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Closure to “improving prediction of dam failure peak outflow using neuroevolution combined with k-Means clustering” by Amir Hossein Eghbali, Kourosh Behzadian, Farhad Hooshyaripor, Raziye Farmani, and Andrew P. Duncan

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1        **Closure to Discussion of “Improving Prediction of Dam Failure Peak Outflow Using**  
2        **Neuroevolution Combined with K-Means Clustering” by Amir Hossein Eghbali, Kourosh**

3                **Behzadian, Farhad Hooshyaripor, Raziye Farmani, and Andrew P. Duncan,**

4                                **July 2017, Vol. 22, No. 6.**

5                                **DOI: 10.1061/(ASCE)HE.1943-5584.0001505**

6                                **By Farhad Hooshyaripor<sup>1</sup> and Kourosh Behzadian<sup>2</sup>**

7  
8        The authors would like to first thank the discussor for making three constructive comments which  
9        can be divided into two groups: (1) comments 1 and 2 related to clarity of a function used in the  
10       model developed and accuracy of the data collected; (2) comment 3 related to the ability of the  
11       developed model to predict new peak discharges of dam failure. To close the discussion and further  
12       clarification, the following are noted for each of the comments:

13  
14       **Comment #1:**

15       The authors of the original paper (Eghbali et al. 2017) applied MATLAB tool as a platform to  
16       generate and combine artificial neural network (ANN) with genetic algorithm (GA) and *k*-means  
17       clustering. However, due to the combination of ANN and GA, the standard ANN as noted by the  
18       discussor was not used and instead all steps were coded in MATLAB. Thus, the tangent sigmoid  
19       (*tansig*) transfer function used in the paper for generating ANN was not the default MATLAB

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20 function denoted as *tansig*(n) in MATLAB. Instead, The following *tansig* transfer function was  
21 used in the paper (Araghinejad 2014):

$$22 \quad \textit{tansig}(x) = 2/(1+e^{-ax})-1=(1-e^{-ax})/(1+e^{-ax}) \quad a>0 \quad (1)$$

23 where  $a$  = constant parameter which was considered 1.

24 The authors did not carry out sensitivity analysis for parameter  $a$  but even if the default MATLAB  
25 function is used instead (i.e.  $a=2$ ), it is unlikely to lead to less accurate predictions although  
26 different weights and biases may be obtained for the same database.

27

## 28 **Comment #2:**

29 The discussor highlighted the importance of the discrepancy of peak flow rates from the failure of  
30 three dams (i.e. Oros Dam in Brazil, Banqiao Dam in China and Hell Hole Dam in the United States)  
31 reported by the original paper and other publications. As the accurate data is of paramount  
32 importance to the results, the authors endeavoured to collect the data from different sources and  
33 impartially pick up those that were widely used. More specifically, failure peak flow rate of Oros  
34 Dam used in the paper (i.e. 9,630 m<sup>3</sup>/s) has been reported by several sources (e.g. Wahl 1998; Xu  
35 and Zang 2009; Pierce et al. 2010; and Thornton et al. 2011) while the value expressed by the  
36 discussor (i.e. 58,000 m<sup>3</sup>/s which is around 6 times larger) can be found in only few works (e.g.  
37 Wahl 2014). In addition, the peak flow rate of 56,300 m<sup>3</sup>/s for the Banqiao Dam failure was only  
38 used by the discussor's publication while peak flow rate of 78,000 m<sup>3</sup>/s was reported by many  
39 independent researchers (e.g. Fujia and Yumei 1994; Xu and Zhang 2009; Pierce et al.  
40 2010; Thornton et al. 2011). Due to large amount of peak discharge in these two data samples (i.e.  
41 Banqiao and Oros Dams), we also agree that the major difference in the collected data can directly

42 affect any developed model. For example, Banqiao Dam failure is an important data sample due  
43 to having the highest peak discharge in the database. Also, the original paper used the widely-  
44 reported value of 7,360 m<sup>3</sup>/s for Hell Hole dam failure (MacDonald and Langridge-Monopolis  
45 1984; Wahl 1998; Xu and Zhang 2009) while peak discharge of 17,000 m<sup>3</sup>/s has only been used  
46 by the discussor. In addition, the frequency of the 92 data samples analysed in the paper shows  
47 that most of the observed peak flow discharges are less than 10,000 m<sup>3</sup>/s (Hoosyaripor et al. 2014).  
48 In this dataset, there are only one peak discharge over 70,000 m<sup>3</sup>/s, 2 cases over 60,000 m<sup>3</sup>/s, 3  
49 cases over 30,000 m<sup>3</sup>/s and 7 cases over 20,000 m<sup>3</sup>/s among 92 data samples.

50 It should also be noted that there is only one predictive model which is trained for all clusters using  
51 90% of all data samples, not based on the data samples in one cluster (e.g. Oros and Banqiao  
52 Dams) as noted by the discussor. In addition, due to insufficient data available (92 samples),  
53 conventional model verification (i.e. dividing database into two subsets of training and test) was  
54 inefficient. Hence, the cross-validation technique was used in the paper, implying that all 92 data  
55 samples were participated in the evaluation of the test set (see “Assessment of Performance  
56 Indicators” section in the original paper).

57

58 **Comment #3:**

59 The comment challenges overfitting of the clustered ANN-GA model. As noted by the discussor,  
60 overfitting often occurs when the number of hidden neurons is large (i.e. model is excessively  
61 complex) while the proposed model has only four neurons which is far less than the number of  
62 data pairs (i.e. 82-83 equal to 90% of data samples). In other words, if the number of parameters  
63 in the ANN is much smaller than the total number of points in the training set which is the case in

64 the paper, there is little chance of overfitting (MATLAB). Also, to avoid overfitting, conventional  
65 ANNs divide the database into two subsets of training and validation, in which the training dataset  
66 will only participate in the model training. Then, the ANN training will carry on to improve the  
67 fitness on training dataset until the mode performance on validation dataset (i.e. independent and  
68 unseen data) is deteriorating. Similarly, the cross-validation technique was used in the proposed  
69 model as unseen data to avoid overfitting during the model training (Eghbali et al. 2017).

70 Furthermore, the authors totally agree with the trends of the profile traces shown in the discussion  
71 for the model developed. However, the reason for the unexpected functional responses in some  
72 profile traces cannot be attributed to a flaw or overfitting in the developed model but it is related  
73 to the discrepancy of the collected data. More specifically, cluster #1 has only two members (i.e.  
74 Oros and Banqiao Dams) in which the profile trace for constant value of  $H_w$  is the opposite of the  
75 expected function response (Fig. 1a in the discussion paper). When looking at the data of these  
76 two dams, it is apparent that given relatively similar  $H_w$  around 33m for both dams and a large  
77 water volume above the breached invert ( $V_w$ ) in Oros Dam (660 mcm) compared to Banqiao Dam  
78 (607.5 mcm), the peak flow discharges are considerably opposite (78,100 m<sup>3</sup>/s for Banqiao Dam  
79 compared to 9,630 m<sup>3</sup>/s for Oros Dam). The other unexpected functional response is related to  
80 variation of  $Q_p$  with  $V_w$  in cluster #3 (Fig. 1c in the discussion paper) which has 3 members.  
81 Similar discrepancy can be observed within the dataset of these members. More specifically,  
82 coefficient of determination ( $R^2$ ) between  $V_w$  and  $Q_p$  is significantly low (i.e.  $R^2=0.21$ ) (Eghbali et  
83 al. 2017). Interestingly, the correlation between  $H_w$  and  $Q_p$  in the members of the same cluster is  
84 very strong (i.e.  $R^2=0.98$ ) which also confirms the profile trace shown in Fig. 2c in the discussion  
85 paper. Similar correlation is in place for the last expected functional response (i.e. Fig. 1d of the  
86 discussion paper related to variation of  $Q_p$  with  $V_w$  in cluster #4. Although this cluster has

87 relatively large number of data samples (i.e. 18 members), a weak correlation is observed between  
88 the members (i.e.  $R^2=0.02$ ).

89 As can be seen in the above discussion, most of the inaccuracies and unexpected functional  
90 responses are mainly referred to the discrepancies between the data collected. Although the highly  
91 controversial data (e.g. the data in clusters #1 and #3 and some of the uncorrelated/outlier data in  
92 cluster #4) can be simply removed and the problem can be apparently solved, the authors do not  
93 recommend it due to the limited number of data available. Instead, the key message of the original  
94 paper is to identify the similar attributes of the data and conduct data clustering to recognize  
95 different specifications and predict their peak failure flows more accurately than the previously  
96 developed models including conventional regression models.

97 In addition, it seems to be inappropriate to stand by for future dam failures to enrich the quality  
98 and quantity of the database of dam failure as it will be unlikely to observe these catastrophic  
99 phenomena frequently in the future due to the advance in monitoring systems. Therefore, although  
100 some data collected from various breach cases may seem to be statistically chaotic, every piece of  
101 data may reveal information of high relevance (Gupta and Singh 2012) and hence they should not  
102 be changed/removed in favour of achieving a better correlation of the developed model for dam  
103 failure analyses.

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