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Cavitation Damage Prediction on Dam Spillways using Fuzzy-KNN Modeling

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ABSTRACT

The present paper deals with a numerical method for prediction of cavitation damage level and location on dam spillways. A method was applied to predict the intensity of cavitation damage to spillways, using the fuzzy k-nearest neighbor algorithm. Five levels of damage intensity were considered to predict cavitation damage in the spillway of Karun-1 Dam in Iran. According to the results, the proposed model could properly predict the location and intensity of damage in comparison with the actual damage reports of past floods. According to the Pearson's correlation coefficient, mean absolute error, coefficient of residual mass, and normalized root mean square error, the fuzzy k-nearest neighbor model is efficient and suitable.

Keywords: Cavitation damage; Spillways; *Fuzzy k*-nearest neighbor model; Damage intensity.

NOMENCLATURE

C	number of Classes
k	number of Nearest Neighbors
n	number of attributes
P	reference flow pressure
P_V	water vapor pressure
V	reference flow velocity
X	training set samples
Y	test data set
μ	the membership degree
θ	spillway angle to horizontal axis
ρ	fluid density
σ	cavitation index
σ_i	cavitation inception index
$\sigma(x)$	standard deviation

1. INTRODUCTION

Spillways are important hydraulic structures, designed for frequent use in conveying both normal and flood releases. They are used to prevent dam overtopping and provide adequate stability and safety during floods (Chow, 2009). Surface irregularities and high-flow velocities on spillways can cause low pressure, result in cavitation, and induce damage over time. Cavitation damage on the structure surface is usually predicted using cavitation index (Eq. (1)). For prevention of damage on a hydraulic structure, $\sigma > \sigma_i$ is required everywhere on the structure (Falvey, 1990 and Khatsuria, 2005).

$$\sigma = \frac{P - P_v}{\rho \frac{V^2}{2}} \tag{1}$$

Where σ is cavitation index, σ_i is cavitation inception index, ρ is the water density, P_v is the water vapor pressure, P is the reference flow pressure, and V is the reference flow velocity.

As cavitation damage has been one of the major engineering concerns about dam spillways, many efforts have been made to verify the damage mechanism. Ramamurthy *et al* (1984), Nie (2001), Momber (2004), Dong *et al.* (2008), Fufeng and Deming (2011) and Frizell *et al.* (2013) have investigated cavitation damage occurrence on dam spillways using experimental modeling under controlled laboratory conditions. Moreover, numerical modelling such as: Falvey (1990), Yuan and Schnerr (2003), Bilušn *et al.* (2007), Dular and Coutier-Delgosha (2009) and Luo *et al.* (2012) have successfully simulated and investigated flow characteristics and cavitation formation.

Falvey (1990) introduced the WS-77 software to

Table 1 The Karun-1 dam characteristics

Type	Length (m)	Height (m)	Reservoir capacity (million m^3)	Type of spillway	Maximum water level (m)	Capacity of spillway (m3/s)
Double curvature concrete	380	200	3000	Ski-chute with gate	530	16500

investigate the mechanism of cavitation damage on spillways. The measurements showed that for all surface irregularities, the cavitation inception index is between 0.076 and 1.2. Yuan and Schnerr (2003) proposed a new model to investigate the cavitating nozzle flow potent interaction with the beyond jet formation using the volume-of-fluid (VOF) method. Bilušn *et al.* (2007) presented a numerical cavitation model to investigate cavitating flows and bubbles formation process. The results obtained by the model were validated with experimental flow examples. Dular and Coutier-Delgosha (2009) examined the possibility of cavitation erosion detection in a hydrofoil using the CFD method. Luo *et al.* (2012) numerically investigated the aeration devices effect on cavitation formation in tunnel spillways using a segmentation algorithm.

According to the past research on the cavitation phenomenon, a method which can predict the extent and location of cavitation damage on spillways is needed. In the present study, for predicting the level and location of cavitation damage to the spillways, a method is utilized using fuzzy k-nearest neighbor (kNN) algorithm. The results of this method are in agreement with the measures of cavitation damage in this phenomenon.

2. FUZZY-KNN ALGORITHM

In data mining and pattern recognition, kNN algorithm is a popular nonparametric instance-based machine learning algorithm (Li and Deogun, 2009). Keller *et al.* (1985) introduced a fuzzy standard kNN model by integrating the fuzzy set theory into the algorithm (fuzzy-kNN). Both fuzzy-kNN and kNN algorithms require the analysis of similarity between the labeled instances in the training set and a new query instance (unknown instance). By finding a set of kNNs and casting a vote on the query instance class, the unknown instance is categorized in a class through combining the votes (Roh *et al.*, 2010 and Derrac *et al.*, 2016).

In the fuzzy-kNN approach, a fuzzy membership function of samples is assigned to different categories rather than individual classes (similar to the kNN algorithm) (Derrac *et al*, 2014). Let *X=(x_1,x_2,…,x_n)* is a training set composed of "n" samples which belong to C classes. For a new query instance Y, a cluster of kNN class attributes can be used to predict class confidence values, using the following equation (Keller *et al.*, 1985):

$$u_i(y)=\frac{\sum_{j=1}^{k}\mu_{ij}(1/\|y-x_j\|^{2/(m-1)})}{\sum_{j=1}^{k}(1/\|y-x_j\|^{2/(m-1)})} \tag{2}$$

where i=1,2,…,C and j=1,2,…, k. To increase the distance of query instances from the elements of the training dataset, the fuzzy strength parameter, m, is used. Its value can be selected as $m\in(1,+\infty)$, which is usually 2 (Derrac *et al*, 2016). $\|y-x_j\|$ is the Euclidean distance of y from its j^{th} nearest neighbor from the training data x_j. In addition, μ_{ij} is the membership degree of instance x_j from the training set in class i, which satisfies the following relations:

$$\mu_{ij}\in[0,1] \tag{3-a}$$

$$0<\sum_{j=1}^{k}\mu_{ij}<k \tag{3-b}$$

$$\sum_{i=1}^{c}\mu_{ij}=1 \tag{3-c}$$

where $1\le i\le C$ and $1\le j\le k$

There are different techniques to define μ_{ij}. In a crisp labeling, each instance has full membership in its determined class and non-membership in others. The kNNs of each training set data (x_k) are determined in constrained fuzzy membership, and x_k membership in each class can be evaluated with the following membership equation (Keller *et al*, 1985):

$$\mu_{ij}(x_k)=\begin{Bmatrix}0.51+\left(\frac{n_j}{K}\right)*0.49, & if\ j=i\\ \left(\frac{n_j}{K}\right)*0.49, & otherwise\end{Bmatrix} \tag{4}$$

where n_j represents the neighbor's number fitting the j^{th} class. This fuzzy scheme causes no arbitrary assignments. Additionally, membership values of the vector should provide adequate assurance for outcome classification.

3. MODEL PROCESSING AND APPLICATION

Data from Karun-1 Dam spillway (Shahid Abbaspour) were used to examine the model. This dam is a double-curvature concrete dam on Karun River, Khuzesten, Iran. Table 1 indicates some of the dam characteristics. The dam chute spillway is comprised of 3 bays (width, 18.5 m), controlled by radial gates (dimension, 20m×15 m) (Mahab Ghodss, 2003).

There are numerous reports of cavitation damage in the operation history of this spillway. In 1977, the first cavitation damage occurred in the spillway, causing damage to the ending spillway regions and flip-bucket. In 1993, the most important cavitation damage was reported in a flood of nearly 92 $m^3/s/m$ (Kiamanesh, 1996).

According to numerical models, flow characteristics including pressure, velocity, and depth for various flow rates were determined along the spillway (Fadaei-Kermani and Barani 2014). The values of

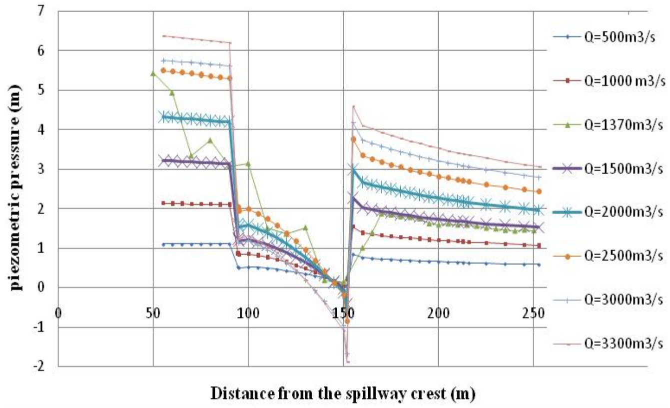

Fig. 1. The values of piezometric pressure for different flow rates.

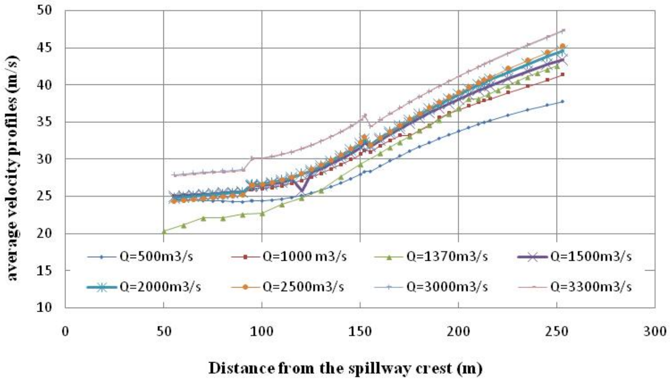

Fig. 2. The profiles of average flow velocity for different flow rates.

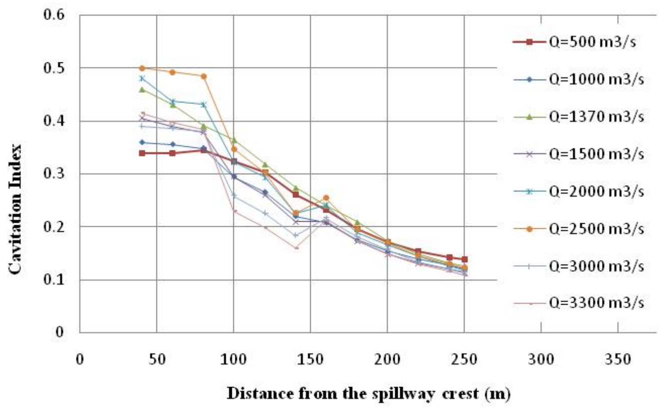

Fig. 3. The values of cavitation index for different flow rates.

piezometric pressure along the spillway and average velocity profiles for 8 different flow rates are shown in Fig. 1 and 2. The flow cavitation index can be calculated using Eq. (1), which is expressed as Eq. (5) on the spillway surface.

$$\sigma = \frac{\frac{P_{At}}{\gamma} - \frac{P_v}{\gamma} + h\cos\theta}{\frac{V^2}{2g}} \tag{5}$$

where atmospheric pressure ($\frac{P_{At}}{\gamma}$) is 10.33 m water height, $\frac{P_v}{\gamma}$ is water vapor pressure equal to 0.25 m water height at 20°C (2450 pascals), and θ is the chute horizontal angle. Figure 3 indicates the results of cavitation index along the spillway.

4. RESULTS AND DISCUSSION

The extent and location of cavitation damage on Karun-1 Dam spillway was predicted with a fuzzy-kNN model. At the beginning of modeling, it is necessary to normalize the data to prevent bias towards an attribute. Using Eq. (6), all input data can be transformed to determine variables with standard deviation of 1 and mean of 0 (Xindung and Kumar, 2009).

$$X' = \frac{x - \bar{x}}{\sigma(x)} \tag{6}$$

where X' is the normalized value of the attribute, $\sigma(x)$ represents the standard deviation, and $\bar{x}$ denotes the mean of attribute in the reference set. Overall, 5 levels of damage (from no damage to major damage) are determined using the cavitation index to identify the risk of damage to the spillway surface. The damage level intervals were characterized according to the cavitation damage intensity, and analyses were conducted on damage mechanisms in the spillway. Table 2 shows the levels of cavitation damage (Kermani *et al*. 2013).

Table 2 Cavitation damage level intervals (Fadaei-Kermani *et al.* 2013)

cavitation index	Cavitation damage risk	level
$\sigma > 1$	No cavitation damage	1
$0.45 < \sigma \leq 1$	Possible cavitation damage	2
$0.25 < \sigma \leq 0.45$	Cavitation damage	3
$0.17 < \sigma \leq 0.25$	Serious damage	4
$\sigma \leq 0.17$	Major damage	5

Due to the results of numerical modeling, the flow pressure and velocity values for all flow rates were measured in every 0.5 m along the spillway length. Moreover, the cavitation index values were also calculated respectively. So the database consists of about 9648 data of the pressure, velocity and cavitation index values. Since the cavitation damage level intervals have been determined relying on cavitation index; so the model main attributes are the values of cavitation index for all different flow rates along the spillway.

The model starts by calculating the distance between the attributes, sorting, and labeling each query. Then, the number of the closest neighbors (k parameter) is identified. Using n-fold cross-validation, the best value of k parameter can be determined (Hastie *et al*. 2008). The k-value was measured with 3-fold cross-validation. The precision of the method is shown in Fig. 4, considering the sum of squared errors (SSEs). As it can be seen, k values equal to 15 and 18 produced the lowest errors. Therefore, k=18 is chosen in the model, as larger values of k often minimize the overfitting risk. After calculating the number of *k* nearest neighbors, fuzzy kNN modeling can be applied to determine the intensity of cavitation damage to the spillway. Figure 5 shows the fuzzy kNN algorithm used to predict cavitation damage.

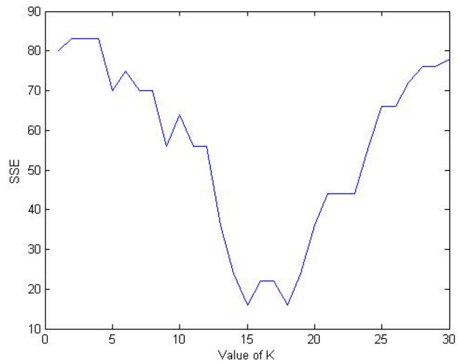

Fig. 4. Threefold- cross validation error estimation.

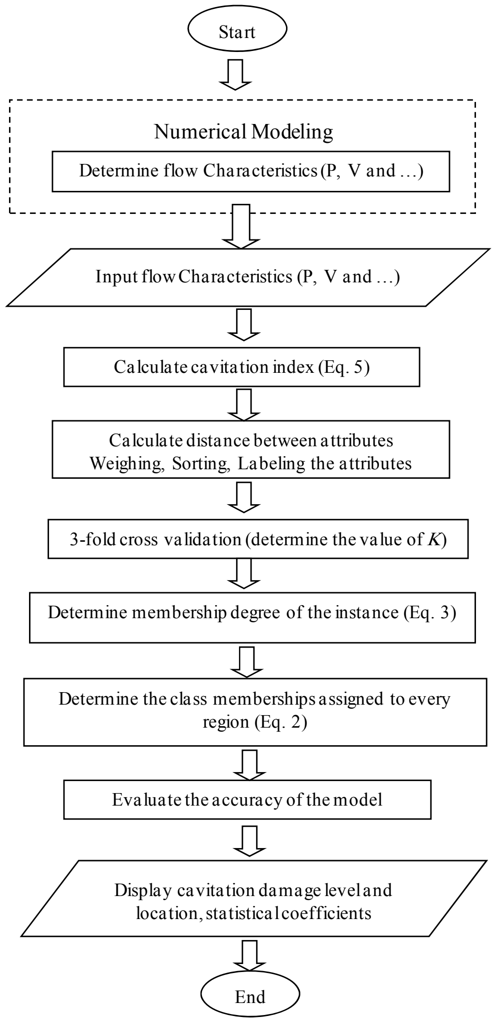

Fig. 5. The fuzzy kNN model algorithm for cavitation damage prediction.

In this study, the fuzzy kNN algorithm was used to determine the risk of cavitation damage. The structure of spillway can be divided into 10 regions from 50 m beyond the crest of spillway to the end of flip bucket. Table 3 shows the predicted cavitation damage intensity and risk along the spillway. Conforming to the results of fuzzy kNN model, the spillway would face the risk of cavitation damage (most probably serious to major

Table 3 Cavitation damage risk predicted by the fuzzy kNN model

Region	Assigned membership to each cavitation damage level				
	Level 1	Level 2	Level 3	Level 4	Level 5
Region 1 From ST. 50m to ST. 70m	0.0000	0.0075	0.9925	0.0000	0.0000
Region 2 From ST. 70m to ST. 90m	0.0000	0.6775	0.3225	0.0000	0.0000
Region 3 From ST. 90m to ST. 110m	0.0000	0.0000	0.7517	0.2483	0.0000
Region 4 From ST. 110m to ST. 130m	0.0000	0.0000	0.1965	0.7773	0.0262
Region 5 From ST. 130m to ST. 150m	0.0000	0.0000	0.0000	0.0662	0.9338
Region 6 From ST. 150m to ST. 170m	0.0000	0.0000	0.0000	0.6553	0.3447
Region 7 From ST. 170m to ST. 190m	0.0000	0.0000	0.0000	0.3864	0.6136
Region 8 From ST. 190m to ST. 210m	0.0000	0.0000	0.0000	0.1800	0.8200
Region 9 From ST. 210m to ST. 230m	0.0000	0.0000	0.0000	0.0000	1.0000
Region 10 From ST. 230m to ST. 250m	0.0000	0.0000	0.0000	0.0000	1.0000

damages), and major damage to the ending regions of chute might happen (distance of 210 to 250 m from the crest of the spillway). Comparison of the fuzzy-kNN model with crisp labeling (Fadaei-Kermani *et al.,* 2015) showed that the present model provides more plausible predictions of damage to the spillway. According to reports of actual cavitation damage to Karun-1 Dam spillway in previous floods, the proposed model can reasonably predict the intensity and location of cavitation damage.

Statistical coefficients including normalized root mean square error (NRMSE), Pearson's correlation coefficient (r), coefficient of residual mass (CMR), and mean absolute error (MAE) were measured to analyze the precision and efficiency of the model. The statistical coefficients were calculated as follows (Gelman *et al,* 2014).

$$r = \frac{n[\sum_{i=1}^{n} y_i x_i] - [\sum_{i=1}^{n} y_i][\sum_{i=1}^{n} x_i]}{\sqrt{[n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2][n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2]}} \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \tag{8}$$

$$RMSE = [\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}]^{0.5} \tag{9}$$

$$NRMSE = \frac{RMSE}{x_{\max} - x_{\min}} \tag{10}$$

$$CRM = \frac{(\sum_{i=1}^{n} x_i) - (\sum_{i=1}^{n} y_i)}{\sum_{i=1}^{n} x_i} \tag{11}$$

where n represents the number of attributes, and x_i and y_i represent the values of i^{th} measured and predicted attributes, respectively. Table 4 shows the calculated values of the coefficients. According to the results, the reasonable Pearson's correlation coefficient value indicates a strong association among variables. Moreover, the low values of CRM, MAE, and RMSE show low error and good precision of the fuzzy kNN model.

5. CONCLUSION

In the present paper, a method was introduced using the fuzzy-kNN algorithm for predicting cavitation damage intensity to the spillways. Data from Karun-1 Dam spillway were collected to examine

Table 4 the fuzzy kNN model evaluation

	r	MAE	NRMSE	CRM
Fuzzy k-nearest neighbor model	0.873	0.167	0.110	0.007
Crisp NN model (Fadaei-Kermani *et al*., 2015)	0.862	0.197	0.1153	0.0087

the model. Pursuant to the results, the proposed model presents appropriate predictions of cavitation damage intensity and location in comparison with actual damage reports on the spillway in previous floods. The model accuracy and efficiency were evaluated and quantified using statistical coefficients. Appropriate values of Pearson's correlation coefficient (r, 0.873), MAE (0.167), NRMSE (0.110), and CRM (0.007) show that the fuzzy-kNN model is efficient and suitable. Therefore, the model results can be useful in design considerations of spillways and adoption of appropriate measures to deal with damages caused by this phenomenon.

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