-layered perceptron model (MLP) ANN for water pressure through the Jeziorsko earth-fill dam in Poland, finding that the finite element model was as functional as the MLP model [5]. Santillán et al. (2013), analysed the seepage flow through the foundations of La Baells arch dam in Spain, based on an ANNs network trained with data recorded over a period about 28 years [6]. Irzoki (2016), developed an empirical equation to compute the seepage quantity in an earth dam with downstream horizontal drain, concluding, based on the use of a neural network technique, that among all variables used in the model, length of drain was the most important factor in determining seepage quantity, while the upstream slope of the dam had minimal effect [7]. Hassan (2017), coupled the finite element model with a genetic algorithm model to find the optimum location and inclination angle for the cut-off of a hydraulic structure that satisfied the minimum exit gradient function. The results showed that the best location was at the upstream with an inclination angle of between 59° to 68°, and the ratio of cut-off depth to floor length equal to or more than 0.4. For other relative depth values, the optimum location was in the last third of the concrete floor [8].

In this paper, the rate of seepage and exit gradient through the foundation of a concrete dam were calculated using finite element software, SEEP/W; then, the statistical program IBM SPSS v.23 was utilised to build two artificial neural network models in order to discover the most important variables affecting the seepage rate and exit gradient.

2.   Geo-studio SEEP/W model

The theory of seepage water through soil is based mainly on Laplace's equation, which is obtained from the combination of Darcy law and a continuity equation. Assuming isotropic homogenous soil and incompressible steady flow [9], the Laplace equation is :

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

The graphical solution of equation (1) is called the flow net, which creates a sketch of flow lines crossed at right angles with equal potential lines. As mentioned, the SEEP/W program was used to calculate the rate of flow and exit gradient beneath the concrete dam, based mainly on using the finite element method to solve the partial differential Laplace equations. The basic concept of this numerical method is to divide the model into simpler and smaller parts or elements which are connected to each other by nodes located on the boundary of the element. All equations involving finite element analysis are created at element nodes. The mutual elements in a single node have the same coefficients and characteristics belonging to

the equation at the node that are used to calculate the unknown parameters at that node. The seepage equation is thus developed for each one, while the properties of material used in the equations are shared by the adjacent element [9]. The general form of finite element equation for steady state seepage analysis is:

$$[K]\,\{H\} = \{Q\} \qquad\qquad (2)$$

where [K] represents the matrix characteristic at the node, such as material properties and geometry, while {Q} and {H} are the flow rate and total head vectors at the node, respectively.

3. Verification of SEEP/W numerical software

An example of flow under a concrete dam [10] was taken as a case study in this paper as in figure (1). Verification of the computer program Geo Studio 2016 SEEP/W was carried out by comparing the seepage rate value obtained by hand calculation with that obtained from the numerical program to establish confidence.

3.1. Hand calculation:

$K = (3.5 \times 10^{-6})$ m/sec,

$\Delta h = 6$ m,

Number of flow channels $N_f = 3$, and equipotential lines $N_d = 10$

$q = k \times \Delta h \times \frac{N_f}{N_d}$

$q = 3.5 \times 10^{-6} \times 6 \times \frac{3}{10}$

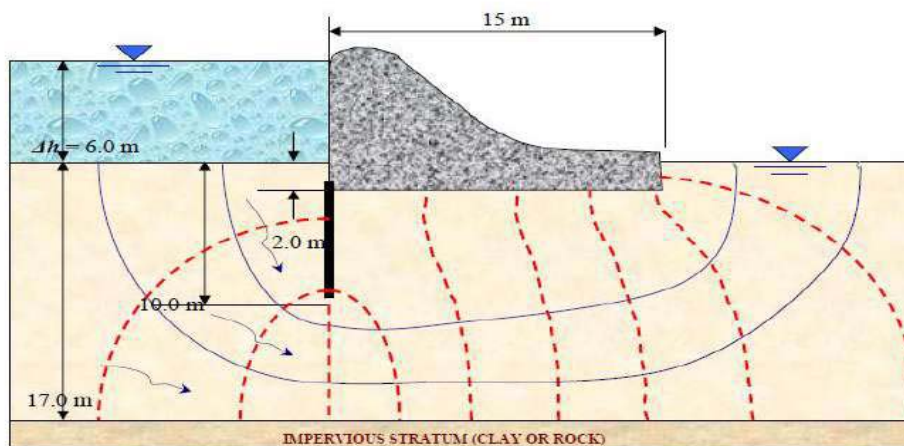$q = 6.3 \times 10^{-6}$ m^2/sec/m width of dam.

Figure 1: The flow net under concrete dam (hand calculation).

3.2.   SEEP/W model:

In a numerical model, the overall size of the grid (total number of nodes) should be sufficient to define the problem and ensure that the results of the procedure are consistent with the modelling objectives, but not so large as to cause excessive computation and preparation requirements. In the current study, the grid size was prescribed by trial and error, with the best approximate element size found to be 1.25 m with 440 nodes in the mesh region.

The result from the numerical model was q= 6.2667E-06 m^2/sec/m width of dam, as shown in the figure below. The percentage error was thus about 0.5% compared with hand calculation.
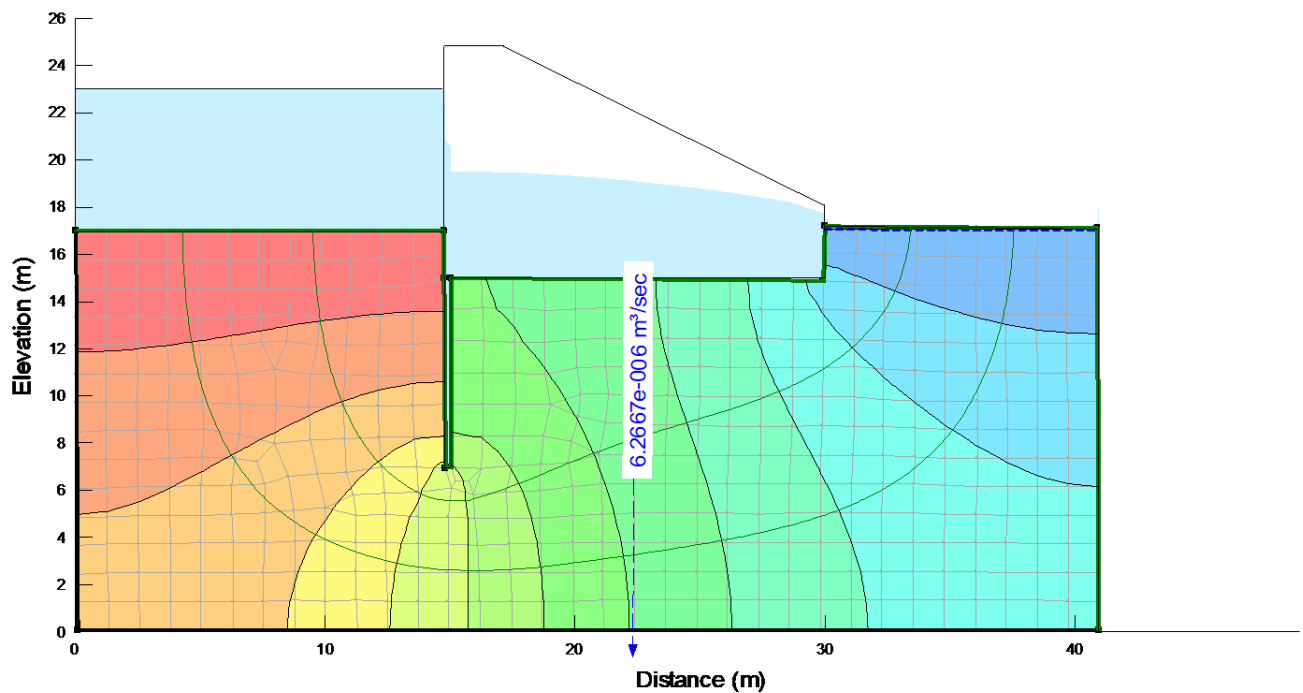

Figure 2: The flow net under concrete dam (SEEP/W) model

4.   Case study

A sketch of the model used in this study is shown in figure 3. This presents a schematic of a concrete dam based on isotropic and homogenous soil. In order to construct the SEEP/W software model, three different values for each input variable were used as follows: the depths of upstream and downstream sheet piles (L_1 and L_2) were taken as 8, 6, and 4 m, head differences (H) were 6, 7, and 8 m, distance between piles (S) was 5, 10, and 15 m, the coefficient of permeability (k) was 1E-05, 1E-06, and 1E-07 m/sec, and the inclined angle of upstream and downstream piles with respect to the horizontal (θ and α) were 30°, 60°, and 90° for each angle. Based on these seven input variables, overall runs which were made in this search for 2,187 cases. For each run, the rate of the seepage (q) per unit length through the dam's foundation and the exit gradient (GE) at the toe were computed.
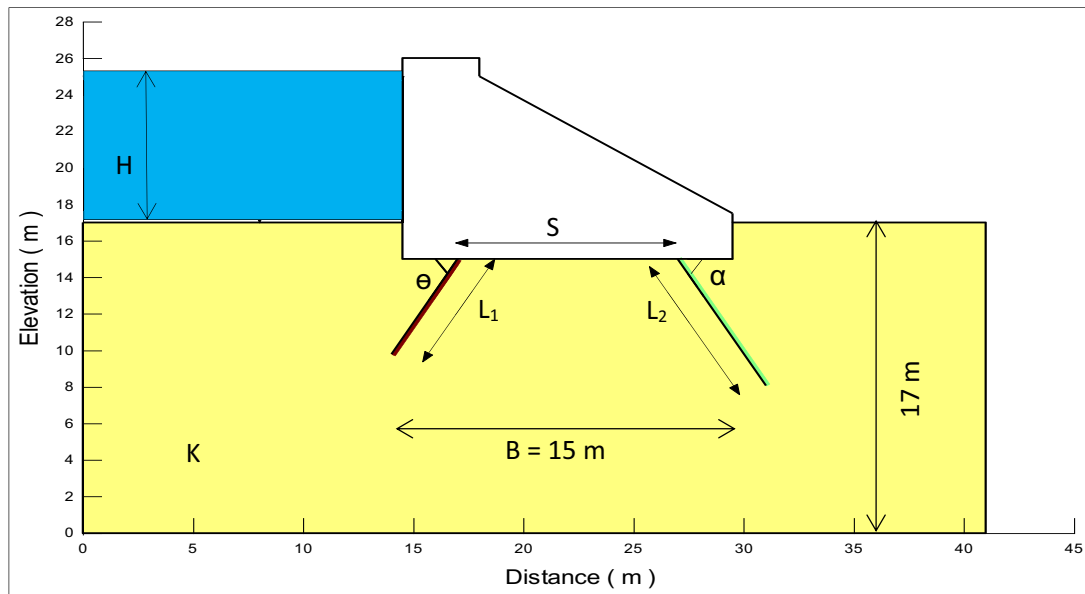
Figure 3. Sketch of SEEP/W model

4.1. Analysis the results of SEEP/W model.

The rate of seepage under the dam and the exit gradient were recorded after each run of the SEEP/W program. Seepage rates increase whenever the head difference and coefficient of soil permeability become higher, so the significant factors that must be taken into consideration are the lengths of piles and the distance between them, in addition to their inclination angle. Figures 4 and 5 show the flow net sketch under the dam in cases of maximum and minimum seepage rates. From the results, it is also clear that the maximum exit gradient occurred where L1=L2=4 m, S= 5 m, H=8 m, and the inclined angles of the two piles were 90°, while the minimum exit gradient occurred where L1=L2=8 m, S= 15 m, H=6 m, θ= 60°, and α= 30°.
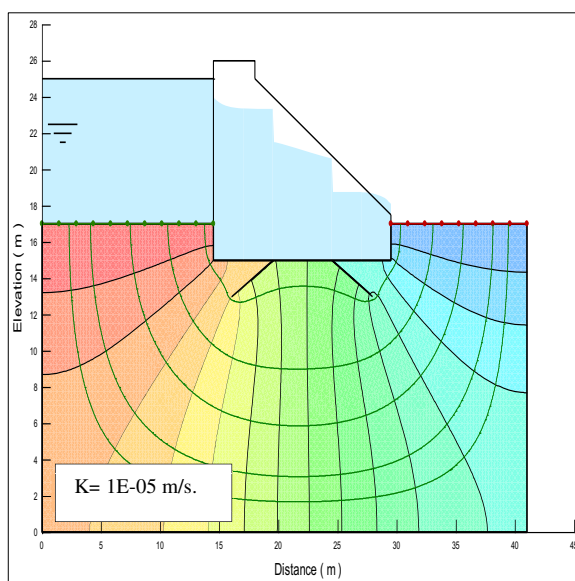

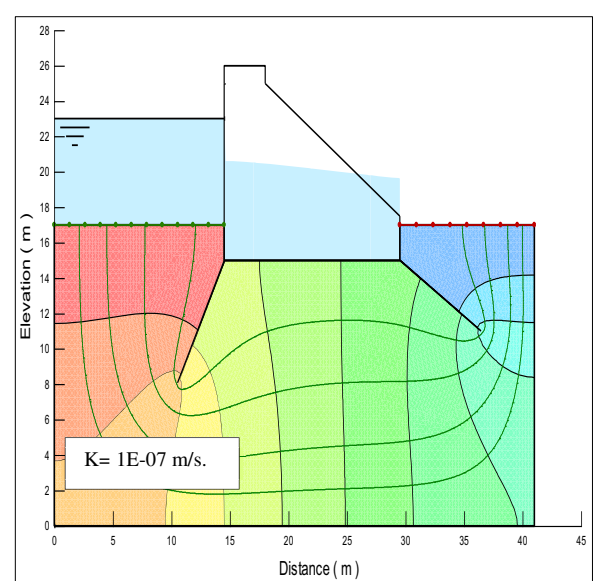**Figure 4.** Flow net under the dam in case of max. seepage rate.

Figure 5. Flow net under the dam in case of min. seepage rate.

The relationship between the dimensionless parameters (q/KH) and the exit gradient with the ratio (S/B) is illustrated in figure 6, where B is the length of the dam base, when the values of variables H, K, θ and α are constant. This figure suggests that increasing the distance between sheet piles leads to a reduced seepage rate and exit gradient, because the line of creep for particles is increased, which leads to a high head loss and thus lower seepage pressure. However, the decrease percentage was higher in the exit gradient compared with the seepage rates for the same cases. The average decrease ratio of exit gradient was about 58% while that for seepage rates was about 18%. The results also showed that the maximum decrease ratio occurred in cases where the length of downstream sheet pile was 8 m; this ratio decreased gradually as the pile length was reduced. The relationships between the seepage rate and exit gradient and the downstream angle (α) with respect to the pile lengths when other variables are constant are shown in figure 7. It is clear from the charts that increasing α from 30° to 90° had no significant effect on the seepage rate; the maximum increase ratio did not exceed 3%. For the same angle α, the decrease in seepage quantity was higher where $L_1 = L_2$ and whenever these lengths were increased. The exit gradient increased markedly as angle α was changed from 30° to 90° to about 120%, 65%, and 24% when $L_2 = 8$ m, 6 m, and 4 m, respectively.

The relationship between the seepage rate and exit gradient when the upstream angle θ was increased from 30° to 90° with respect to the pile lengths and when other variables are constant is shown in figure 8. It is clear that increased θ contributes to the reduction of both seepage rate and exit gradient, but only by a small percentage; the maximum decrease ratios were about 4% and 5%, respectively. This can thus be considered as only negligibly effective, a result consistent with many studies which confirm that the existence of inclined sheet piles at the heel of a hydraulic structure is not suggested under any inclined angle [11].

It can be concluded from previous results that the exit gradient is decreased when the creep line of water particle is longer, which results in a high head loss; thus, the distance between sheet pile, inclination angle, and length of downstream pile can be considered important factors affecting the exit gradient over other variables. For the seepage rate, the most prominent factors after coefficient of permeability and head difference are the space between piles, as the seepage rate reduces as this distance is increased.
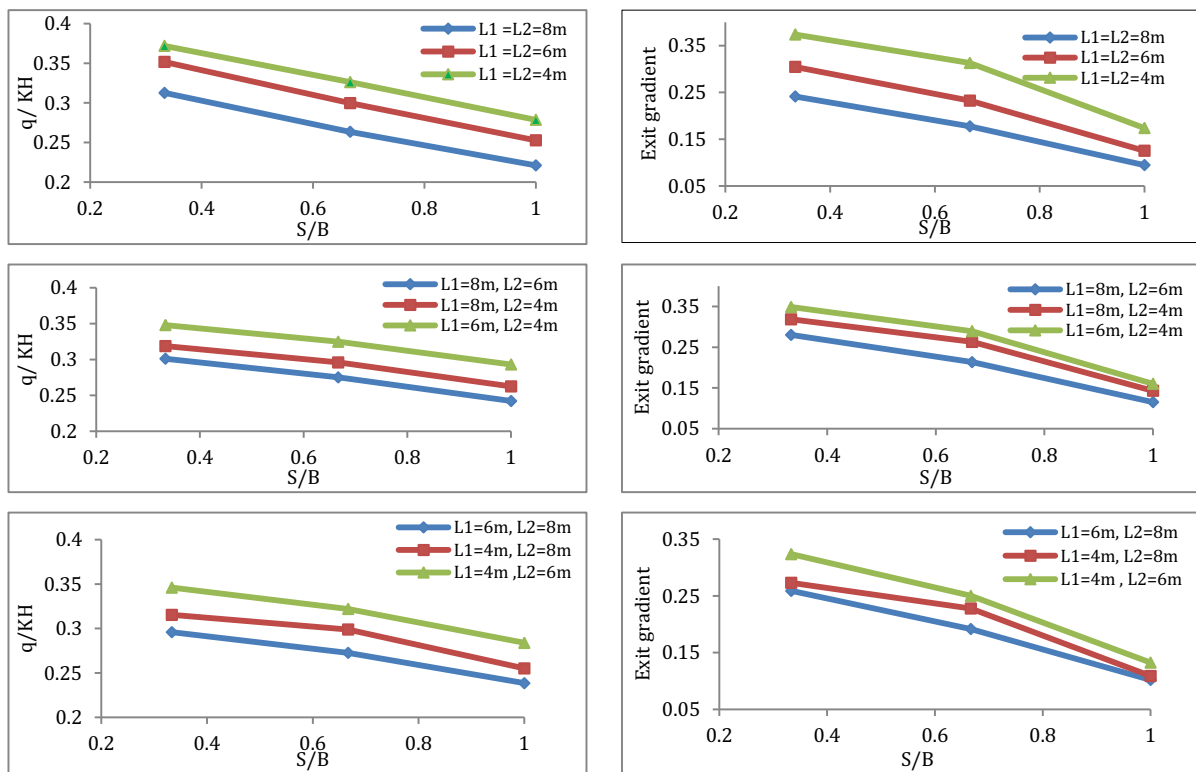
Figure 6. The relation between the dimensionless parameter (q/KH), exit gradient with the (S/B) for different lengths of sheet piles at K=0.00001m/s, H= 7m ,ө =60° and α= 60°.

Figure 7. The relation between the dimensionless parameter (q/KH), exit gradient and α for different lengths of sheet piles   at K=0.00001m/s, H= 7m , S=10m and θ= 60°.

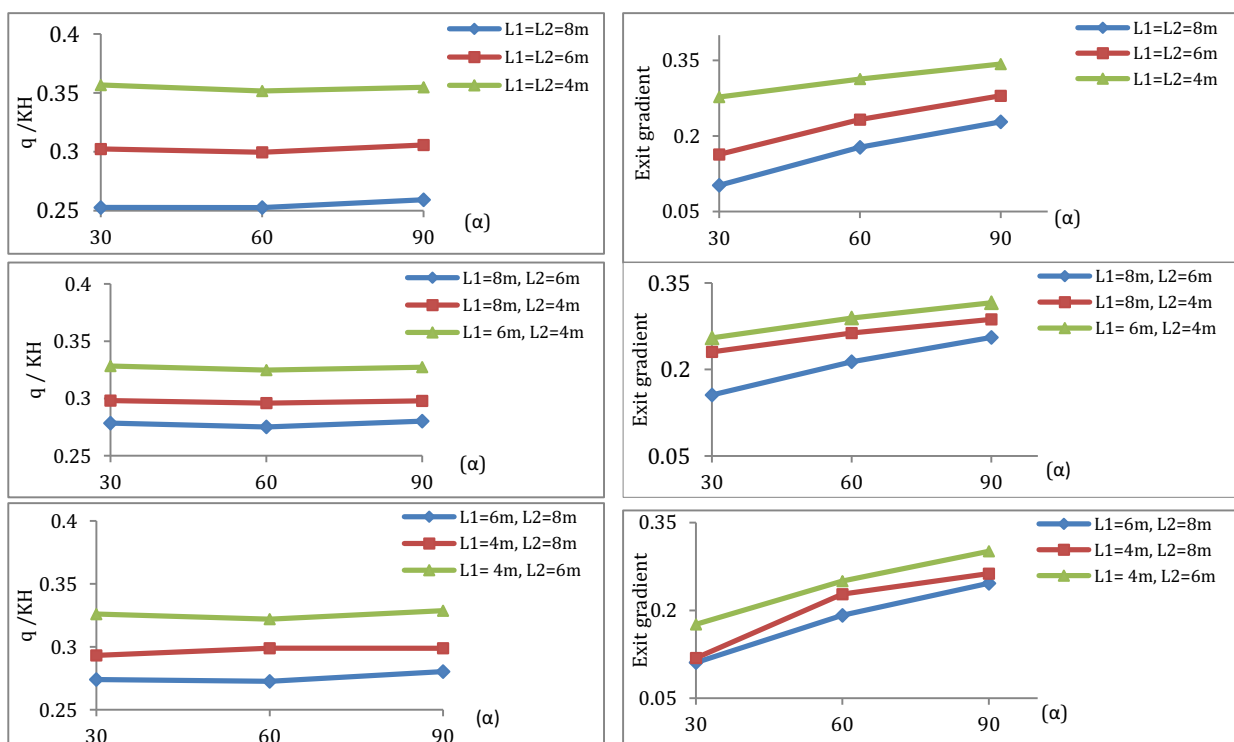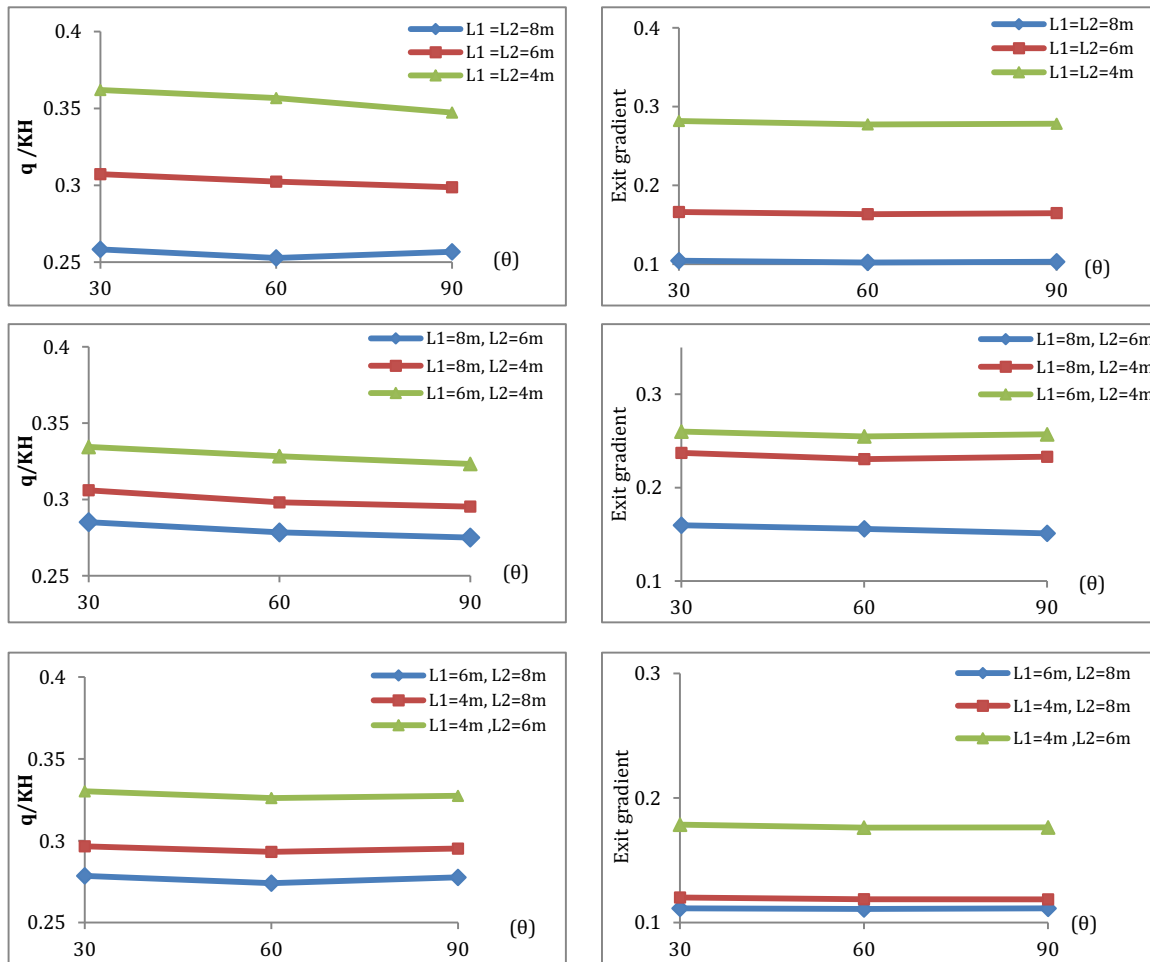**Figure 8.** The relation between the dimensionless parameter (q/KH), exit gradient and θ for different lengths of sheet piles   at K=0.00001m/s, H= 7m and α= 30°.

5.   Neural Network (ANN) model

An Artificial Neural Network form of artificial intelligence can be constructed to simulate the action of a human brain. These are now widely used in many different scientific fields [12]. The most common structure of artificial neural networks consists of three parts: an input layer, a hidden layer, and an output layer, which are connected to each other by neurons (nodes) to form a parallel distributed processing system where each node creates a non-linear function of its input [13]. The operation system of processing element within an artificial neural network is simply illustrated in figure 9. The variables x_1, x_2,…,x_n represent the raw data fed to the network through the input layer. Each input value is multiplied by an adjustable connection weight (w), and the bias or threshold value (β) is added, as shown. Then, the combined input (I) moves to activation function, and the output result of the processing elements forms the input for the next layer of nodes [14].
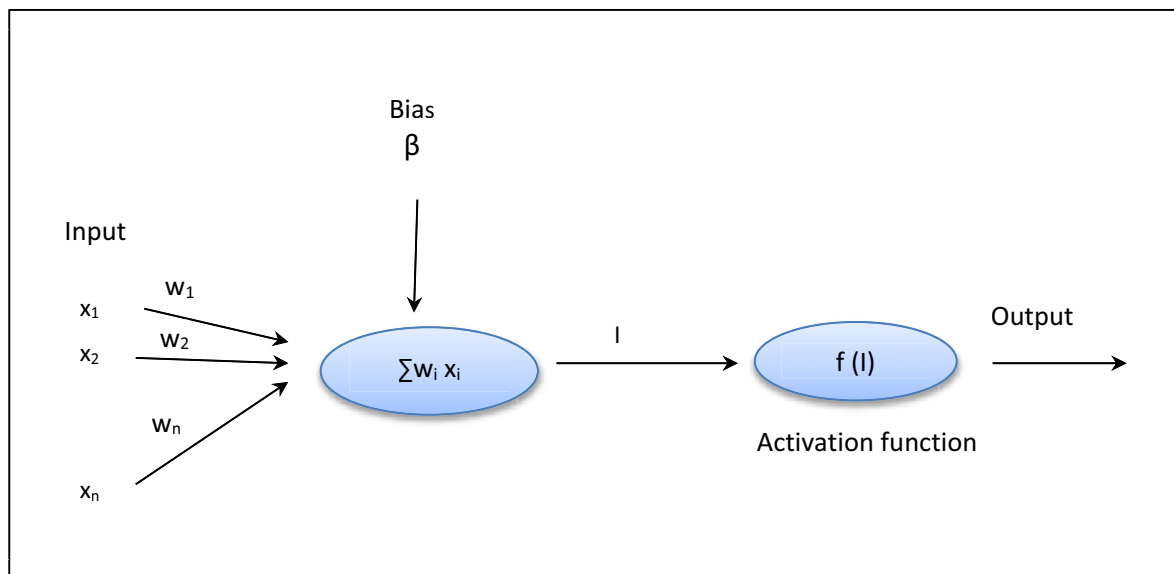
Figure 9. Typical form of processing element in an artificial neural network.

5.1.   *Design of artificial neural network*

The design of the artificial neural network model (ANN) aims to find the best function that describes the relationship between input and output variables. In this research, two ANN models (A and B) were developed to study the seepage rate and exit gradients under the concrete dam. The multilayer perceptron (MLP) artificial neural network with a back-propagation algorithm, which is the most commonly used in engineering problems, was applied with aid of IBM SPSS v. 23 (IBM 2013) to build the two models. The structure of ANN models is based on feed forward architecture, as the connections in the network from the input layer to the output layer flow forward without any feedback loops. The steps below were adopted to build both ANN models:

5.1.1. *Data preparation*

 The data set developed using Geo studio, SEEP/W software was used to build the artificial neural network models. The input data for each model included head difference (H), coefficient of soil permeability (K), inclined angle of the upstream sheet pile (θ), inclined angle of the downstream sheet pile (α), length of the upstream pile (L_1), length of the downstream pile (L_2) and the horizontal distance between piles (S), while the dependent variables (outputs) were be the rate of seepage per unit length (q) for model (A) and exit gradient (GE) for model (B). The database for each model consisted of 2,187 cases.

5.1.2. *Partition*

Input data must be divided into three groups: training, testing, and validation. The training set is the largest set and is used by the neural network to obtain the model, while the testing set, which is about 10% to 30% of the training set, is used to evaluate the ability of the proposed trained model. A validation set is used to check the performance of the trained network, and the size of the chosen verification group must achieve a balance between retaining a sufficient sample size for validation and having enough remaining data for both training and testing [15]. The dataset in this search was spilt into three groups of random members, with training taking 75%, testing 15%, and validation 10%.

5.1.3. Reprocessing:

An important step to improve net training is rescaling the input data to a proper scale. The main purposes of this step include reducing the size of the input space, creating smoother relationships, noise reduction, normalisation of the data, and feature extraction . There are many ways to re-scale data, such normalisation, adjusted to normalised values, z-scores, and so on. In this study, a standardized (z score) method was applied; this involves subtracting the value of the mean and dividing by the standard deviation.

5.1.4. Model architecture:

 The most important and difficult steps are building the structure of the MLP model, i.e. choosing the best number of hidden layers and number of nodes in each layer and activation function. More than one hidden layer usually slows down the training process significantly and increases the chance of falling into a local minima pitfall [18]; thus, a single hidden layer was adopted to develop the present models. The number of nodes in the hidden layer must achieve the following requirements: minimising the training time, maximising performance of the generalisation process, and avoiding over fitting problems. Consequently, to achieve satisfactory performance, it is always preferable to minimise the number of hidden nodes [15]. One of the methods used to identify the number of nodes in a single hidden layer is to take the upper limit of testing hidden nodes as (2i+1) [16], where i is the number of input nodes: thus, the upper limit of nodes in this case was 15 neurons. With regard to the activation function, SPSS software provides two functions for hidden layers, Hyperbolic tangent and Sigmoid, while in the output layer, the Identity function is added to the previous two functions. All of these functions were tested in order to obtain optimal models with fewer relative errors.

5.1.5. Type of training and optimisation algorithm

 Neural networks are often trained using either batch or online techniques. In batch training, the changes in weights are accumulated during all training runs before being adjusted, while in online training, the weights and bias are applied after each training run [17]. Batch training is often chosen because it directly reduces the total error [18]; in this study, a batch technique with gradient descent optimisation algorithms was adopted to discover the best synaptic weights. The values of the initial learning rate and momentum were 0.4 and 0.9, respectively.

5.1.6. Stopping Criteria:

After performing a fixed number of training processes or when the change in relative errors become small enough were the stopping criteria selected for the constructed models. In this study, the minimum change in relative error chosen as a stopping criterion was equal to 0.0001.

5.2.   Results of Predictive ANN model

In the models developed as above, 1,651 cases were specified as the training sample, 318 used for testing, and 218 cases were a holdout sample for verification; the division was made randomly for each model. The structure of each proposed model had a single hidden layer, and the maximum number of testing nodes in the hidden layer was 15 nodes. As explained in the previous section, each node was tested with two activation functions for the hidden layer (hyperbolic tangent and sigmoid), and three functions for the output layer (hyperbolic tangent, sigmoid, and identity). Based on the criteria introduced to the software, the results showed the most appropriate design, with minimum relative errors, possessed a 7 3 1 structure for both model A and model B. This refers to the fact that the models had seven nodes in the input layer, three nodes in the hidden layer, and one node in output layer, as shown in figures 10 and 11. The selected models A and B had lower relative errors, which means that the ratio between the sum of squares error for

observed and calculated variables was close to the sum-of-squares error for each case; thus, the mean value of the dependent variable could be replaced with the predicted value, i.e., the null model. Table (1) shows the relative errors for each model. It can be concluded for all processes that there were more errors in predication of exit gradients in model B than seepage rates in model A.
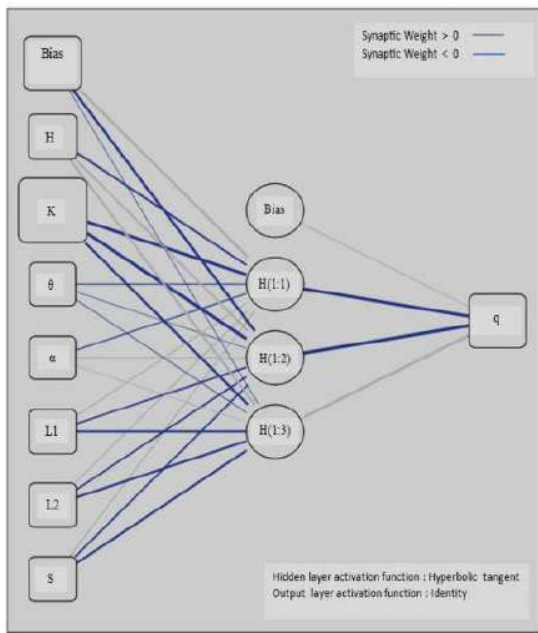

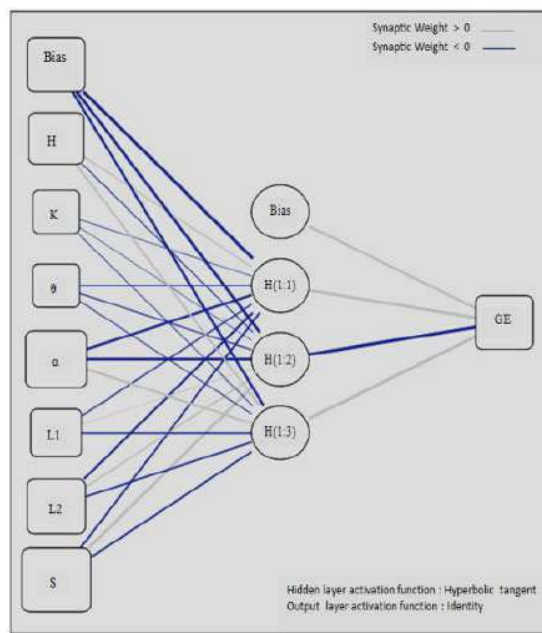**Figure 10.** The structure of ANN model (A).   **Figure 11.** The structure of ANN model (B).

The connection weights and bias values for the two models are summarised in tables (2) and (3). As explained previously, activation functions link the summation of connection weights and bias of nodes in a layer to the values of units in the next layer. The functions used in the selected models were hyperbolic tangents, which take the form f(x) = tanh (x) within the hidden layer, while for output neurons, the activation function was identify i.e. f (x)= x. The following expression was formulated to predict the output values for the developed models:

$$y^{\wedge} = \sum_{j=1}^{n}(W_j * (\tanh(\sum_{i=1}^{7}(w_{ji} \,.\, x_i) + \beta_j))) + \beta \qquad (3)$$

where $y^{\wedge}$ is the predicted output, n is numbers of nods in hidden layer, w_{ji} is the weight connecting the ith neuron in the input layer with the jth node in the hidden layer, β_j is the bias value for the jth neuron in the hidden layer, W_j is the output layers weight that is connected with the jth neuron in the hidden layer, β is the bias value for the output node, and x_i is the input variable for the input layer. Figures 12 and 13 show good agreement between predicted and observed values for seepage rates and exit gradients obtained from ANN and SEEP/W models.

Table 1. The relative errors for ANN models A and B.

Process	Relative error	
	Model A	Model B
Training	0.002	0.049
Testing	0.003	0.058
Validation	0.003	0.051

Table 2. Parameters estimate of ANN model (A)

Predictor		Predicted			Output Layer
		Connection weights (w_{ji})			
		$j=1$	$j=2$	$j=3$	Seepage rate (q)
	β_j	0.536	-0.626	-0.004	
	$x_1 = H$	-0.178	0.274	0.341	
	$x_2 = K$	-1.009	-1.042	-0.454	
Input Layer	$x_3 = \theta$	-0.019	0.001	-0.012	
(x_i)	$x_4 = \alpha$	-0.035	0.021	0.017	
	$x_5 = L_1$	0.086	-0.144	-0.181	
	$x_6 = L_2$	0.117	-0.160	-0.191	
	$x_7 = S$	0.137	-0.170	-0.201	
Hidden Layer	β				0.045
	W_1				-1.013
	W_2				-1.082
	W_3				0.807

Table 3. Parameters estimate of ANN model (B)

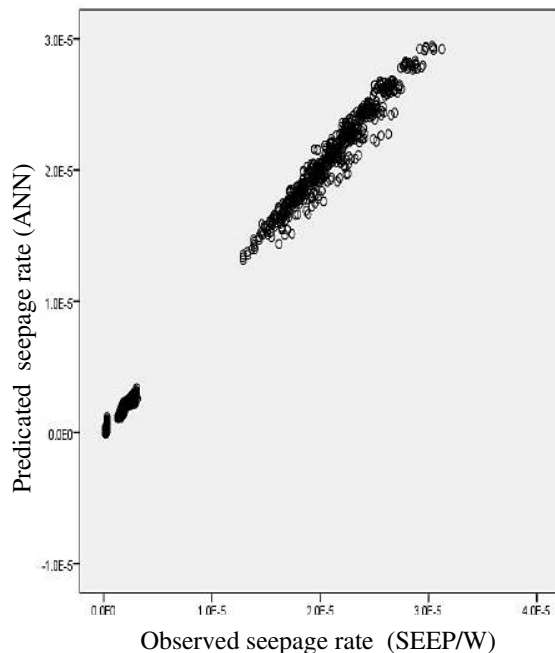| Predictor		Predicted			Output Layer
		Connection weights (wji)			
		j=1	j=2	j=3	Exit gradient (GE)
	β_j	-1.436	-0.952	-0.797	
	$x_1 = H$	0.093	-0.030	0.395	
	$x_2 = K$	-0.005	-0.001	-0.018	
Input Layer	$x_3 = \theta$	-0.045	-0.038	-0.020	
(x_i)	$x_4 = \alpha$	-0.589	-0.750	0.427	
	$x_5 = L1$	-0.064	0.013	-0.209	
	$x_6 = L2$	-0.519	0.185	-0.257	
	$x_7 = S$	-0.377	0.832	-0.343	
Hidden Layer	β				0.679
	W1				0.822
	W2				-0.981
	W3				1.027

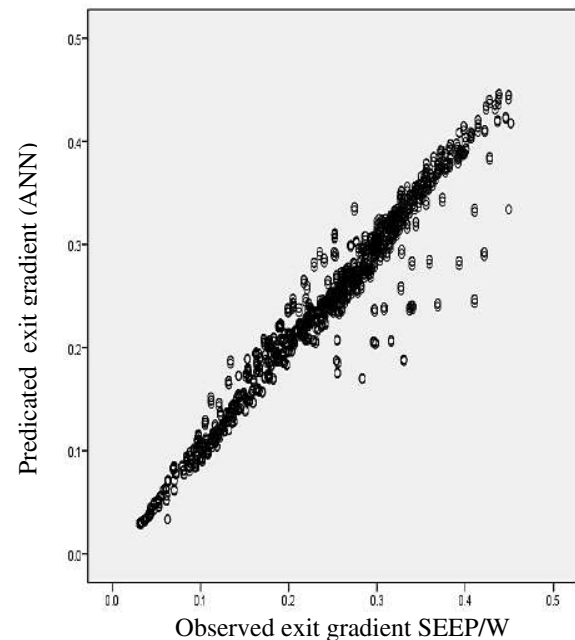**Figure 12.** Predicated and observed seepage rate model (A).

Figure 13. Predicated and observed exit gradient model (B).

The importance of the independent variable indicates how much the predicted values obtained from the ANN network models are changed as various independent variables change. The results indicate that the coefficient of permeability of the soil (K) was the most influential factor on the seepage quantity beneath the concrete dam, with an importance ratio of about 76%; this was followed by head difference (H), distance between piles (S), length of downstream sheet pile (L_2), length of upstream sheet pile (L_1), inclined angle of downstream sheet pile (α), and inclined angle of upstream sheet pile (θ), with importance ratings of 8%, 5.5%, 5%, 4%, 1%, and 0.5%, respectively. On the other hand, the most influential factor on exit gradient was the distance between piles (S) with an importance percentage of 35%, followed by the inclination angle (α), length of downstream pile (L_2), head difference (H), the length of upstream pile (L_1), upstream sheet pile angle (θ), and soil permeability (K) with importance of 23%, 19%, 14%, 7.5%, 1% and 0.5%, respectively. These results accorded with those obtained from SEEP/W analysis. Figures 14 and 15 show the ranking of independent variables according to relative importance in model (A) and model (B).
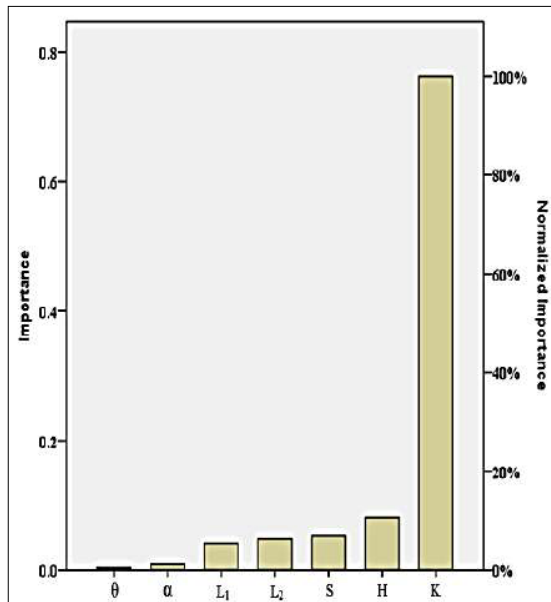
Figure 14. The importance of independent variables on seepage rate (model A).
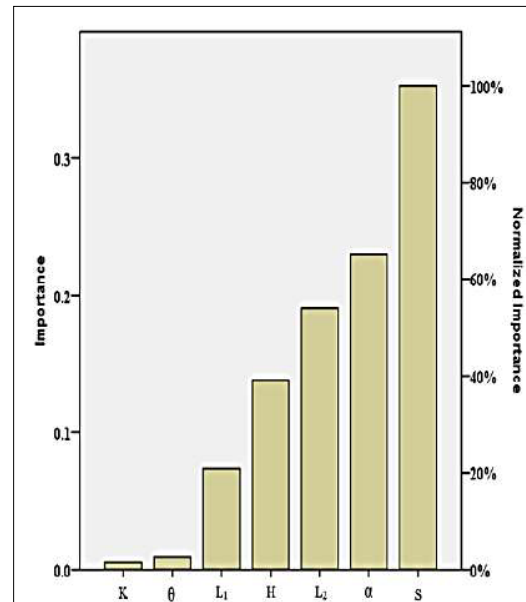

Figure 15. The importance of independent variables on exit gradient (model B).

6.   Conclusion

In this study, SEEP/W and ANN network models were developed to study the seepage flow and exit gradients under a concrete dam provided with two sheet piles and resting on isotropic homogenous soil. The models were run under different cases and the following results were obtained:

1- The seepage rate and exit gradient decreased when the space between sheet piles was increased and this decreasing ratio was seen more in the exit gradient than the seepage rate for the same cases; the decrease ratios also became greater as the lengths of the sheet piles increased, especially the downstream pile.

2- Increasing the inclined angle of the downstream pile with respect to the horizontal from 30° to 90° led to an increase in the exit gradient at a higher ratio compared with the seepage rate; this ratio became greater as the length of downstream sheet pile length increased.

3- Increasing the inclination angle of the upstream pile with respect to the horizontal from 30° to 90° had a small effect in terms of reducing both of seepage rate and exit gradient by a small percentage, such that the maximum decrease ratios were about 4% and 5%, respectively.

4- The ANN model shows that the distance between piles is the variable that most greatly affects the exit gradient, with a percentage of importance of 35%; this was followed by the inclination angle of the downstream sheet pile, length of the downstream pile, head difference, the length of the upstream pile, the inclined angle of the upstream pile, and soil permeability.

5- For seepage rates, the results obtained from the ANN model indicated that the most important variable was the coefficient of soil permeability for the foundation, which had an importance ratio of 76%; this was followed by the difference in the head, the distance between piles, the length of the downstream pile, the length of the upstream pile, and the downstream and upstream inclined angles of piles.

6- As the importance ratio of the upstream sheet pile angle (θ) did not exceed 0.5% and 1% for seepage and exit gradient, respectively, it can be considered as a negligible influence factor compared to other variables.

7.   Reference

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