



MODELLING OF FUNCTIONAL PARAMETER OF EARTHEN DAM BREACH BY ARTIFICIAL NEURAL NETWORK AND RANDOM FOREST

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ABSTRACT

The paper investigates the modelling of functional parameter of earthen dam breach. The output values of breach depth of embankment dam were calculated by with the help of artificial neural network (ANN) and Random Forest (RF) modelling techniques. Two standard statistical potential evaluation calculated, such as the correlation coefficient (CC) and root mean square error coefficient (RMSE) have been utilized to judge the performance of modeling techniques. . Data set consists of 60 observations were obtained from the laboratory experiments. Out of 60 samples arbitrarily selected 42 observations were used for training whereas residual 18 were used for testing the models. Input data set consist of discharge, time and depth whereas width of dam is considered as output. A comparison of results suggest that random forest works well than artificial neural network (ANN) and it could successfully use in modelling of width of embankment dam.

Keyword: Breach formation, Random Forest, Artificial Neural Network, breach parameter.

I. INTRODUCTION

Embankments are constructed for the retention of water for irrigation and supply, and for protecting people, land, and property from flooding. Failure of any embankment poses risks to people and property nearby and the services provided by the embankment. A dam is a boundary that appropriates water or underground streams. Supplies made by dams smother surges as well as give water to exercises, for example, water system, human utilization, mechanical utilize, aquaculture, and safety. Hydropower is regularly utilized as a part of conjunction with dams to create power. A dam can likewise be utilized to collect water or for capacity of water which can be equally circulated between areas. Earth and rock fill dams are by and large used all through the world, and the vast majority of the past dam failure included such dams.

In specialized writing, dam failure examination is partitioned into two principle parts. In the first place, examination of the failure and breach process and, second, stream directing and extraction of the immersion maps because of dam break. The failure of a solid dam ordinarily happens quickly; be that as it may, then again, earthen dams step by step bomb because of the constant increment of an underlying break. For this situation, the yield hydrograph is identified with the disintegration condition that happens inside the rupture. Accordingly, the arrangement needs assist examination to study security administration of the dams. Distinctive reasons may lead to failure of an earth dam, for example, stream overtopping, funneling release, arrive slide, war and so on.;



however the initial two are the most widely recognized and vital causes. Although some dam failure because of stream overtopping have been now observed and investigated by water driven designers, there is as yet a need promote bits of knowledge into the wonder and to grow more powerful recreation models. As in an earth dam failure prepare the piping mode is changed to an overtopping mode after some time, the specific worry in this review is centered dam failure because of flow overtopping.

A few scientists have created recipes in view of discovery models and historical dam break information that have empowered them to anticipate rupture parameters, for example, time of breach arrangement, breach geometry and peak outflow from break. For example, Johnson and Illes (1976) were the first to predicted failure shapes for earth, gravity and curve solid dams. Additionally, MacDonald and Monopolis (1984), Singh and Snorrason (1984), FERC (1987), Von Thun and Gillette (1990) and Froehlich (1995) created equations to predict the time breach development and break geometry. Kirkpatrick (1977), the US Bureau of Reclamation (1982), Costa (1985), Froehlich (1995) and Webby (1996) have directed reviews to decide the peak outflow as a component of dam height and reservoir storage volume.

II. METHODOLOGY AND DATA SET

The tests were conducted in a straight flume 12m long, 0.4m wide and 0.60m deep (see Figure 1). In this water recirculation during experiments, this flume had a silt trap toward one side and a water channel at the other side. The breach develops mainly vertically with only ignorable widening due to limited width of flume. To get test information on the breaching of overtopped homogeneous embankment, small scale physical investigations were conducted at research laboratory. In whole experiments discharge were keep constant. A homogeneous bank show comprising of material was utilized on a fixed bed. The breach procedure was started by overtopping the embankment crest. Each test was performed under identical pore volume and moisture content. Two modeling approaches, ANN and Random Forest were applied on the experimentally observed data (Table 1) to predict the value of width of embankment dam. The detailed description of the applied modeling approaches are described in next section. Data set consists of 60 observations were used and Obtained from the laboratory experiments. Input data set consists of discharge, depth and time whereas width of dam was considered as output. The characteristics of experimental data are specified in Table 1

Table 1: The characteristics of training and testing data set

| Input parameters | units | Training data | | | |
|------------------|---------|---------------|-------|--------|---------------|
| | | Min. | Max. | Mean | Standard Dev. |
| Discharge | m^3/s | 25 | 25 | 25 | 0 |
| Time | min | 0.5 | 290.6 | 145.55 | 205.131 |
| Depth | cm | 1.23 | 19.12 | 10.175 | 12.650 |
| Width | cm | 2.3 | 20.8 | 11.55 | 13.081 |
| | | Testing data | | | |
| | | Min. | Max. | Mean | Standard Dev. |
| Discharge | m^3/s | 25 | 25 | 25 | 0 |



| | | | | | |
|--------------|-----|-------|-------|---------|---------|
| Time | min | 0.333 | 360.5 | 180.416 | 254.676 |
| Depth | cm | 1.98 | 18.63 | 10.305 | 11.773 |
| Width | cm | 2.4 | 19.8 | 11.10 | 12.303 |

III. ANN MODELLING TECHNIQUE

Artificial neural network (ANN) is an elastic numerical structure, which is able to identify the complex nonlinear associations between input data sets to output data sets (Onen, 2014). It is inspired by the functioning of nervous system and brain architecture. The networks comprise a huge no. of simple processing element linked to each other by weighted connections according to specified architecture. It has one input, one or more hidden and one output layers. Each layer consists of number of nodes and the weighted connection between these layers represents the link between nodes. Input layers having nodes equal to number of input parameters, distributes the data presented to the network and does not help in processing. This layer follows one or more hidden layers which help in processing of data. The output layer is final processing unit. Artificial neural networks are computational methodologies that perform complex analyses. The purpose of most favorable number of hidden layers and hidden neurons is regularly cumbersome, as no general methodology is accessible for their determination. Many applications of artificial neural networks have been reported in the literature, and applications in medicine are growing. The artificial neural system (ANN), with the error back-spread technique, is at the origin of an interesting methodology similar with regression examination, yet especially productive for non-linear information (Lendasse et al., 2000). In the last decade, research into ANNs has shown explosive growth. They are often applied in physics research like speech recognition (Chu, 1998) and image recognition (Dekruger and Hunt, 1994; Kung and Taur, 1995). A large number of trials have been carried out to find the optimal values of parameter of ANN. The optimal parameters were selected on the basis of statistical parameters (C.C. and RMSE). Table 2 shows the optimal values of user-defined parameters of ANN.

Table 2: Optimal values of user-defined parameters of ANN

| Learning rate | Momentum | Hidden layer neuron | No. of iterations |
|----------------------|-----------------|----------------------------|--------------------------|
| 0.3 | 0.2 | 4 | 100 |

IV. RANDOM FOREST REGRESSION

Random forest is a classification and regression process, consisting of a combination of tree predictors where every tree is produced utilizing a random vector sampled autonomously from the input vector. In regression, tree predictor proceeds on numerical values as arbitrary to class labels used by the random forest classifier (Breiman, 1999). Random forest regression used in present study consists of using a combination of variables or randomly selected variable at each node to mature a tree. Plan of a tree predictor required the decision of a variable choice measure and a pruning strategy. Different approach to manage the decision of variable for tree acknowledgment is proposed in writing and most methodologies dole out a quality measure specifically to the variable. The most



regularly utilized variable choice measures in tree enlistment are Information Gain Ratio basis (Quinlan1992) and Gini Index (Brieman et. al., 1984).

The plan of random forest regression allows a tree to create to the most extreme depth of new preparing information utilizing the mixing of factors. These full-created trees are not pruned back. This is one of the primary favourable circumstances of random forest regression over other tree systems like M5P tree show (Quinlan 1992). Thinks about recommend that the choice of the pruning procedure and not the variable assurance, impact the execution of tree based calculations (Pal and Mather, 2003). Breiman (1999) proposes that as the amount of trees builds, the theory mistake dependably focalizes even without pruning the tree and over fitting is not an issue in perspective of the Strong Law of large numbers (Feller, 1968).

V .ANALYSIS OF RESULTS

To assess the effectiveness of ANN model and RF model in predicting width of the embankment dam. Correlation coefficient (C.C.) and root mean square error (RMSE) values obtained with test data set were used to compare the performance of ANN with RF. Table 3 provides the values of the correlation coefficient and RMSE values provided by different predictive approaches. Comparison of results suggests improved performance by ANN regression in terms of C.C., RMSE values used with this data set. A substantial improvement in predictive accuracy of ANN approach indicates that it can be effectively used in predicting of width of dam. Fig. 1 and 2 shows the agreement of actual and predicted width of embankment dam for training and testing data set using ANN shows the agreement diagrams of actual and predicted width of embankment dam using ANN and RF respectively.

Table 3: Detail of performance evaluation parameters using RF and ANN of training and testing data set

| Modeling Approach | Training | | Testing | |
|-------------------|----------|--------|---------|--------|
| | C.C | RMSE | C.C | RMSE |
| RF | 0.9957 | 0.5075 | 0.9916 | 0.7814 |
| ANN | 0.9913 | 0.7401 | 0.9942 | 0.6152 |

Fig. 3 and 4 shows the agreement of actual and predicted width of embankment dam for training and testing data set using Random Forest (RF) respectively. The values of correlation coefficient 0.9957, 0.9916 and values of Root Mean Square Error 0.5075, 0.7814 were achieved for training and testing data set using Artificial Neural Network respectively. Fig. 5 indicates that the performance of RF is better than ANN in training and testing period. RF estimated values is closer the actual values and follows the same path of actual values.

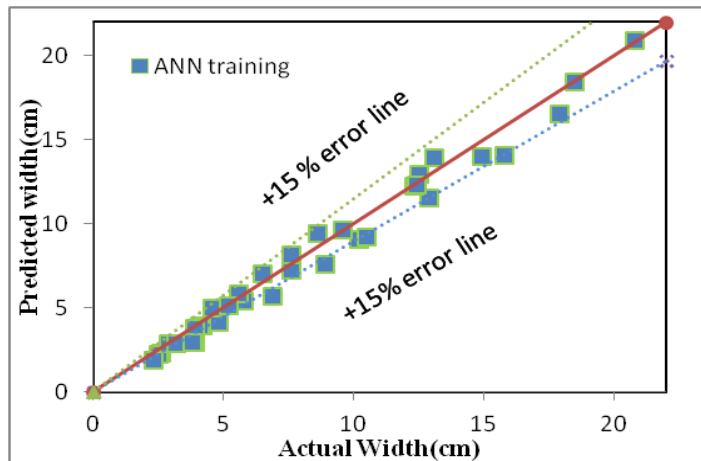


Figure 1: actual vs. predicted values of width of embankment dam using ANN model with training data

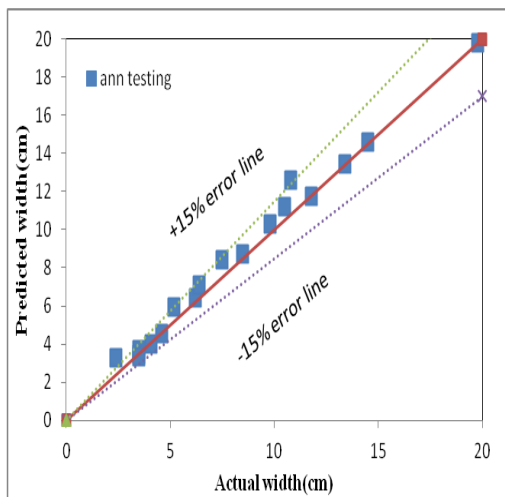


Fig 2: actual vs. predicted values of width of embankment dam using ANN model with testing data

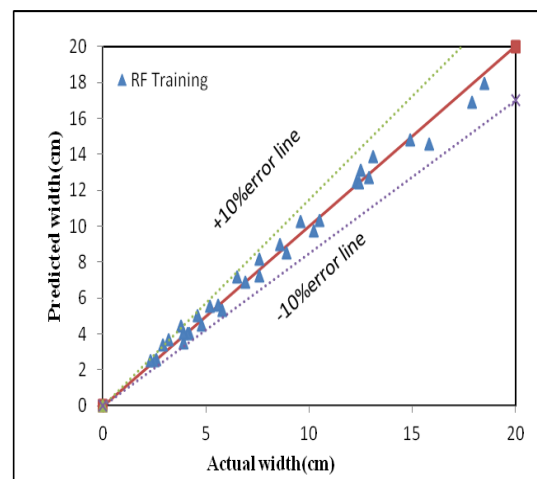


Fig 3: actual vs. predicted values of width of embankment dam using RF model with training data

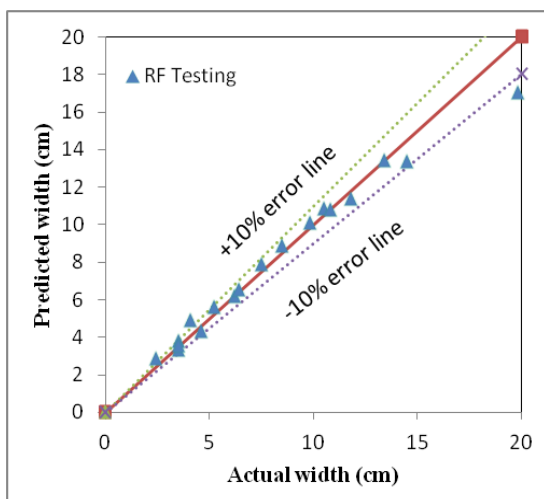


Fig 4: actual vs. predicted values of width embankment dam using RF model with testing data

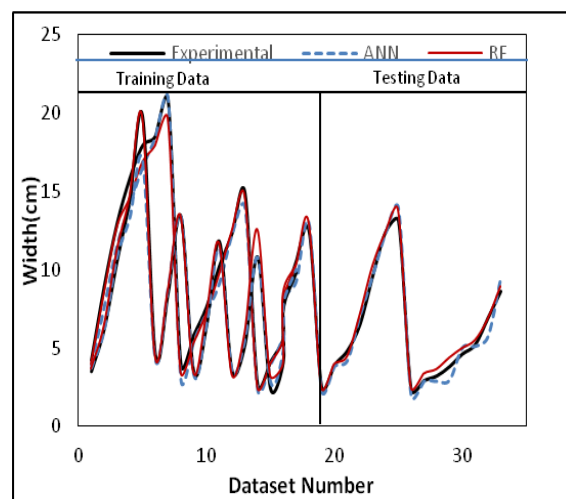


Fig 5: Variation in predicting values of width of embankment dam using the different regression approach in comparison to actual values of width of embankment dam



VI. CONCLUSION

This paper examines the potential of artificial neural network (ANN) and random forest (RF) approaches in predicting the width of embankment dam. From the comparison of performance evaluation parameters, it has been observed that RF approach works well than ANN. It can be successfully used in estimation width of embankment dam.

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