

Computation of Seepage through Non-Homogenous Earth-Fill Dams Resting on Pervious Foundations



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Dedication

I Dedicate this Dissertation

To

*My Beloved Parents who gave me a lot of Support and
Encouragement*

Abstract

Excessive and uncontrolled seepage through an earth-fill dam is detrimental to its stability. In this study, an empirical correlation was formulated for calculating the rate of seepage discharge through a non-homogenous earthen dam resting on a pervious foundation. Seepage analysis has been performed on SEEP/W program with three different values of each physical and geometrical parameter of the embankment (upstream slope, dam's height, downstream slope, crest width, core's slope, depth of pervious foundation, free board, permeability of foundation material, and permeability ratio of core to shell material). Altogether 4374 dam models were analyzed to obtain the seepage datasets. The comparison of seepage values obtained from SEEP/W program with the analytical equations revealed an average percentage error of less than 15 %. Non-linear regression analysis was then performed on the seepage datasets using SPSS-19 software to obtain an empirical equation for seepage calculation. Furthermore, a seepage prediction model was developed using artificial neural networks via MATLAB software. The difference of seepage discharge determined from SEEP/W against its amount computed from the developed empirical correlation and ANN model gave coefficient of determination (R^2) of 0.96 and 0.971 corresponding. Sensitivity analysis indicates that a minor change in the dam's height brings a huge change in the rate of seepage (31.26%), while variation in the upstream slope has the least impact on the rate of seepage (0.93%).

Table of Contents

Copyright Statement	iii
Plagiarism Certificate (Turnitin Report).....	iv
Thesis Acceptance Certificate.....	v
Dedication	vi
Abstract	vii
Table of Contents	viii
List of Figures	1
List of Tables	3
Chapter 1	4
1.1 Background	4
1.2 Problem statement.....	5
1.3 Aims and objectives of the study	6
1.4 Scope of work.....	6
Chapter 2.....	7
2.1 Introduction	7
2.2 Analytical Methods for Seepage Calculations	7
2.3 Numerical Methods for Seepage Calculations based on FEM.....	12
2.4 Estimation of seepage by ANN.....	13
2.5 Empirical equations for Seepage prediction based on FEM analysis	14
Chapter 3.....	18
3.1 General	18
3.2 Dimension Analysis	19
3.3 Procedure of Experimental Setups	19
3.4 Numerical Analysis on SEEP/W program	22
3.4.1 General Settings and Drawing Regions.....	22
3.4.2 Material Properties	23
3.4.3 Boundary Conditions.....	26
3.5 Statistical analysis of seepage data (Non-linear regression analysis)	27
3.6 Designing of Artificial Neural Network (ANN) Models	27
3.6.1 Data Collection	27
3.6.2 Data pre-processing	28
3.6.3 Building the network	28

3.6.4 Training the network	29
3.6.5 Testing the network	29
3.7 Programming the neural network model in MATLAB	30
Chapter 4.....	33
4.1 Relation Between the Variables	33
4.1.1 Seepage through the foundation of earth-fill dam	33
4.1.2 Seepage through the dam body	34
4.2 Empirical equation for computing seepage flow of water from an earth-fill dam lying on pervious foundation.....	36
4.3 Artificial Neural Network (ANN) Model.....	37
4.4 Sensitivity Analysis.....	42
Chapter 5.....	44
References.....	45

List of Figures

Figure 2.1: Dupuit's Solution (Harr, 1991)	8
Figure 2.2: Schaffernak & Van Iterson Method (Harr, 1991)	8
Figure 2.3: Casagrande Method (Harr, 1991)	9
Figure 2.4: Pavlovsky's Solution (Harr, 1991)	10
Figure 2.5: Parameters used in Equations (2.7) and (2.8) for calculation of seepage through the foundation of the dam	10
Figure 2.6: Parameters used in the analytical equation of Rozanov (1978) (Rezk and Senoon, 2011) for calculation of seepage through the dam body	11
Figure 3.1: General cross section of the earthen dam model laying on pervious foundation ..	19
Figure 3.2: Different combinations of the dam models analyzed in SEEP/W program	21
Figure 3.3: Basic Unit Settings	22
Figure 3.4: Sketching Axes	23
Figure 3.5: Different regions of a dam model	23
Figure 3.6: Define material of foundation region	24
Figure 3.7: Volumetric water content function	25
Figure 3.8: Hydraulic conductivity function	25
Figure 3.9: Boundary conditions and meshing	26
Figure 3.10: (a) Location of Boundary conditions of earth dam (b) Seepage rate through earth dam using SEEP/W program	26
Figure 3.11: MLP model with 9 inputs and 1 output used in this study	29
Figure 4.1: Variation of Seepage (q) through the foundation of dam for different parameters of the dam (a) Upstream water level (b) Depth of pervious foundation (c) Permeability of foundation (d) Bottom width of core	35
Figure 4.2: Variation of seepage (q) through the dam body for different parameters of the dam (a) Permeability ratio of core to shell material (b) Crest width of the dam	36
Figure 4.3: Comparison between measured seepage discharge from SEEP/W and computed by empirical equation (4.1)	37
Figure 4.4: Optimal R ² of MLP models with different architectures	38
Figure 4.5: Schematic diagram of the developed MLP-ANN Model	39
Figure 4.6: Detailed Architecture of suggested ANN Model	39

Figure 4.7: Comparison between observed seepage discharge from SEEP/W and predicted by ANN.....	40
Figure 4.8: Comparison between the seepage discharges of randomly twenty tests with different methods:	41
Figure 4.9: Performance of different machine learning models	42
Figure 4.10: Relative importance of dam parameters effecting the rate of seepage.....	43

List of Tables

Table 3.1: Different values of geometrical and physical parameters of the dam effecting the rate of seepage.....	20
Table 4.1: Statistical Validation of Equation (3)	37
Table 4.2: Summary of Well Trained MLP-ANN model for seepage prediction	40
Table 4.3: Performance of Machine Learning (ML) models for seepage prediction	41
Table 4.4: Relative importance of input variables effecting the rate of seepage.....	43

Chapter 1

Introduction

1.1 Background

A dam is a water-retaining structure used to create a reservoir for a specific function i.e. water supply, hydropower, flood control, irrigation, sedimentation control and navigation etc. (Doherty, 2009). Earth-fill dams are mostly welcomed by the designers as it can be easily constructed with less technical problems and less cost. Failures of dams may take place due to a variety of triggers. The most frequent triggers of dam failure are piping (35%), overtopping (25%), erosion (14%), settlement (11%), sliding (10%), gate failure (2%), defective construction (2%), and instability due to earthquake (2%) (Zumrawi, 2013). (Omofunmi *et al.*, 2017) stated that around 40%, 35% and 25% of failures of earth-fill dams are owing to hydraulic, seepage and structural failures correspondingly. Investigations conducted by (Talukdar and Dey, 2019) also disclosed that around 35%, 20% and 30% of failures of earth-fill dams are owing to hydraulic, structural and seepage failures correspondingly, while natural disasters cover the remaining 7% of the failures. According to Fell et al. (Fell et al., 2003), 25% of earth-fill dam failures are due to the seepage flow of water. Due to its significance, the calculation of seepage discharge from an earth-fill dam has gained a great deal of attention

Seepage is the most common type of failure in the earthen dams. Hence seepage analysis of earthen dam is of greater significance. Piping phenomenon will start as seepage exceed beyond its permissible limits and further increase the permeability of flow paths (Bendahmane, Marot and Alexis, 2008). The most important phenomenon to be considered when designing dams is the seepage flow of water across and under the body of the dam. If seepage continues to occur without protection, with the passage of time, the dam may fail, triggering loss of life and property.

Various techniques are used to assess seepage across dam body and its foundation i.e. (1) Analytical approaches, (2) Numerical techniques and (3) Experimental / physical models. Many researchers utilized analytical techniques to compute the rate of seepage across the dam. Among the analytical techniques, (Dupuit, 1863), (Schaffernak, 1917), (Casagrande, 1937), (Stello, 1987), (Rezk and Senoon, 2011) and (Fakhari and Ghanbari, 2013) are worth

noting. The disadvantage of the analytical solution is that, it involves lot of assumptions and merely simple seepage problem can be resolved.

Physical models that simulate the flow of water through porous media are sometimes used to compute seepage in earth-fill dams. Example of such physical models are: electrical analogy, sand models and viscous models. Physical models are rarely used these days. Conventional flow net method is also used to approximate seepage through the dam and its foundation, flow net is commonly used due to its relative simplicity. However, it becomes more complex with zoned earth-fill dams.

In addition to analytical approach, numerical methods for instance finite element method, finite difference method and finite volume method are also employed to calculate seepage through the earthen dams. Several authors have used numerical solution, such as finite element (Freeze, 1971; Kasim and Fei, 2002; Nasim, 2007; Özkul and Baykal, 2007; Kazemzadeh-Parsi and Daneshmand, 2012; Olonade and Agbede, 2013; Arshad and Babar, 2014), finite difference (Kermani and Barani, 2012), finite volume (Darbandi *et al.*, 2007) and boundary element (Abdel-Gawad and Shamaa, 2004), to analyze the phenomenon of seepage. Among these numerical approaches, FEM is the most prevalent and broadly used technique. With the help of FEM, complex seepage problems can be resolved. Here in this research FEM approach will be used for seepage analysis across an earth-fill dam with core resting on pervious foundation.

1.2 Problem statement

Analytical equations are available for seepage calculation through earth-fill dams i.e., Dupuit's solution, Schaffernak & Van Iterson method, Casagrande's method and Pavlovsky's Solution. But all these analytical equations are based on a lot assumptions and can only be used for a simple type of dam geometry (Harr, 1991). When the dam geometry is very complex then FEM based analysis give better solutions. (Irzooki, 2016; Jamel, 2016, 2018; Abbas, 2017) have suggested empirical equations based on FEM analysis to predict the rate of seepage through the earth-fill dams resting on impervious foundation. (Ghanbari and Zaryabi, 2014) have suggested empirical equation to predict seepage through the foundation of the earth-fill dam. However, the empirical equations for seepage calculation through both dam body and its foundation are still unexplored.

In this research an empirical equation based on FEM analysis will be developed for seepage evaluation through an earthen dam with core resting on unsealed pervious foundation. The suggested empirical equation will be simple to use for seepage calculation through dam and its foundation; consequently the designers may use this equation as an extra check to their designs. ANN model will also be developed to predict seepage through dam and its foundation.

1.3 Aims and objectives of the study

The primary intention of this study is to estimate the rate of seepage through an earthen dam with core resting on pervious foundation by using seepage data obtained from SEEP/W program.

Below are the key objectives of this research:

1. To obtain the seepage data by performing simulations on SEEP/W program considering different combinations of geometrical parameters of the dam and its foundation.
2. To develop an empirical equation for seepage prediction by performing non-linear regression analysis with the help of statistical software SPSS 19.
3. To develop ANN model for seepage prediction by using MATLAB (R2021b) program.

1.4 Scope of work

Following tasks are included in the scope of this work

1. Collection of seepage data by performing simulations on SEEP/W program.
2. Developing an empirical equation for seepage prediction.
3. To develop ANN model for seepage prediction by using MATLAB (R2021b) Neural Network Toolbox.

Field investigations of seepage are not included in the scope of this work.

Chapter 2

Literature Review

2.1 Introduction

Seepage is a most common type of failure in the earth-fill dams. Hence seepage analysis of an earthen dam is of greater importance. When seepage exceeds beyond its permissible limits, internal erosion may occur leading to piping phenomenon and increase the permeability of flow paths (Bendahmane, Marot and Alexis, 2008). Different methods are used to estimate seepage flow of water across the dam i.e. (1) Analytical approaches, (2) Numerical approaches and (3) Experimental / physical models and other techniques such as Artificial Neural Networks (ANNs) or Regression Analysis.

2.2 Analytical Methods for Seepage Calculations

Different analytical equations are available for seepage computation from the earth-fill dams i.e., Dupuit's solution, Schaffernak & Van Iterson method, Casagrande's method and Pavlovsky's Solution. As explained by (Harr, 1991), these methods for calculating seepage amount are based on several assumptions. (Dupuit, 1863) had used the Darcy's Law to approximate the seepage flow of water through any vertical cross-section of the dam for the condition of tail water as shown in Figure 2.1. Dupuit assumed that both seepage discharge and free surface are independent of the slope of the dam. Equation 2.1 demonstrates that the rate of seepage across the dam body is independent of the upstream and downstream slope angle.

$$q = k \left(\frac{h_1^2 - h_2^2}{2L} \right) \quad (2.1)$$

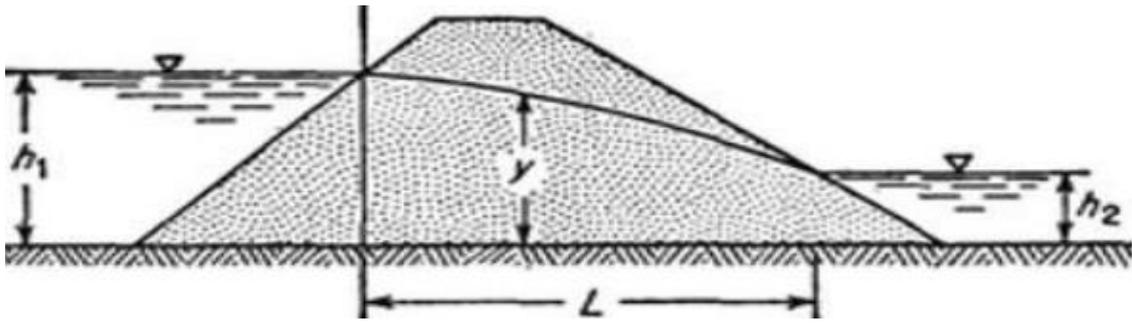


Figure 2.1: Dupuit's Solution (Harr, 1991)

Schaffernak (1917) had proposed an approximate method to compute the rate of seepage through a homogeneous earth-fill dam with no downstream head by presuming that the phreatic surface has crossed the downstream slope at a distance (a) from the impervious base as show in Figure 2.2 (Harr, 1991).

$$a = \frac{d}{\cos \alpha} - \sqrt{\frac{d^2}{\cos^2 \alpha} - \frac{h^2}{\sin^2 \alpha}} \quad (2.2)$$

$$q = -k a \sin \alpha \tan \alpha \quad (2.3)$$

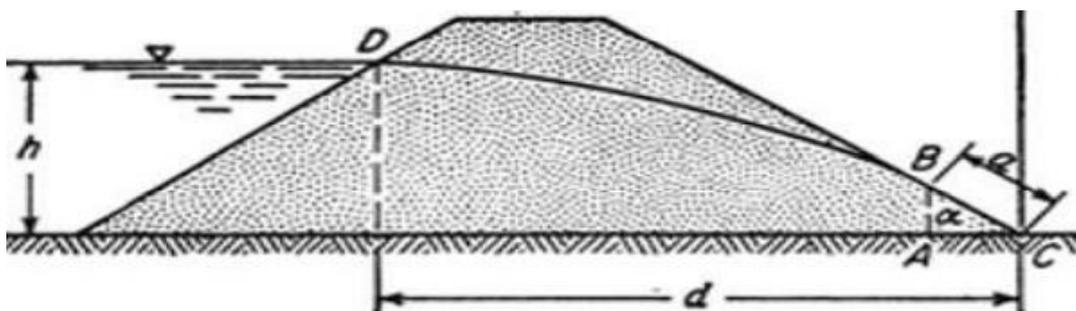


Figure 2.2: Schaffernak & Van Iterson Method (Harr, 1991)

Casagrande (1937) had developed approximate method to predict the quantity of seepage through the earth-fill dam laying on an impervious base, assuming no downstream head. Casagrande made a modification in the entrance condition by suggesting that the parabolic free surface originate at a point D_0 rather than D as shown in figure 2.3. The real entrance condition is achieved by drawing the arc DF normal to the upstream slope and tangent to the parabolic surface (Salmasi and Abraham, 2021).

$$a = \sqrt{d^2 + h^2} - \sqrt{d^2 - h^2 \cot^2 \alpha} \quad (2.4)$$

$$q = k a \sin^2 \alpha \quad (2.5)$$

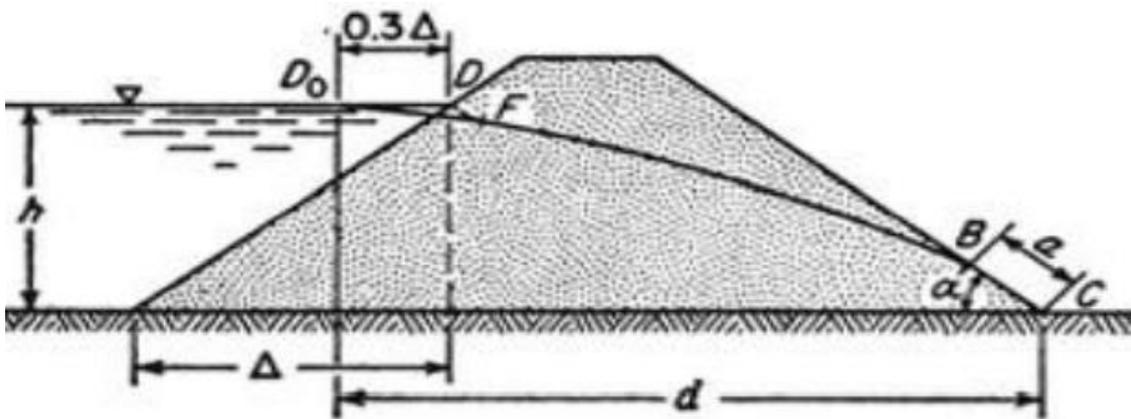


Figure 2.3: Casagrande Method (Harr, 1991)

Pavlovsky had studied the drop in the phreatic surface at different zones of dam. The overall dam body was subdivided into three zones as indicated in figure 2.4. The flow lines in zone (I) are curvilinear, however, Pavlovsky replaced them with horizontal flow lines of equivalent length (ed) (Harr, 1991). Finally differential equation 2.6 was recommended by Pavlovsky for seepage calculation.

$$dq = k \frac{a_1}{\cot \beta (h_d - y_o)} \quad (2.6)$$

Rozanov (1978) (Rezk and Senoon, 2011) recommended equation (2.9) to calculate seepage across the dam body laying on an impervious foundation.

$$Q = q_1 + q_2 \quad (2.9)$$

where q_1 and q_2 correspond to the amount of seepage through the upper and the lower portion of the core, respectively, as demonstrated in Figure 2.6, and are provided by the equations (2.91-2.96):

$$q_1 = 1.35K_c \left[\sqrt{1.82(\delta_c)^2 + (H - h_1)^2} - 1.35\delta'_c \right] \quad (2.91)$$

$$q_2 = K_c \left[\frac{H-h_1}{\delta'_c} \right] h_1 \quad (2.92)$$

$$\delta'_c = \left(\frac{K_c}{K_d} \right) S_1 + \delta_c \quad (2.93)$$

$$S_1 = \lambda H + (T - H)m_1 \quad (2.94)$$

$$\lambda = \frac{m_1}{1+2m_1} \quad (2.95)$$

$$m_1 = \cot \alpha \quad (2.96)$$

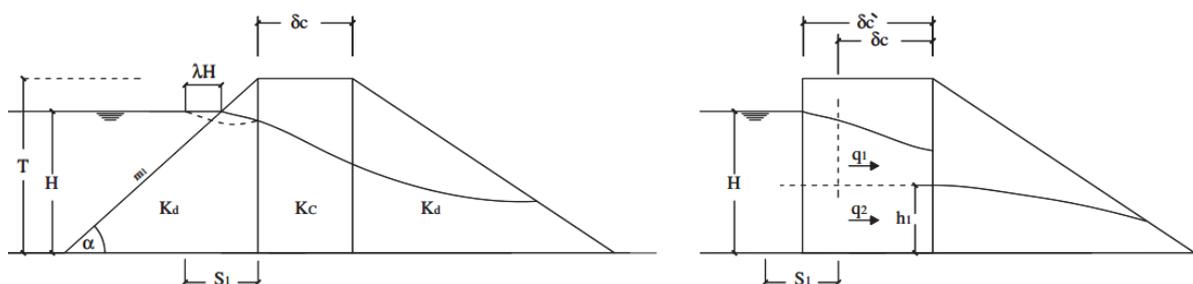


Figure 2.6: Parameters used in the analytical equation of Rozanov (1978) (Rezk and Senoon, 2011) for calculation of seepage through the dam body

2.3 Numerical Methods for Seepage Calculations based on FEM

Furthermore, the finite element approach has been established for solving the governing equations of flow through earth-fill dams. (Olonade and Agbede, 2013) utilized the finite element method to examine seepage through the Oba Dam. The FEM was used to obtain the potential heads at different locations. The potential heads obtained by conventional flow net method and FEM were compared. It was concluded that finite element program (SEEP2D1 and SEEP2D2) can be used to monitor seepage through the homogeneous and isotropic earth-fill-dam as in Oba dam. Phreatic surface obtained by FEM is also compared with conventional flow net method and it was observed that flow lines obtained by both methods are almost similar.

(Salmasi and Abraham, 2021) analyzed the amount of seepage across homogeneous earthen dam laying on impervious base using numerical and analytical methods. The FEM based simulation outcomes were compared with analytical solutions of Schaffernak and Casagrande. It was concluded that the numerical approach predicts more seepage rate than the other two analytical solutions. Further it was concluded that the analytical solutions are valid for simple type of problems i.e., homogeneous dam etc. but numerical solutions based on FEM has the capability to simulate complex dam geometries.

(Arshad and Babar, 2014) studied the rate of seepage through Hub dam using SEEP/W program. The original dam is made up of three distinct types of reaches, but only one reach with the core wall is simulated by using SEEP/W program. Seepage analysis was performed under different reservoir levels i.e., maximum, normal and minimum pool level. Authentication of the SEEP/W model was made by comparing the simulated outcomes against the observed ones. It was concluded that SEEP/W model can be used to evaluate seepage through the dam body. This study has approved the applicability of SEEP/W for the seepage evaluation.

(Kamanbedast and Delvari, 2012) studied the rate of seepage through Maroon dam using FEM based software i.e., Ansys and Geo-studio. Seepage rate obtained from both software under different conditions were compared. It was concluded that seepage rate given by Ansys was 18 percent less than the Geo-studio. This difference might be attributed to a different way of analysis. Stability analysis of the two programs was also compared and

deduced that Ansys answers are more acceptable. Dam was at a suitable situation according to the software results.

2.4 Estimation of seepage by ANN

(Tayfur *et al.*, 2005) established FEM and ANN based models for seepage estimation through the Jeziorsko earthen dam. Both models were verified and calibrated using piezometric data obtained from a particular section of the dam. Results concluded that ANN models predict as good as FEM based models. Hence this study proved the accuracy of ANN against FEM in predicting the rate of seepage across the body of earthen dam.

(Baghalian, Nazari and Malihi, 2012) used multilayer perceptron (MLP) artificial neural networks for seepage prediction through the foundation of dam. Continuity Laplace equation was solved to calculate piezometric values under the dam body and then these piezometric values were used to trained ANN model for seepage prediction. It was concluded that seepage predicted by the ANN model agrees well with the observed seepage.

(Kokaneh *et al.*, 2013) explored the rate of seepage through the “Fileh Khase” dam via SEEP/W program. SEEP/W data was then analyzed in SPSS software to generate GMDA (a type of ANN model) to forecast seepage flow of water through the dam. The goal of this job was to build an ANN model for predicting seepage through the “Fileh Khase” dam.

(Miao *et al.*, 2012) had developed seepage prediction model using machine learning techniques. The dataset used to train machine learning models was gathered from an earth-fill dam in China's Liaoning region. Seepage values predicted by “GA-LM model” correlate well with the field measurements. Further, a comparison was made between GA-LM model and other conventional ANN type models like BP and LM. Out of 381 field datasets, 366 were utilized for training while 15 seepage datasets were used for testing of ANN model. The genetic algorithm (GA) was used to improve the structure and variables of the Neural Network mode.

(Rehamnia *et al.*, 2021) employed 4 machine learning models named, “RBF-NN, MLP”, “RF” and “EKF-ANN (hybrid model)”, to anticipate seepage flow of water across the Fontaine Gazelles Dam. Altogether, 164 seepage datasets obtained from a section of the dam were used to train machine learning models. The models were developed using 7 observed

piezometer levels, level of water, and data observation date (owing to the recurring type of data). Seepage discharge was the yield of the machine learning models. 4 setups with permutations of input data were studied: Setup 1) the water level, Setup 2) observed data of 7 piezometers, Setup 3) Piezometric data and water level, and setup 4) Piezometric data, level of water and measurement date. Assessment of outcomes of different setups showed that setup 4 provided the peak precision with “RBF-NN (R = 0.9616, RMSE = 0.4463 l/s)”, “RF (R = 0.9630, RMSE = 0.3785 l/s)” and “EKF-ANN (R = 0.9891, RMSE = 0.2131 l/s)” and “MLP model (R = 0.9781, RMSE = 0.2766 l/s)”, setup 3 also showed good accuracy. Comparison of the performance of the machine learning models used in the study revealed that “EKF-ANN (R = 0.9891, RMSE = 0.2131 l/s, MAPE = 4.7251, U95% = 2.5055) model” had higher accuracy in seepage prediction across the embankment dam. The “MLP model (R = 0.9781, RMSE = 0.2766 l/s, MAPE = 3.3963, U95% = 2.5320)” was rated second-best model after the “EKF-ANN model”. Error analysis utilizing the cumulative frequency of absolute relative error proves the “EKF-ANN model's” superiority on rest of the models.

2.5 Empirical equations for Seepage prediction based on FEM analysis

Numerous researchers have developed empirical equations for seepage prediction by using FEM based programs. (Jamel, 2016) analyzed the seepage flow of water through homogenous earthen dam without toe drain, laying on impervious foundation via SEEP/W program. Using SEEP/W, simulations were performed considering 3 different values of each geometrical and physical parameter i.e., three downstream slopes (2.5:1, 2.25:1 and 2:1), three upstream slopes (3:1, 2.5:1 and 2:1), three variable downstream freeboard (11, 12, 13) m, three upstream freeboard (1, 1.5, 2) m, three height of earth-fill dam (14, 15, 16) and three top width of earth-fill dam (4, 5, 6). The overall 729 models were simulated for seepage calculation. Then, SPSS software was used to develop empirical equation for seepage prediction. ANN model was also developed for seepage prediction through homogenous dam without toe drain resting on impervious foundation.

(Irzooki, 2016) used the SEEP/W program to investigate a novel empirical correlation for estimating seepage through a homogeneous earth-fill dam with a horizontal toe filter laying on an impermeable base. Simulations were carried out considering three downstream slopes (1:2, 1:2.25 and 1:2.5), three upstream slopes (1:2.5, 1:2.75 and 1:3), three dam heights (H) (14, 15 and 16m), three crest widths (b) (4, 5 and 6m), three lengths of horizontal

toe filter (L) (10, 15 and 20m), three free boards (FB) (1, 1.5 and 2m) and three permeabilities (k) (0.0001, 0,00001 and 0.000001 m/sec). The overall 2187 models were simulated for seepage calculation. Dimensional analysis was then performed to generate an empirical correlation for seepage prediction. ANN model was trained with 70 percent of SEEP/W data and it showed good agreement with the 30 percent residual seepage values. Sensitivity analysis revealed that the length of the horizontal toe drain has a significant influence on the seepage value.

Using the SEEP/W software, (Jamel, 2018) investigated the quantity of seepage through an earthen dam with a core laying on an impermeable base. Simulations were carried out considering three upstream slopes (1:3, 1:2.25, 1:2.5), three downstream slopes (1:2.5, 1:2.25, 1:2), four upstream slopes of core (1:1, 1:0.75,1:0.5 ,90°) and downstream slopes of core (1:1, 1:0.75 ,1:0.5 ,90°). But some of the geometrical parameters were considered constant throughout the analysis like permeability of dam body (0.0001m/sec), permeability of core material (0.000001 m/sec), upstream water level (30m), crest width of dam (10m), and height of dam (35m). Altogether, 144 dam models were simulated for seepage calculation. Dimensional analysis was then performed to generate an empirical correlation for seepage prediction. Further, ANN model was developed for the verification of SEEP/W and suggested equation results. Results showed that the quantity of seepage predicted by both ANN and suggested empirical equation are in conformity with the SEEP/W data.

(Mamand, 2020) developed two empirical equations for seepage prediction through homogeneous earth-fill dam with horizontal toe filter resting on impervious foundation using SEEP/W and SLIDE programs. The overall 972 models were simulated for seepage with two unlike D/S slope (1:2 and 1:2.5), two U/S slope (1:2.5 and 1:3), three varying dam heights (H) (14, 16 and 18m), three different top widths (b) (4, 5 and 6m), three different lengths of horizontal toe drain (L) (10, 20 and 25m), three different free board (FB) (1, 1.5 and 2m) and three different permeability (k) (0.0001, 0,00001 and 0.000001 m/sec). The comparison of seepage quantity measured by SEEP/W and Slide against its quantity calculated from empirical equations gave a coefficient of determination ($R^2 = 0.815, 0.788$) respectively. Further the rate of seepage calculated by ANN model is compared with the seepage values obtained from SEEP/W and SLIDE programs gave a coefficient of determination ($R^2 = 0.923, 0.942$) respectively. Results showed that the ANN model predicted the seepage rate more accurately than the two empirical equations.

(Abbas, 2017) developed empirical equation for seepage prediction through homogeneous earth-fill dam with triangular toe filter resting on impervious foundation utilizing SEEP/W program. The impact of different geometrical parameters of the dam on the quantity of seepage were studied. The overall 2592 models were simulated with three different upstream angles of dam (α) (22, 20 and 18), three different downstream angles of dam (β) (22, 24 and 26.5), three different angles of toe filter (θ) (25, 50 and 70), three different dam heights (hd) (16, 15 and 14m), three different crest widths (Cw) (4, 5 and 6m), three different free boards (Fw) (1, 1.5 and 2m), three different lengths of toe filter (L) (10, 15 and 20m) and three values of permeability (k) (0.0001, 0.00001 and 0.000001 m/sec.). Finally statistical software (SPSS) was used to develop empirical equation for seepage prediction through earth-fill dam with triangular toe filter. Results demonstrated that the seepage values predicted by the suggested equation match well with the SEEP/W seepage values.

(Ghanbari and Zaryabi, 2014) studied the rate of seepage through the foundation of earthen dam with clay trench and horizontal upstream blanket. An empirical correlation was also developed to predict the reduction of seepage due to the provision of clay trench and upstream blanket. Empirical equation was developed by performing 1382 simulations using SEEP/W program. The main aim was to predict the optimum dimensions of clay trench and upstream blanket for reducing the rate of seepage through the foundation of the dam. Results showed that the seepage values predicted by the suggested equation match well with the SEEP/W seepage values.

(Fakhari and Ghanbari, 2013) studied the rate of seepage across dam with core laying on impervious foundation. The overall 600 simulations were performed using SEEP/W model considering vertical and oblique core of varying thickness. Additionally, different values of other geometrical parameters of the dam like height of reservoir, crest of dam and the angle of the core were considered during simulations. Based on the simulation results, an empirical equation was developed for seepage prediction. The seepage values predicted by the suggested empirical equation were compared with the SEEP/W and other analytical equations of Casagrande and Schaffernak. Results showed that the seepage values predicted by the suggested empirical equation are in good agreement with the SEEP/W. (Fakhari and Ghanbari, 2013; Irzooki, 2016; Jamel, 2016, 2018; Abbas, 2017; Mamand, 2020) have developed empirical equations based on FEM analysis to predict the rate of seepage through the specific type of earth-fill dams resting on impervious foundation. However, the empirical

correlation for seepage calculation across a non-homogenous earthen dam lying on pervious foundation is yet to be investigated.

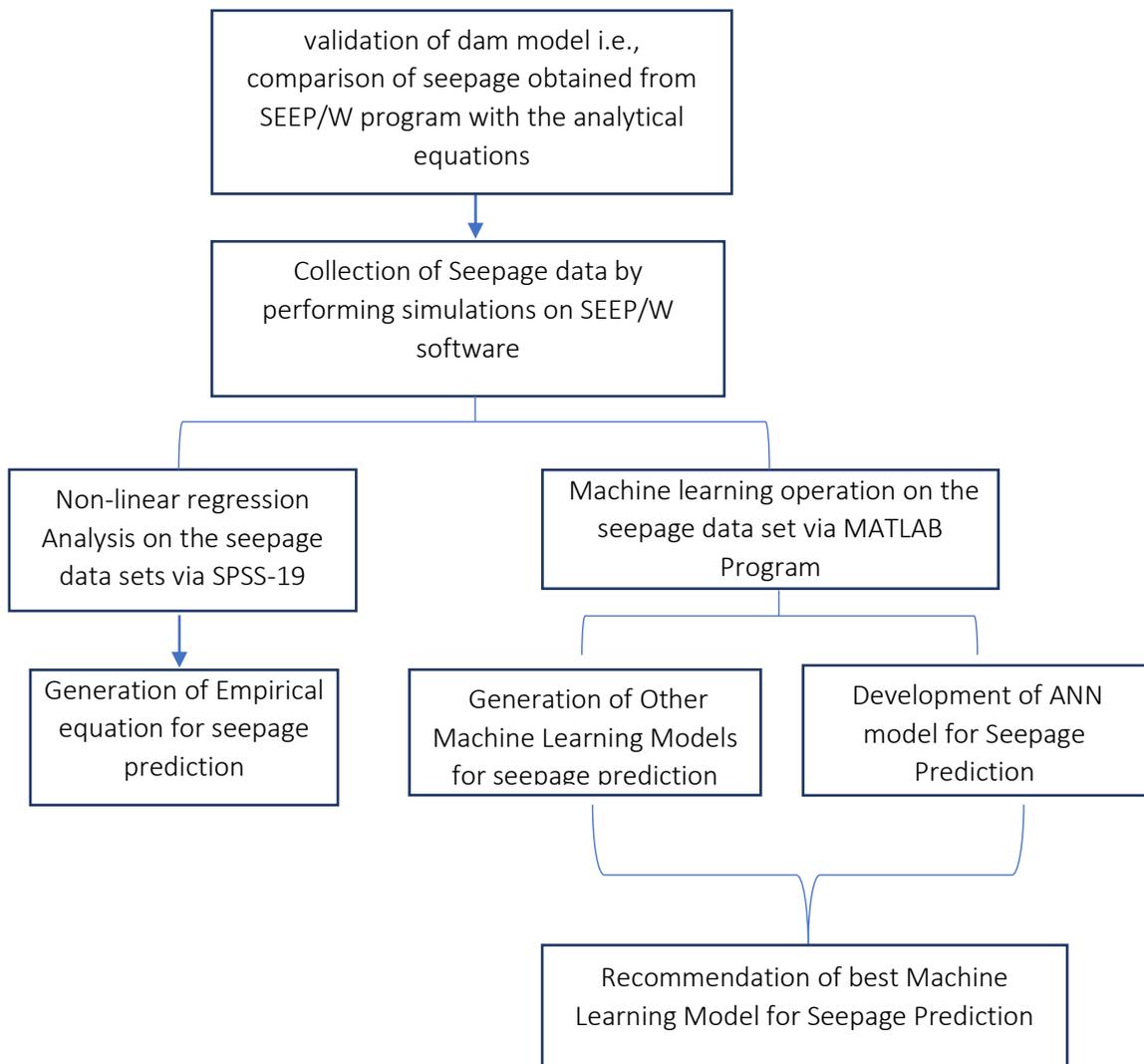
The present study analyzed the rate of seepage through earthen dam with core laying on pervious foundation by using SEEP/W program. The overall 4374 models were analyzed in this study using different combinations of geometrical and physical parameters of the dam and its foundation. Finally, an empirical equation was developed to predict seepage across the dam via SPSS 19 software. The seepage data obtained from SEEP/W analysis was also used to develop ANN model for seepage prediction by using MATLAB(R2021b) program.

Chapter 3

Methodology

3.1 General

The basic intend is to study the rate of seepage through earthen dam with core laying on pervious foundation. The actual dam model under consideration is shown in the Figure 3.2. This chapter reports the specification of earth-fill dam under consideration and procedure used for the numerical simulations in SEEP/W program. This chapter reports the methodology used for achieving all the objectives of this study.



3.2 Dimension Analysis

Dimension analysis helps in developing the relationship between physical quantities. In this research dimension analysis was used to develop an empirical equation for seepage prediction. From the Figure 3.1, all possible variables effecting the rate seepage (q) through dam and its foundation are as: upstream slope ($\tan\alpha$), dam's height (H), downstream slope ($\tan\theta$), crest width (B), core's slope ($\tan\beta$), depth of pervious foundation (D), free board (F_b), permeability of foundation material (K_f), and permeability ratio of core to shell material (K').

Therefore:

$$q = f(\tan\theta, \tan\alpha, \sin\beta, K_f, H, F_b, k', B, D) \quad (3.1)$$

Applying Buckingham π Theorem on equation (3.1), following dimensionless terms are obtained as shown in equation (3.2)

$$\frac{q}{H \times K_f} = f(\tan\theta, \tan\alpha, \sin\beta, k', \frac{F_b}{H}, \frac{D}{H}, \frac{B}{H}) \quad (3.2)$$

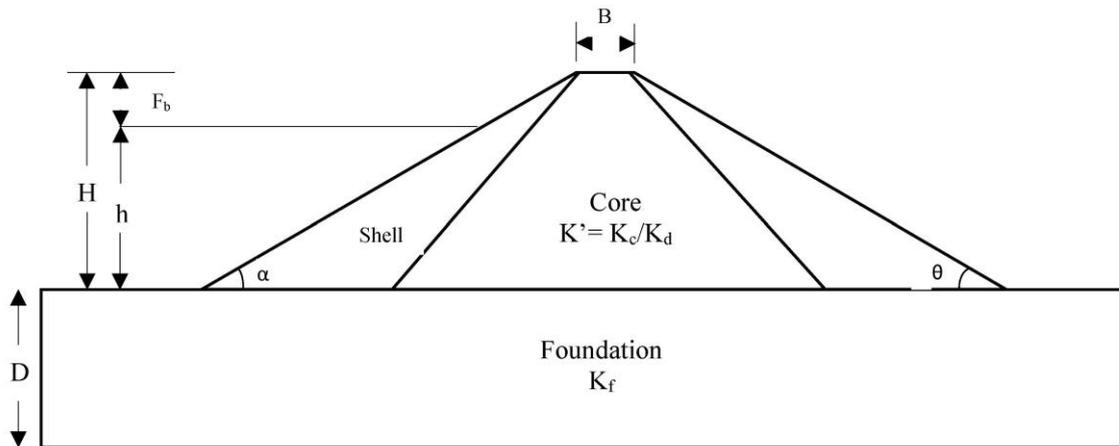


Figure 3.1: General cross section of the earthen dam model laying on pervious foundation

3.3 Procedure of Experimental Setups

To develop an empirical equation for calculating seepage flow of water from an earth-fill dam lying on pervious base, 4374 models of the dam with different combinations of physical and geometrical parameters were analyzed in SEEP/W program. The general section of the earthen dam model laying on pervious base is shown in the Figure 3.1. Three different values

of each physical and geometrical parameter of the dam effecting the rate of seepage are listed in Table 1. These tests were divided into 3 groups (A, B, C) for upstream slope of the dam ($\tan\alpha$) 1/3, 1/2.75, 1/2.5 respectively. Each group's tests were conducted with three different downstream slopes of the dam ($\tan\theta$) (1:2.5, 1:2.25 and 1:2), two different slope angles of the core (β) (45°, 90°) three unlike dam's heights (H) (14, 16 and 18 m), three different crest widths (B) (4, 5 and 6m), three different depths of pervious layer (D) (20, 30 and 40 m), three different free board (F_B) (1, 1.5 and 2m), three different values for the permeability of foundation material (k_f) (0.00001, 0.000001 and 0.0000001 m/sec) and three different permeability ratios of core to shell material (K_c/K_d) (1.00E-06, 1.00E-04 and 1.00E-02). Figure 3.2 shows different combinations of the dam models analyzed in SEEP/W program.

Table 3.1: Different values of geometrical and physical parameters of the dam effecting the rate of seepage

Parameters	1	2	3
Tan α : Upstream slope of the dam	1/3	1/2.75	1/2.5
Tan θ : Downstream slope of the dam	1/2.5	1/2.25	1/2
K $_f$: Permeability of foundation material (m/sec)	1.00E-05	1.00E-06	1.00E-07
H: Height of the earth-fill dam model (m)	14	16	18
F $_b$: Freeboard (m)	1	1.5	2
K': Permeability ratio of core to shell material i.e. (K_c/K_s)	1.00E-02	1.00E-04	1.00E-06
B: Crest width of the dam (m)	4	5	6
β : Upstream and downstream slope angle of core (degree)	45	90	
D: Depth of pervious foundation (m)	20	30	40

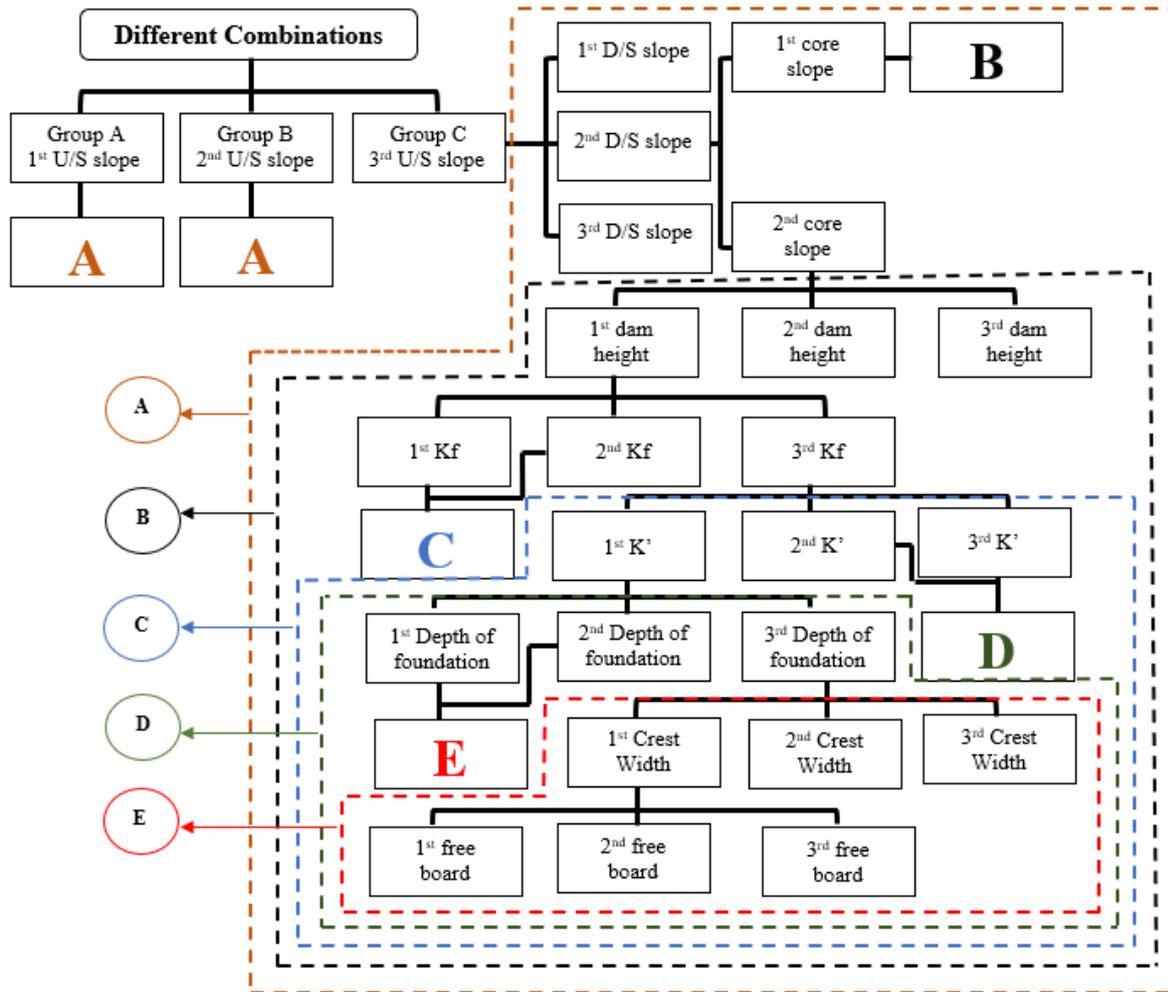


Figure 3.2: Different combinations of the dam models analyzed in SEEP/W program

3.4 Numerical Analysis on SEEP/W program

SEEP/W (a sub-program of GeoStudio 2018 R2) is a finite element software used to analyze the earth-fill dam models for seepage calculations. 2-Dimensional steady state analysis was carried out in this study. The overall 4374 dam models were analyzed in this study. The complete procedure for the analysis of dam models in SEEP/W software for seepage calculation is described in this section.

3.4.1 General Settings and Drawing Regions

The general settings for the analysis of dam model in SEEP/W program are unit settings, sketching axes and drawing regions (see Figure 3.3-3.5). The dam model consists of three different regions i.e. (1) Shell region (2) Core region (3) pervious foundation region. Figure 3.5 shows the three regions of a dam model.

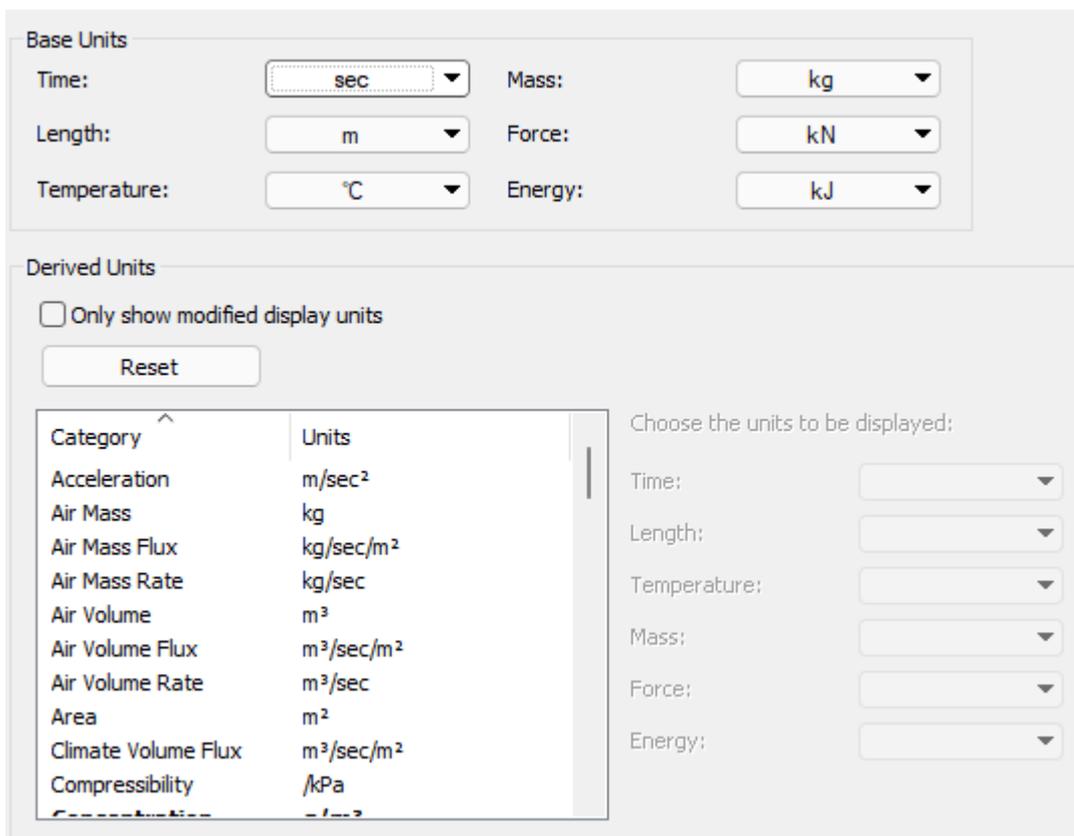


Figure 3.3: Basic Unit Settings

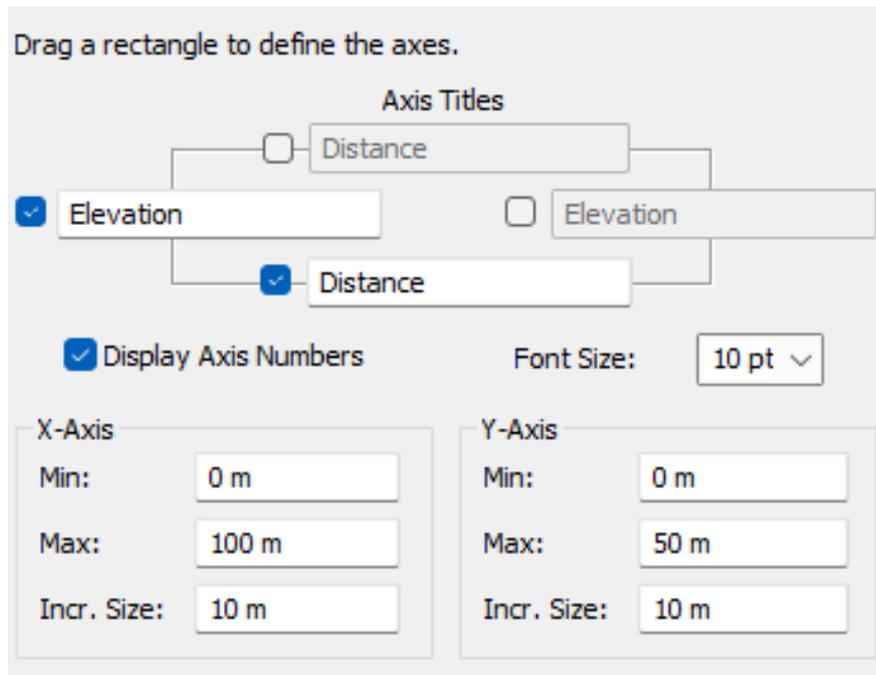


Figure 3.4: Sketching Axes

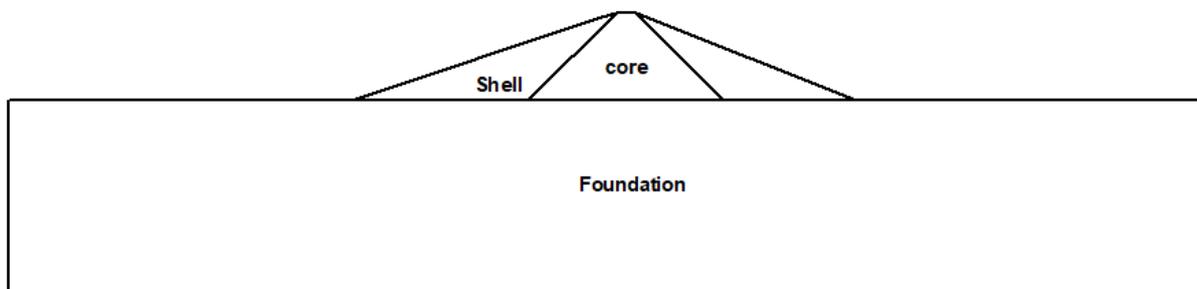
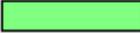
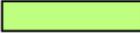


Figure 3.5: Different regions of a dam model

3.4.2 Material Properties

The material present in the foundation region is considered as saturated. While the material presents in the shell and core region is considered as unsaturated. Also, the permeability of saturated material is always constant while the permeability of unsaturated material vary with the negative pore water pressure.

Materials

Name	Color
Shell sand material	
foundation silty material	
core clay material	

Add | ▾

Delete

Assigned...

Name: foundation silty material Color:  Set...

Hydraulic

Material Model: Saturated Only ▾

Saturated X-Conductivity: 1e-07 m/sec

Sat. Vol Water Content:

Compressibility: 0 /kPa

Anisotropy

Ky'/Kx' Ratio: 1 Rotation: 0 °

Activation PWP: 0 kPa

Figure 3.6: Define material of foundation region

As the material present in the shell and core region is considered as unsaturated, hence permeability will not be constant. Permeability will vary with the negative pore water pressure. So, in these regions volumetric water content function and hydraulic conductivity functions along with permeability values are defined as shown in the Figure 3.7 and 3.8.

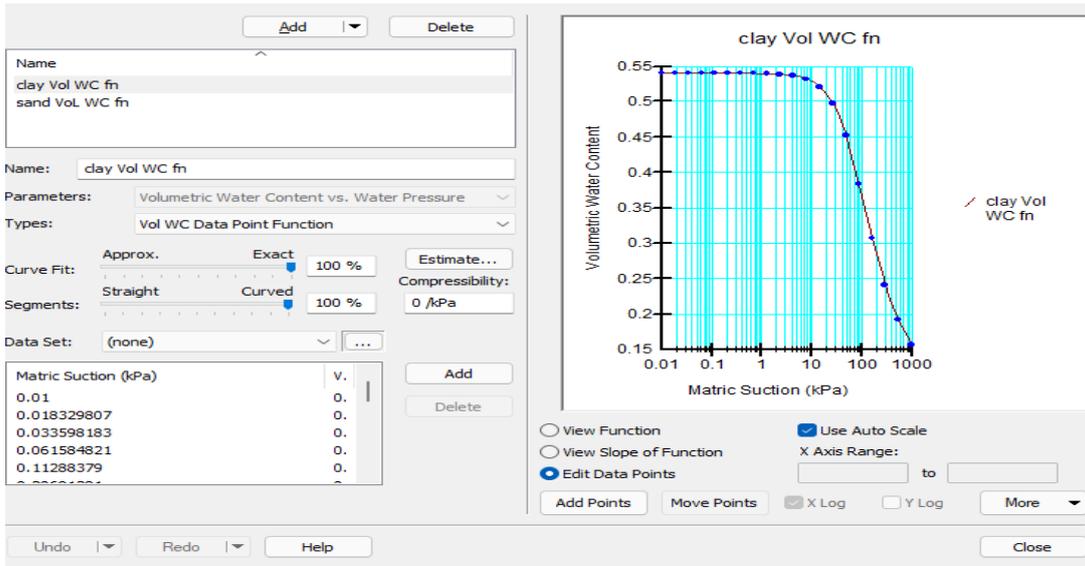


Figure 3.7: Volumetric water content function

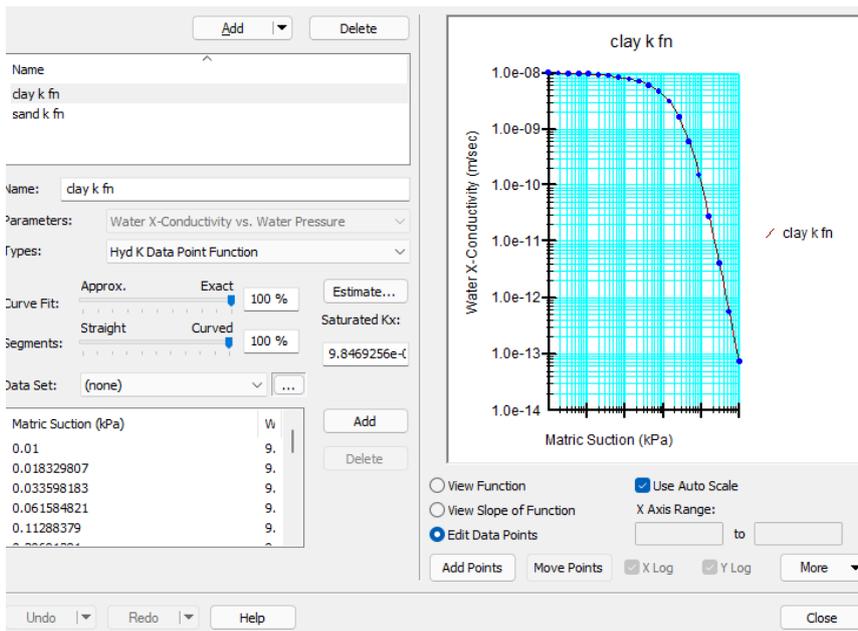


Figure 3.8: Hydraulic conductivity function

3.4.3 Boundary Conditions

Two boundary conditions were defined i.e. (1) total head boundary condition on the upstream face of dam (2) Potential seepage face boundary condition on the downstream face of dam as shown in the Figure 3.9.

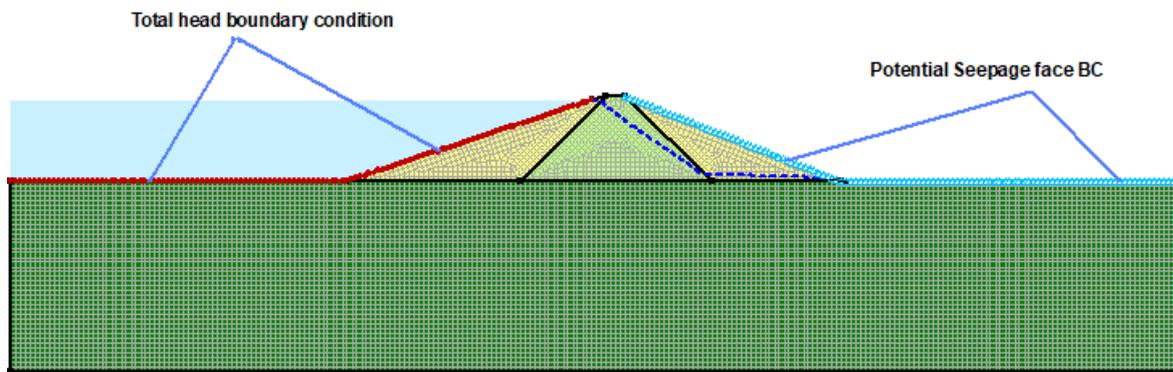


Figure 3.9: Boundary conditions and meshing

As explained in Figure 3.10 (a), the upstream slope is assigned a total head boundary condition with head equivalent to the water level. The downstream slope is allocated a potential seepage face type of boundary condition. Figure 3.10 (b) shows the seepage rate through one example of the dam model using SEEP/W program.

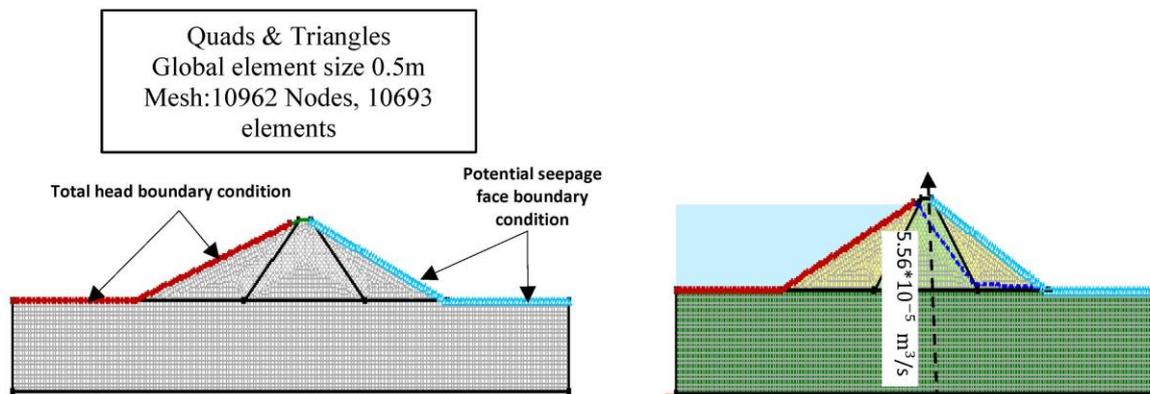


Figure 3.10: (a) Location of Boundary conditions of earth dam (b) Seepage rate through earth dam using SEEP/W program

3.5 Statistical analysis of seepage data (Non-linear regression analysis)

SPSS software was used for statistical analysis of seepage data. The non-linear regression analysis was performed by substituting approximately two thirds of the seepage data in SPSS program to develop an empirical correlation between dependent (seepage) and independent variables. Rest of the seepage data was used for the validation of suggested empirical equation. Different statistical parameters were calculated to check the validation of suggested equation for example coefficient of correlation and root mean square error. Nonlinear regression is a type of regression analysis in which data is fitted to a model and then represented numerically. The validation of the suggested equation is carried out by comparing the seepage obtained from equation and SEEP/W program.

$$RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (I_{p,i} - I_i)^2} \quad (3.3)$$

$$R^2 = 1 - \frac{\text{Residual sum of squares}}{\text{Corrected sum of squares}} \quad (3.4)$$

3.6 Designing of Artificial Neural Network (ANN) Models

ANN model design involves several systematic steps: (1) Gathering data, (2) Preprocessing data, (3) Constructing the Network, (4) Training, and (5) Testing Model Performance. In this study, the performance of ANN and other machine learning models will be examined for seepage prediction using MATLAB (R2021b). In the following sections, detailed procedure for designing ANN model is explained. A flow chart for designing an artificial neural network model is shown in Figure 3.11.

3.6.1 Data Collection

The initial step in designing ANN models is to collect and prepare sample data. As it is summarized in the section 3, the seepage data point was collected by performing simulations on SEEP/W software. The overall 4374 seepage datasets were collected by performing simulations on dam models using different combinations of dam parameters.

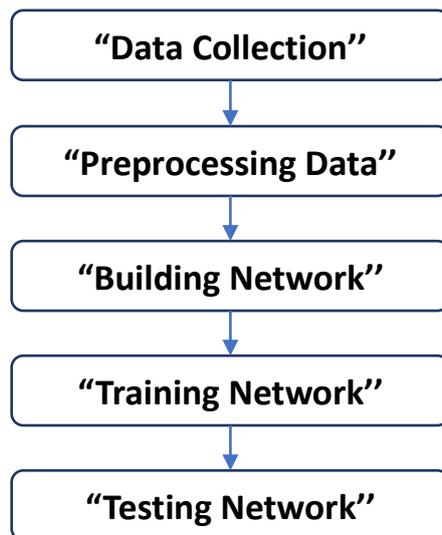


Figure 3.2: An artificial neural network model design flowchart

3.6.2 Data pre-processing

Following data collection, 3 data preprocessing operations are carried out in order to train ANNs more proficiently. These operations are as follows: (1) Solve the missing data problem, (2) Normalize data, and (3) Randomize data.. The missing data are swapped with mean of adjacent values. In our case there was no missing data. It is generally a good idea to normalize the input data before feeding it to the network since variables with small and large magnitude may make the learning algorithm uncertain of the relative significance of each variable and may even drive it to discard the variable with the lower magnitude. (Tymvios, Michaelides and Skouteli, 2008). To get a zero mean and a unity standard deviation, the “mapstd” function was used to standardize the inputs and target. The output is then converted back to the original target's unit. Training and testing data are switched to rows since MATLAB needs all information to be given as row vectors. The function “randperm” was used to randomize the training dataset.

3.6.3 Building the network

In this stage designer allocates number of hidden layers, number of neurons in each hidden layer, transfer function between the layers, training function, weight/bias learning function, and performance function. For developing MLP neural network, 14 different back-propagation training algorithms were checked to get the most suitable algorithm for training. The training functions are: “Levenberg-Marquardt, Bayesian regularization, BFGS quasi-Newton, Powell -Beale conjugate gradient, Gradient descent, Gradient descent with

momentum, Gradient descent with adaptive learning rate, Gradient descent with momentum & adaptive learning rate, One step secant, Fletcher Powell conjugate gradient, Random order incremental training with learning, Resilient, Polak-Ribiere conjugate gradient, and Batch training with weight and bias learning rules”. Furthermore, other transfer functions in the hidden layer were also examined, including the “log sigmoid”, “tangent sigmoid” and “linear functions”.

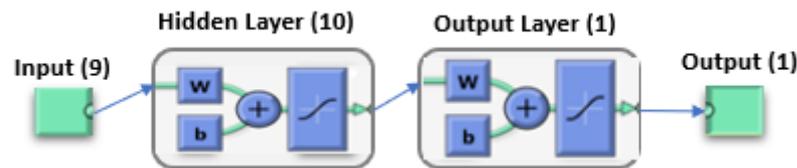


Figure 3.11: MLP model with 9 inputs and 1 output used in this study

3.6.4 Training the network

In the training phase, the weights are modified to bring the outputs closer to the network's goal (measured) outputs. The data set is manually separated into 2 subgroups: 70% of the total data points (3061 seepage values) were used for training, while the remaining data points (1312 seepage values) were used for testing. For the development of the MLP network, 14 different types of training algorithms were investigated. The algorithms include: “Levenberg-Marquardt”, “Bayesian regularization”, “BFGS quasi-Newton”, “Powell-Beale conjugate gradient”, “Gradient descent”, “Gradient descent with momentum”, “Gradient descent with adaptive learning rate”, “Gradient descent with momentum & adaptive learning rate”, “One step secant”, “Fletcher Powell conjugate gradient”, “Random order incremental training with learning”, “Resilient”, “Polak-Ribiere conjugate gradient”, and “Batch training with weight and bias learning rules”. MATLAB gives built-in transfer functions which are utilized in this research i.e. linear “purelin”, Hyperbolic Tangent Sigmoid “logsig” and Logistic Sigmoid “tansig”.

3.6.5 Testing the network

In this stage the performance of the established model is checked. Unseen datapoints are subjected to the model. In this study, 30 percent of the total seepage data points were used for testing the established MLP-ANN models. Statistical analysis including the coefficient of

determination (R^2), the root mean square error (RMSE), and the mean bias error (MBE) were performed to quantitatively assess the performance of the established ANN model and check whether there is any fundamental trend in the performance of ANN models. The smaller the RMSE, the more precise is the prediction. Similarly, the smaller MBE, the better is the long-term model prediction. The value of R^2 closer to unity indicates that the real value and the value predicted by the ANN model correspond well.

$$MBE = \frac{1}{n} \sum_{i=1}^n (I_{p,i} - I_i) \quad (3.5)$$

$$RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (I_{p,i} - I_i)^2} \quad (3.6)$$

$$R^2 = 1 - \frac{\text{Residual sum of squares}}{\text{Corrected sum of squares}} \quad (3.7)$$

where I_{pi} denotes the predicted seepage value from the ANN model, I_i denotes the measured seepage from SEEP/W model, and n indicates the number of observations.

3.7 Programming the neural network model in MATLAB

The MATLAB contains a Neural Network Toolbox for modelling neural networks. It also offers extensive support for numerous well-known network models, as well as graphical user interfaces (GUIs) that allow users to create and maintain neural networks in a fairly easy way. In this study MATLAB (R2021b) was utilized to enter script files for creating MLP-ANN models and performance functions for assessing the model performance error statistics namely, ‘RMSE’ and ‘MBE’. The procedures follow to create the ANN models are shown in Figure 3.11. The program initiates by taking data from an Excel file “Training.xlsx” and “Testing.xlsx”. Data from specified excel files was read via “xlsread” function.

```
“Data_Inputs = xlsread('Trainingset.xlsx');”
```

```
“Testing_Data = xlsread('TestingSet.xlsx');”
```

The function “randperm” is used to randomise the training data samples.

```
“Shuffling_Inputs = Data_Inputs (randperm (1531),1:8)”
```

Then, the input variables ($HK_f, \tan\theta, \tan\alpha, k', \frac{F_b}{H}, \frac{D}{H}, \frac{B}{H}$) and output variable (seepage) are specified for training and testing. The training samples comprise 1531, whereas the testing samples are 656.

```
“Training_Set = Shuffling_Inputs (1:1531,1:7) % specify training set [1531]”
```

```
“Target_Set = Shuffling_Inputs (1:1531,8) % specify target set [1531]”
```

```
“Testing_Set = Testing_Data (1:656,1:7) % specify Testing set [656]”
```

```
“Testing_Target_Set = Testing_Data (1:656, 8) % specify Testing set, Target [656]”
```

For data training and testing, a normalisation method was used. The inputs and target are normalised using the "mapstd" function to provide a zero mean and a unity standard deviation. The output is then switched back to the target's initial unit. Training and testing data are switched back to rows (MATLAB needs all data to be displayed as row vectors).

```
“[pn, ps] = mapstd (Training_Set)”
```

```
“[tn, ts] = mapstd (Target_Set);”
```

Normalized input and output values are included in the settings structures pn and tn, respectively, whereas ps and ts include the original inputs and target means and standard deviations. MATLAB assists in the development of the MLP model by utilising the built-in function “newff,” which generates a feed-forward back-propagation network. The number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function may all be specified. Furthermore, this programme will spontaneously adjust the weights and biases. Following is the argument of the function:

```
“MyNetwork = newff (pn, tn, [i], {tf});”
```

where pn and tn represent the normalised input and output, respectively. [i] infers that the network structure comprises of 1 hidden layer and “i” neurons. For “j” hidden layers [i, j] is used. The argument {tf} indicates the transfer function of the ith layer. The network is called as follows:

```
“MyNetwork.trainFcn = LM;”
```

```
“MyNetwork.trainparam.min_grad = 0.00000001;”
```

```
“MyNetwork.trainParam.epochs” = 1000
```

```
“MyNetwork.trainParam.lr” = 0.4;
```

```
“MyNetwork.trainParam.max_fail” =20;
```

Where

“trainFcn”: describes the function utilized for training of model. It can be assigned to any training function name (LM = ‘trainlm; %Levenberg-Marquardt back-propagation’)

“trainparam.min_grad”: represents the least gradient of performance.

“trainParam.epochs”: designates the highest No. of epochs for training.

“trainParam.lr”: represents learning rate.

“trainParam.max_fail”: indicates the highest validation failures.

After completion of training process, the performance of the network is checked. For this the untested data is delivered to the already trained network. The model testing procedure is called with the argument:

```
y = “sim (MyNetwork, testn); % simulate network”
```

The performance function is then applied in order to compute and save the performance error statistics, namely R2, RMSE, and MBE. The stored results for all tested models are analysed and compared in order to determine the ideal network architecture with the maximum R2 and minimum RMSE and MBE.

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Chapter 4

Results and Discussions

4.1 Relation Between the Variables

For the validation of dam model, seepage obtained from SEEP/W program was compared with the analytical equations of seepage calculation. Seepage through the foundation was validated using analytical solution of USBR (1987). While seepage through the dam body was compared with the analytical equation of Rozanov (1978)

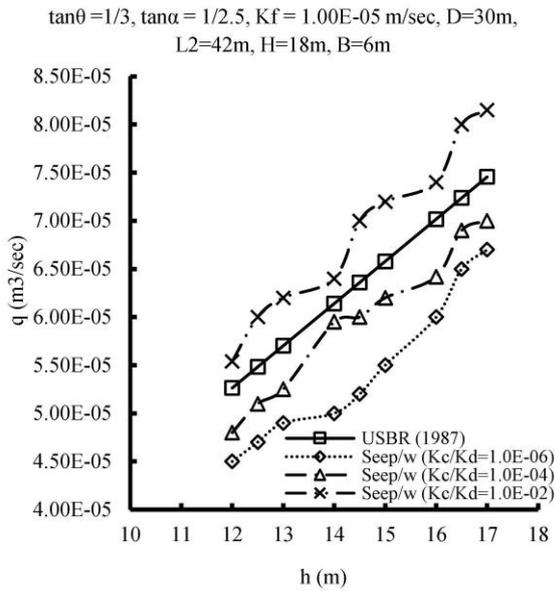
4.1.1 Seepage through the foundation of earth-fill dam

Increase of seepage through the foundation of dam for various permeability ratios of core to shell materials (K_c/K_d) is shown in Figure 4.1 (a). It shows that the higher permeability ratio (core to shell) will result in higher seepage rate through the foundation keeping the upstream water level and other parameters constant. The passage of more flow lines through the dam body will also result in higher seepage rate through the foundation as more water will flow from the dam body to foundation. USBR (1987) has ignored the permeability ratio of core to shell material (K_c/K_d) in his analytical equation, hence the numerical results are somewhat deviating from the USBR (1987) solution. Figure 4.1 (b) shows the increase of seepage in the foundation for various crest width (B) of the dam. It shows that the smaller crest width will result in higher seepage rate through the foundation of dam keeping the depth of pervious foundation (D) and other parameters constant. Smaller crest width will allow more seepage through the foundation as more water will flow from the dam body to foundation. Figure 4.1 (c) illustrates the increase of seepage in the foundation for various upstream slope ($\tan\alpha$) of the dam. It shows that the higher slope angle will result in higher seepage rate through the foundation of dam keeping the permeability of foundation (K_f) and other parameters constant. Similarly, Figure 4.1 (d) illustrates the decrease of seepage in the foundation for various bottom width of the core (L_2). It shows that the higher slope angle will result in lower decrease of seepage through the foundation and vice versa keeping the bottom width of core (L_2) and other parameters constant. Steep slope of dam will allow more seepage through the foundation as more water will flow from the dam body to foundation.

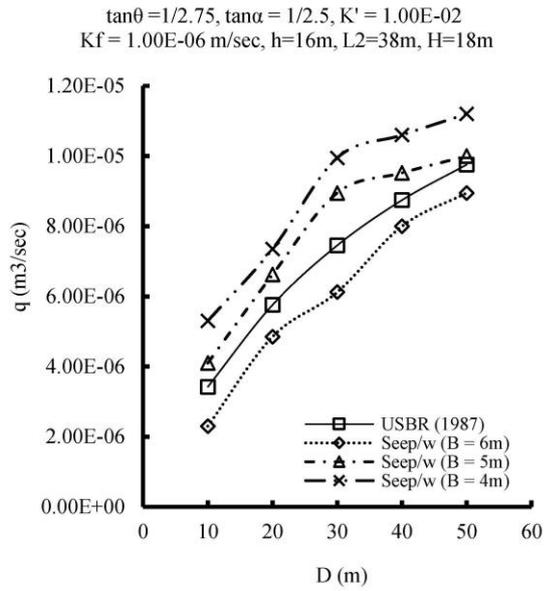
4.1.2 Seepage through the dam body

Figure 4.2 (a) shows that the seepage through the dam body increases with increase in the permeability ratio of core to shell material. It shows that the higher downstream slope angle of the dam will result in higher seepage rate through the dam body keeping the permeability ratio (K_c/K_d) and other parameters constant. Similarly, Figure 4.2 (b) shows that the seepage through the dam body decreases with increase in the crest width of dam. It shows that the lower downstream slope angle of the dam will result in lower seepage rate through the dam body keeping the crest width and other parameters constant. Rozanov (1978) has not considered downstream slope ($\tan\theta$) in his analytical equation, hence the numerical results are somewhat deviating from the Rozanov (1978) solution.

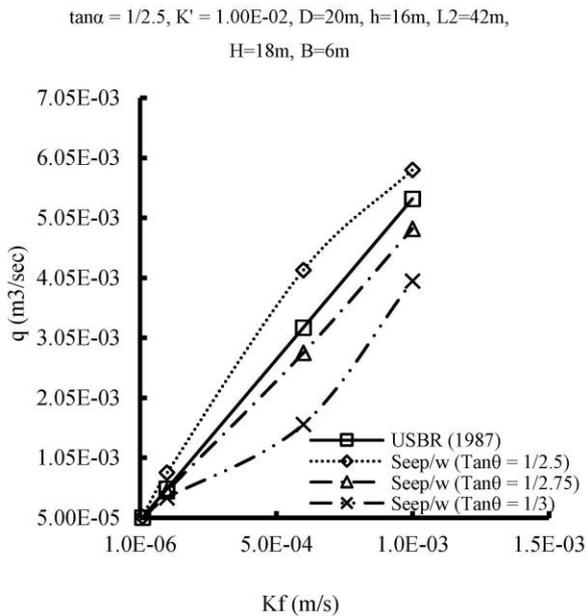
The comparison of numerical seepage values with the analytical equations of USBR (1987) and Rozanov (1978) reveal an average percentage error of less than 15 %.



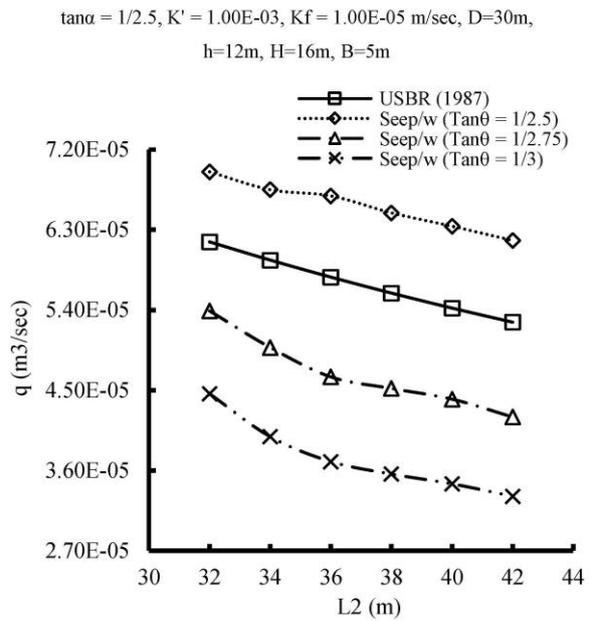
(a)



(b)



(c)



(d)

Figure 4.1: Variation of Seepage (q) through the foundation of dam for different parameters of the dam (a) Upstream water level (b) Depth of pervious foundation (c) Permeability of foundation (d) Bottom width of core

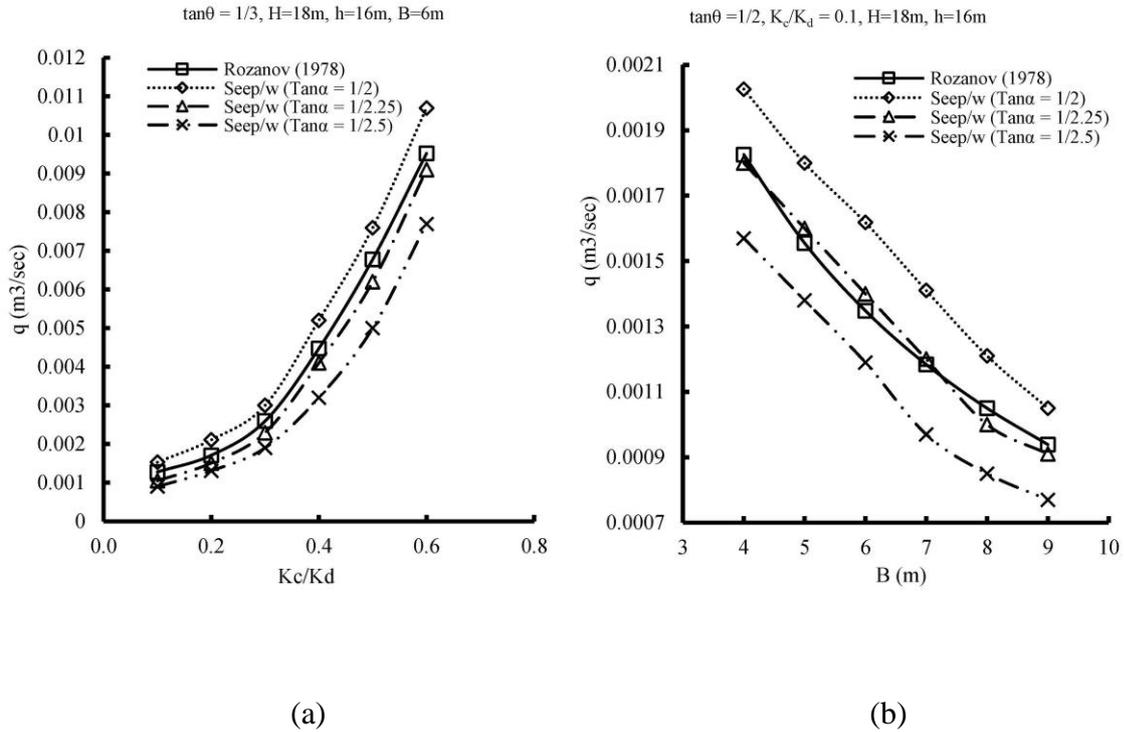


Figure 4.2: Variation of seepage (q) through the dam body for different parameters of the dam (a) Permeability ratio of core to shell material (b) Crest width of the dam

4.2 Empirical equation for computing seepage flow of water from an earth-fill dam lying on pervious foundation.

To develop an empirical equation for calculating seepage flow of water from an earth-fill dam lying on pervious foundation, a statistical analysis was performed on approximately 70 percent of the seepage data via SPSS-19 software. Rest of the seepage data (30 percent) was used for the validation of the proposed empirical equation. Equation (4.1) is the proposed empirical equation for seepage calculations.

$$q = \frac{0.194 HKf \times \left(\frac{D}{H}\right)^{0.431} \times (\tan\theta)^{0.006} \times (\tan\alpha)^{0.213} \times (\sin\beta)^{1.827}}{\left(\frac{B}{H}\right)^{0.18} \times \left(\frac{Fb}{H}\right)^{0.093} \times (Kc/Ks)^{0.07}} \quad (4.1)$$

Figure 4.3 shows the comparison of remaining one third seepage results obtained from SEEP/W and from that of proposed empirical equation (4.1). Figure 4.3 has shown an excellent agreement between the computed seepage flow from proposed equation and measured flow from SEEP/W with coefficient of determination (R^2) equal to 0.96. Table 4.1 shows the statistical validation of proposed empirical equation.

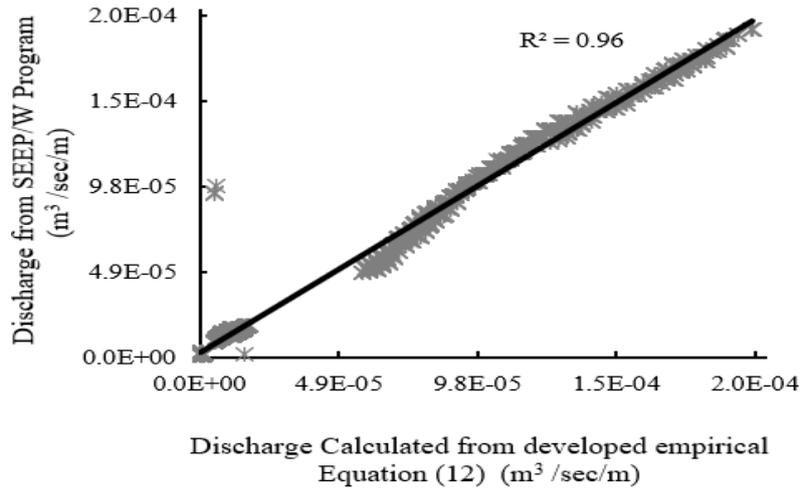


Figure 4.3: Comparison between measured seepage discharge from SEEP/W and computed by empirical equation (4.1)

Table 4.1: Statistical Validation of Equation (3)

Statistical Standards	Statistical Values
“Coefficient of Determination (R^2)”	0.96
“Mean Absolute Percentage Error (MAPE%)”	2.53%
“Average Accuracy Percentage (AA%)”	97.47%

4.3 Artificial Neural Network (ANN) Model

MATLAB (R2021b) was used to develop multilayer perceptron (MLP) artificial neural network model for seepage estimation. Each MP-ANN model has 3 layers: input layer, hidden layers and output layer. The number of neurons in an input layer equals the number of input variables in a problem. In the same way, the number of neurons in the output layer equals the number of target variables. The MP-ANN model under consideration has nine neurons in the input layer and only one neuron in the output layer. However, the number of hidden layers and neurons within each hidden layer can be determined through trial-and-error method. The optimal value of R^2 was obtained by using 10 neurons in the hidden layer as indicated in Figure 4.4. Finally, the optimal architecture of the MLP-ANN model for seepage prediction was (9-10-1), which indicates nine input neurons, ten neurons in a hidden layer, and one output neuron. The schematic diagram of the developed MLP-ANN model is

displayed in Figure 4.5. Each neuron of the input layer is linked with all neurons of the hidden layer, while each neuron of the hidden layer is connected with a single output neuron as shown in the Figure 4.6. Back error propagation (BEP) technique was used to train the model. The 9 input variables were the geometrical and physical parameters of the dam effecting the rate of seepage: as the upstream slope ($\tan\theta$), downstream slope ($\tan\alpha$), slope angle of the core (β), dam's height (H), crest width (B), depth of pervious layer (D), free board (F_B), permeability of foundation material (k_f) and permeability ratio of core to shell material (k'). while the rate of seepage (q) is the single output variable. The comparison of the seepage values obtained from SEEP/W and predicted by the developed ANN model gives coefficient of determination (R^2) equal to 0.97 as shown in the Figure 4.7. A complete summary of well-trained MLP-ANN model is shown in the Table 4.2. Figure 13 illustrates the comparison among the calculated seepage discharges for randomly twenty tests using different method. The seepage values obtained from MLP-ANN model and empirical equation (4.1) are almost overlapping with the seepage values obtained from SEEP/W program. In addition, as shown in Table 4.3, accuracy of the MLP-ANN model was compared with other machine learning techniques using three distinct statistical standards: R^2 , ‘‘mean absolute percentage error (MAPE)’’ and ‘‘average accuracy percentage (AA%)’’. Coefficient of determination (R^2) of different machine learning models are compared graphically in Figure 4.9.

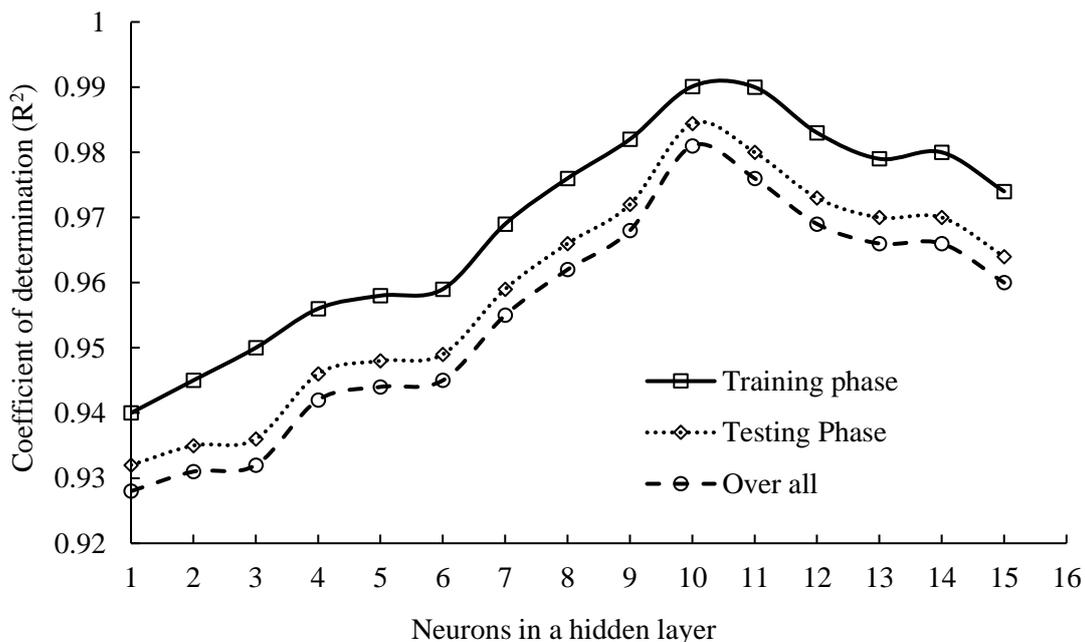


Figure 4.4: Optimal R^2 of MLP models with different architectures

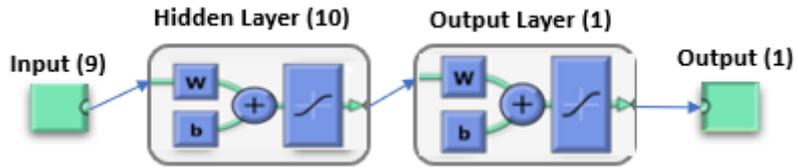


Figure 4.5: Schematic diagram of the developed MLP-ANN Model

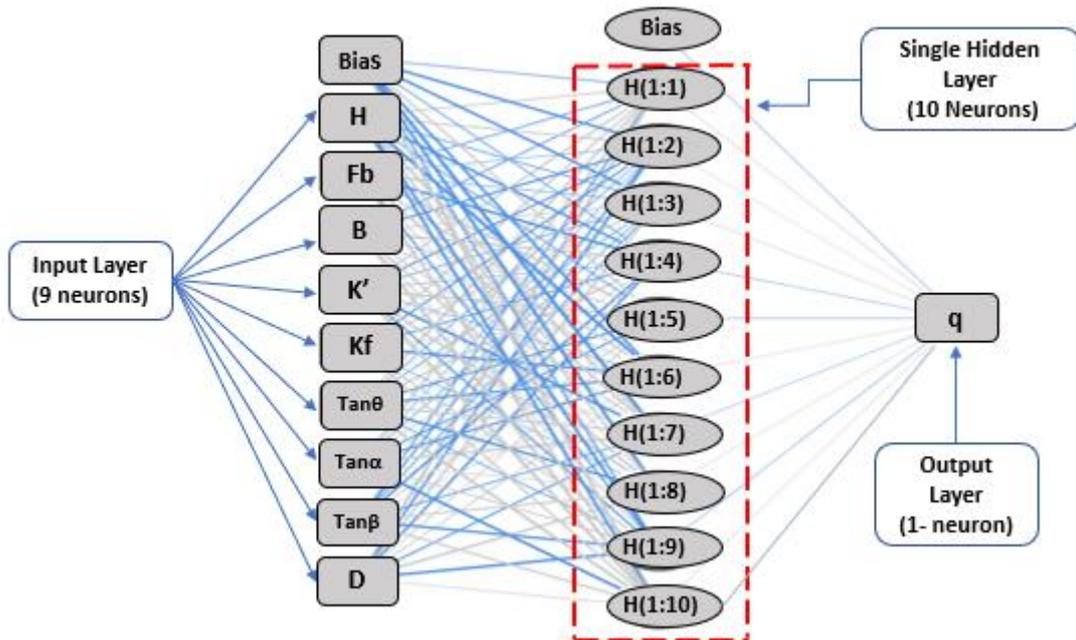


Figure 4.6: Detailed Architecture of suggested ANN Model

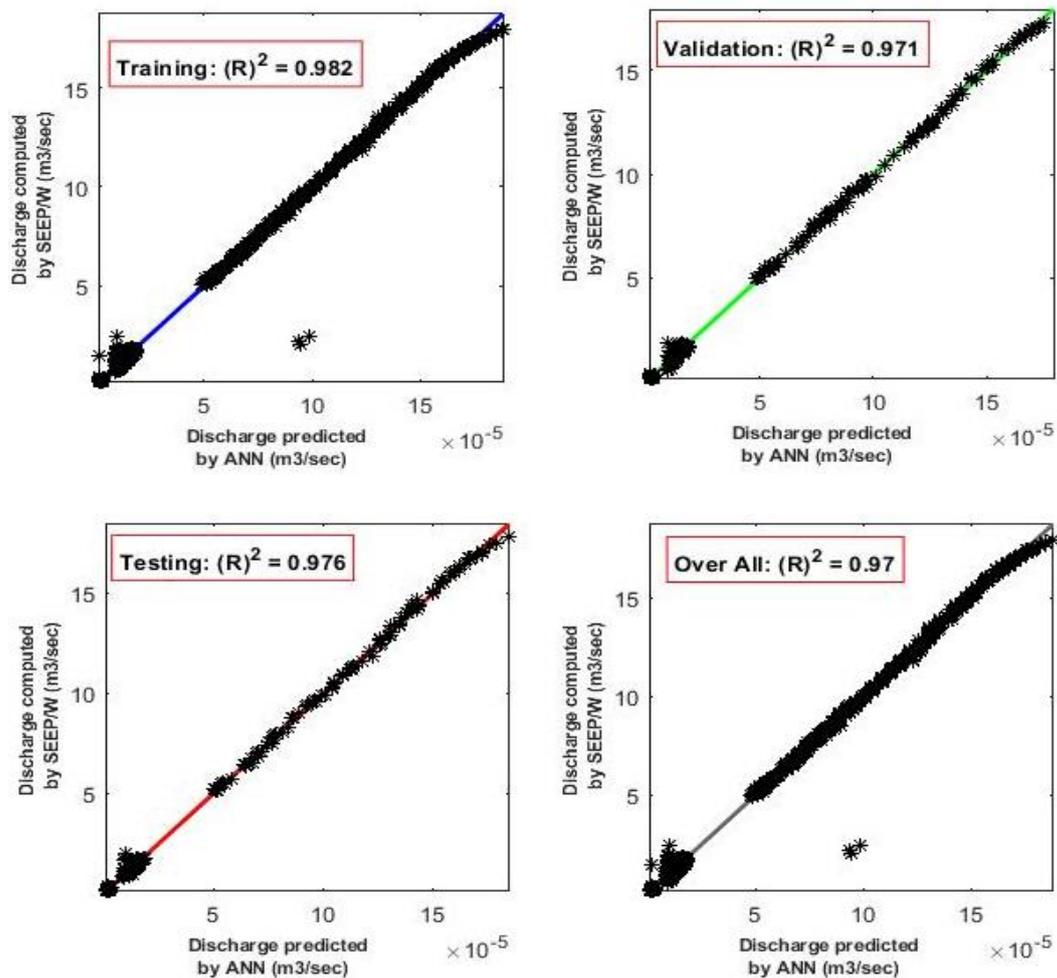


Figure 4.7: Comparison between observed seepage discharge from SEEP/W and predicted by ANN

Table 4.2: Summary of Well Trained MLP-ANN model for seepage prediction

Summary of developed MLP-ANN Model	
Network Type	Feed Forward Back-propagation MLP
Total Dataset	4374
Training Dataset	70% (3062)
Testing Dataset	30% (1312)
Neurons in the input layer	9 (No. of inputs)
“Hidden layers”	1
Neurons in the Hidden layer	10
Neurons in the output layer	1 (No. of Output)
“Training function”	“TRAINLM”
“Adaption learning function”	“LEARNGDM”
“Transfer function”	“PURELIN”

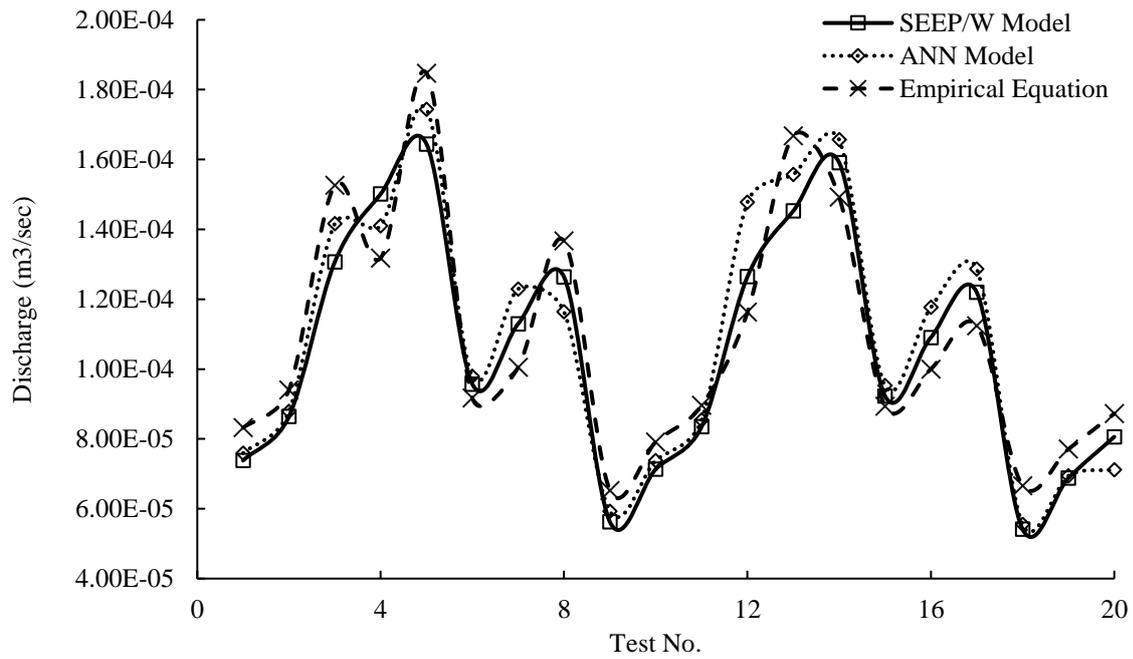


Figure 4.8: Comparison between the seepage discharges of randomly twenty tests with different methods:

Table 4.3: Performance of Machine Learning (ML) models for seepage prediction

Predictive Models	Coefficient of determination (R^2)	Mean absolute percentage error (MAPE%)	Average accuracy (AA%)
"MLP-ANN"	0.98	1.1	98.9
"Linear regression models"	0.83	5.3	94.7
"Regression trees"	0.79	4.5	95.5
"Support vector machine"	0.75	12.2	87.8
"Gaussian process regression models"	0.7	8.6	91.4
"Ensembles of trees"	0.8	4.9	95.1

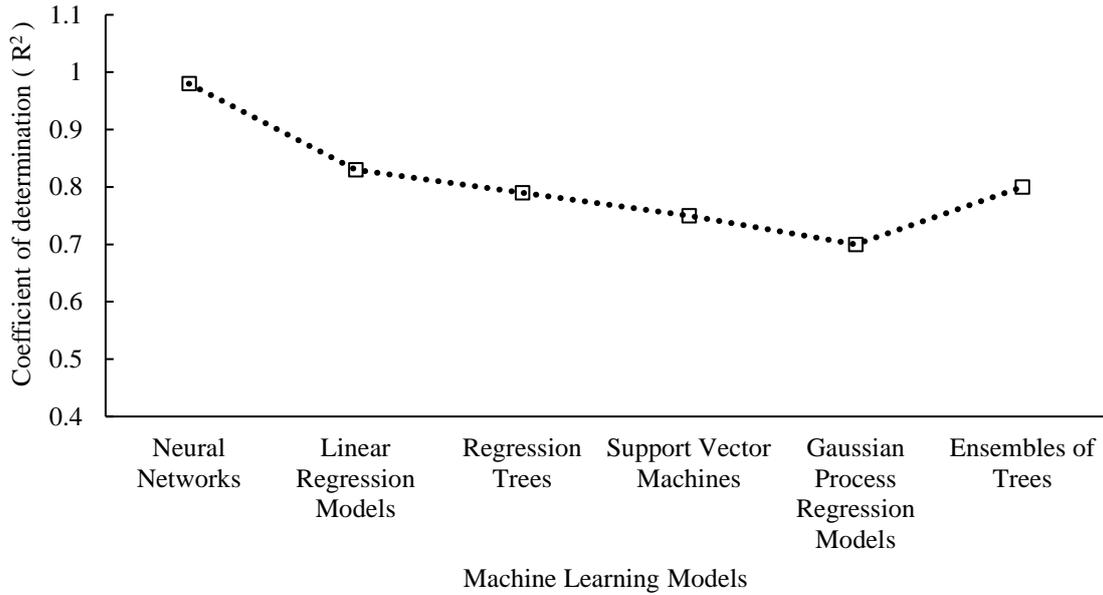


Figure 4.9: Performance of different machine learning models

4.4 Sensitivity Analysis

The sensitivity of night input variables ($\tan\theta$, $\tan\alpha$, $\tan\beta$, K_f , H , F_b , k' , B , D) affecting the rate of seepage was assessed using the Garson method. The relative importance, RI_i (in percentile), of the input neuron i , as given by Garson method is:

$$RI_i = \frac{|r_i|}{\sum_{i=1}^m |r_i|} \times 100 \quad (4.2)$$

The relative importance, RI , provides an index for evaluating the impact of each input parameters to the output parameter. Table 4.4 indicates the RI of nine input variables effecting the rate of seepage. Figure 4.10 shows the relative importance (RI) of input variables graphically. The analysis indicates that a minor change in the dam's height (H) brings a huge change in the rate of seepage with relative importance 31.26%. While variation in the upstream slope has least impact on the rate of seepage with relative importance 0.93%. The relative importance of downstream slope, free board, crest width, depth of pervious foundation, and permeability of foundation, is 1.01%, 11.39%, 10.35%, 3.19% and 6.41% respectively.

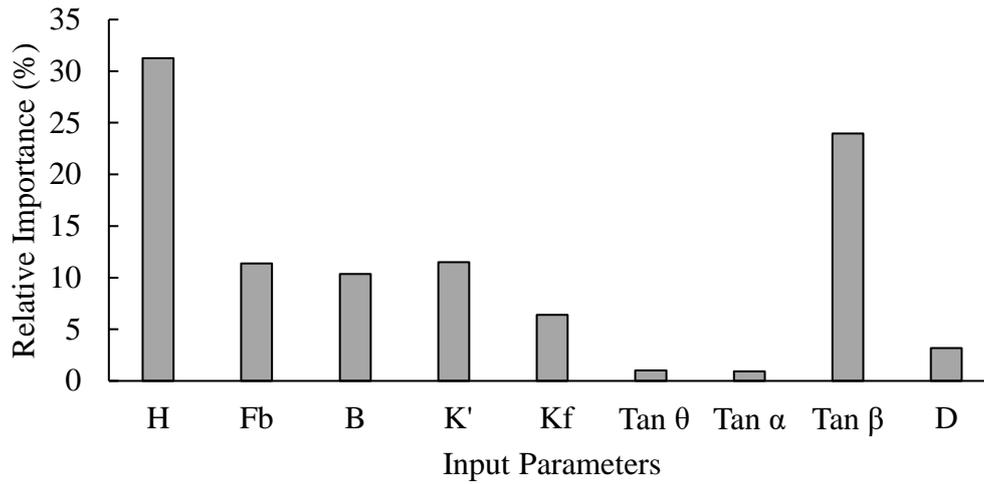


Figure 4.10: Relative importance of dam parameters effecting the rate of seepage

Table 4.4: Relative importance of input variables effecting the rate of seepage

Input Parameters	Relative Importance (RI %)
H: Dam's height (m)	31.26
Fb: Freeboard of the dam (m)	11.39
B: Crest width of the dam (m)	10.35
K': Permeability ratio of core to shell material i.e. (K_c/K_s)	11.51
Kr: Permeability of foundation material (m/sec)	6.41
Tan θ : Upstream slope	0.93
Tan α : Downstream slope	1.01
Tan β : Slope of core	23.95
D: Depth of pervious foundation (m)	3.19

Chapter 5

Conclusion

In the current research, seepage discharge through a non-homogenous earthen dam resting on pervious foundation was studied with the help of SEEP/W program. The comparison of seepage values obtained from SEEP/W program with the analytical equations of USBR (1987) and Rozanov (1978) reveal an average percentage error of less than 15 %. The following are the main outcomes of this research.

- A simple empirical equation was established for estimating the rate of seepage from a non-homogenous earthen dam lying on a pervious foundation. When the seepage values acquired via SEEP/W were compared to the quantity calculated from the proposed empirical equation, the coefficient of determination (R^2) was 0.96.
- A multilinear perceptron (MLP) has been found as a viable form of artificial neural network (ANN) for seepage prediction with a basic composition (9-10-1). When the seepage values acquired via SEEP/W were compared to the quantity calculated from the developed MLP-ANN model, the coefficient of determination (R^2) was found to be 0.971. Furthermore, the MLP-ANN model outperformed other machine learning models.
- The sensitivity of input variables ($\tan\theta$, $\tan\alpha$, $\tan\beta$, K_f , H , F_b , k' , B , D) affecting the seepage rate was assessed using the Garson method. The analysis indicates that a minor change in the dam's height (H) brings a huge change in the rate of seepage with relative importance 31.26%. While the same change in the upstream slope has least effect on the rate of seepage with relative importance 0.93%. The relative importance of downstream slope, free board, crest width, depth of pervious foundation, and permeability of foundation, is 1.01%, 11.39%, 10.35%, 3.19% and 6.41% respectively.

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