# Evaluating the Capability of Adaptive Neuro-Fuzzy Inference System to Predict of Flushing Half-Cone Volume in Reservoirs

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***Abstract:*** *Volume of flushed sediment from reservoir can be considered as one of the main points in sediment management issues. Retrieving the storage capacity, cleaning adjacent of power plant intakes and sediment replenishment at downstream area are relatively related to precise prediction of flushed sediment volume. Therefore presenting the intelligent models is necessary to increase the accuracy of calculations, decrease of response time and avoid the uncertainties of multiple regressions models. In this paper, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed on a wide database of 3 different experimental studies. The results show ANFIS model simulated the actual experimental data quite successfully. The predicted flushed sediment volume in ANFIS was more accurate than multiple regressions results. Finally sensitivity analysis was conducted on the best ANFIS model to select the key parameter affected on flushing processes. It was found that the height ratio of sediment to water is an important parameter to predict the flushing half-cone volume.*

***Keywords:*** *ANFIS, reservoir sedimentation, pressure flushing, half-cone volume, Sensitivity analysis.*

## 1. INTRODUCTION

One of the most effective techniques for removing the deposited sediments from reservoirs is pressure flushing through which the deposited sediments are hydraulically removed by the flow. It is often applied as a clearing process to remove sediments around the entrance of bottom intakes. Pressurized flushing has been studied extensively by Brant (2000), Emamgholizadeh (2005) and Kantoush *et* al (2008). In pressurized flushing, sediment at the vicinity of the outlet openings is scoured and a half-cone shaped crater is scoured, which has an important role in preventing sediment to enter power plant intakes (Fang & Cao, 1996). In this technique, an accurate estimation of sediment volume removal (i.e. volume of flushing half-cone) is important both for dam engineering and environmental engineering. From viewpoint of dam engineering to increase the efficiency of pressure flushing operation in reservoirs and in viewpoint of environmental engineering to assume the environmental hazard affected of releasing the sediment to downstream of dams. Moreover, the flushing of the sediments has three-dimensional effects for flow pattern which creates several complicated erosion processes. Due to nonlinear relationships between effective parameters on pressure flushing, there are large uncertainties in regression analysis for the estimation of flushing half-cone dimensions and characteristics.

ANFIS is a soft computing tool, which can approximate the nonlinear behaviour exist in complex phenomena. Also, it is widely used to outline input-output data sets in engineering problems. Some of the recent applications of ANFIS model in hydraulics and environmental engineering include prediction of wave characteristics by Kazeminezhad *et* al (2005), sediment concentration modelling by Nagy *et* al (2002), estimating scour depth around pile by Bateni *et* al (2007), estimating of current-induced scour depth around the pile groups by Zounemat-Kermani *et* al (2008), predicting flow conditions over stepped chutes by Hanbay *et* al (2009), the aeration performance of weirs by Baylar *et* al (2008).

The main objective of this paper is to evaluate the capability of ANFIS model comparing with multiple regression models (MRMs) to predict the volume of flushing half-cone after the pressure flushing operation. Using a large database of three different studies on pressure flushing is the key point in the present study. By collecting these data series approximately all of parameters affected on flushing half-cone shape were considered in the models. Also the new important normalized parameter affected on pressure flushing half-cone has been introduced as input set. The results are summarized in terms of statistical measures and also illustrated in the scatter plots.

## 2. MATERIAL AND METHODS

### 2.1. Flushing half-cone phenomena

A process, through which flushing takes place under a pressurized condition while the water level in reservoir remain unchanged approximately, is called pressure flushing. As above mentioned, pressure flushing technique has a very local effect for removing sediment deposited from reservoir. By accelerating the flow, the excess in shear force created by sudden opening of the bottom outlets of dam loosen and re-suspend the sediments. At the beginning of pressure flushing operation high concentration of sediments release from reservoir while after equilibrium condition clear water with negligible sediments (Fang & Cao, 1996). The development of flushing half-cone and reached to equilibrium is very fast, and the process finished in less than one minute to ten minutes in the experimental model (Scheuerlein *et* al, 2004).

### 2.2. Dimensional analysis

Volume of flushing half-cone depends on some main parameters such as: outlet discharge ($Q_O$) or in other mean velocity of outflow at the entrance of bottom outlet ($U_{Outlet}$), water depth from centre of outlet ($H_W$), sediment height measured from the centre of outlet ($H_S$), diameter of outlet ($D_O$), properties of sediment particle ($d_{50}$), the density of sediment ($\rho_S$), water density ($\rho_W$), and the acceleration gravity (g) and Kinematic viscosity (v). Figure 1 illustrates the schematic longitudinal view of flushing half-cone in reservoirs storage. Thus, the volume of flushing half-cone ($V_{Scouring}$) after equilibrium may be written as a function of the following parameters:

$$V_{Scouring} = \phi(U_{Outlet}, D_O, H_W, H_S, d_{50}, \rho_S, \rho_W, g, \upsilon) \qquad (1)$$

By using $\pi$-Buckingham theorem and choosing the $\rho_W$, $H_W$ and $U_{Outlet}$ as repeating parameters, the nine independent parameters in Eq. (1) are reducible to four non-dimensional parameters as Eq. (2):

$$\frac{\sqrt[3]{V_{Scouring}}}{H_W} = \phi\left(\frac{U_{Outlet}}{\sqrt{gH_W}}, \frac{U_{Outlet}D_O}{\nu}, \frac{H_S}{H_W}, \frac{D_O}{d_{50}}\right) \qquad (2)$$

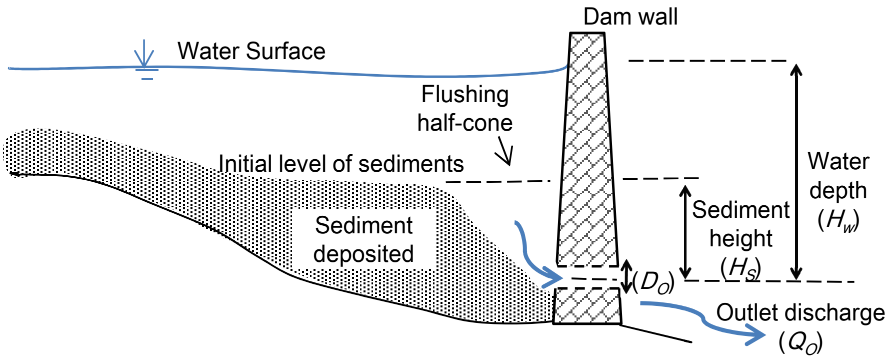


**Figure 1 Schematic view of longitudinal flushing half-cone**

### 2.3. The database used

ANFIS model was developed by using the database of three different studies on pressure flushing operation that carried out by Emamgholizade *et* al (2005) and Meshkati *et* al (2010, a and b). It is noteworthy to mention, all data in these studies were measured after equilibrium of flushing half-cone. Table 1 shows the details information about the experimental model and main parameters used in these studies. The experimental data consist of 153 data series that are divided into two parts randomly: a training (calibration) set including 107 series (69.93 %) and a testing (validation) set containing 46 data series (30.06%). The test set was never used in the model construction phase, thereby allowing investigating the forecasting capability of models. To select the most robust representation, a statistical analysis was performed on the input and output data set to ensure that the statistical properties of data in each of the subsets were as close to each other.

**Table 1 Details information about the parameters considered in three different studies**

| Study Reference | Model | Sediment | $H_w$ (cm) | $Q_O$ (l/s) | $D_O$ (cm) | $H_S$ (cm) | No. Experiment |
|---|---|---|---|---|---|---|---|
| Emamgholizadeh (2005) | Rectangular 4×1.5×2 m | $d_{50}$=1.2, 0.42,0.27 mm | 42<br>80<br>110 | 1-8 | 5.08 | 32 | 45 |
| Meshkati (2010, a) | Rectangular 3×2×1.5 m | Silica Sand $d_{50}$=1 mm | 36<br>66<br>96 | 0.15-15 | 2.54<br>3.8<br>5.08<br>7.62 | 16 | 68 |
| Meshkati (2010, b) | Rectangular 3×2×1.5 m | Silica Sand $d_{50}$=1 mm | 36<br>66<br>96 | 0.16-6 | 5.08 | 6<br>11<br>16 | 40 |
| Total number of experiments | | | | | | | 153 |

Based on Eq. 2 input/output pairs contain four non-dimensional inputs (Froude number, Reynolds number, ratio of height and ratio of diameter) and one output (normalized sediment removal volume). Both of inputs and output parameters were first normalized between (0,1) and after that used in the models. The ranges of non-dimensional parameters involved in this study are given in Table 2.

**Table 2 Range of non-dimensional parameters**

| Parameters | Variations |
|---|---|
| Normalized flushing half-cone volume ( $\frac{\sqrt[3]{V_{Scouring}}}{H_W}$) | 0.049- 0.944 |
| Froude number ($\frac{U_{Outlet}}{\sqrt{gH_w}}$) | 0.015- 1.072 |
| Reynolds number ( $\frac{U_{Outlet}D_O}{v}$) | 3761.47- 250764.83 |
| Ratio of height ($\frac{H_S}{H_W}$) | 0.062- 0.76 |
| Ratio of diameter ($\frac{D_O}{d_{50}}$) | 25.4- 188.14 |

## 2.4. Experimental results

In this section several dimensional figures are presented to discuss the effect of main parameters that introduced in Eq. (1) on flushing half-cone volume. The experimental results show that by increasing the discharge from outlet and decreasing reservoir's water depth, the amount of flushed sediment increased. Figure 2(a) shows the variation of flushing half-cone volume versus the outlet discharge for a constant bottom outlet diameter, unchanged sediment height and given sediment particle size. Figure 2(b) depicts for a given outlet discharge and by decreasing the water depth level, flushing half-cone volume increased. Also under the same conditions the volume of flushed sediments increased when the size of sediments changed from coarse to fine Figure 2(c). Moreover, by increasing both diameter of outlet and sediment height above the bottom outlet, dimensions of flushing half-cone will be increase. Figure 2(a) illustrates for given outlet discharge, increasing of outlet diameter causes to greater flushing half-cone volume release. Figure 2(d) illustrates the changes of flushing half-cone volume with height sediment in reservoir for a given outlet discharge.

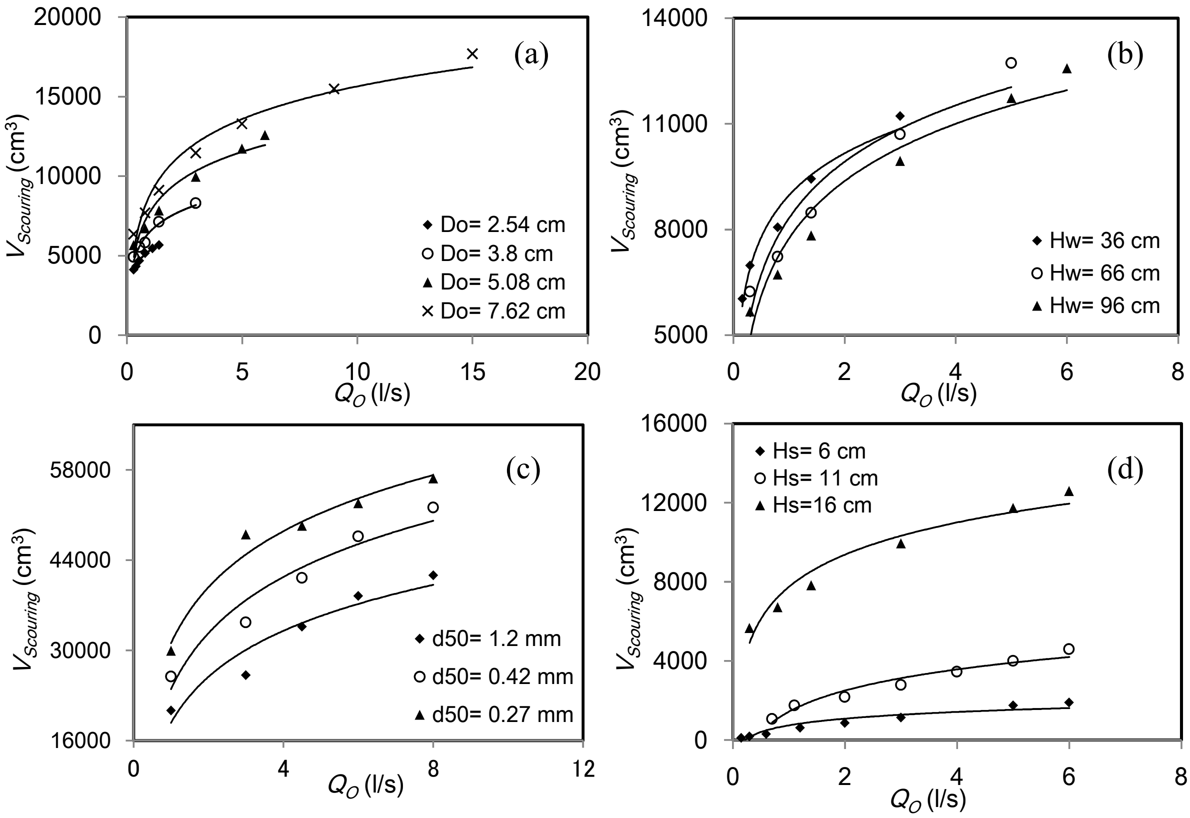


**Figure 2 Variation of flushing half-cone volume versus the outlet discharge for different parameters considered in this paper, vertical axis is volume of flushing half cone, $V_{scouring}$ (cm$^3$), horizontal axis is outlet discharge $Q_O$(l/s), $D_O$ is the outlet diameter (cm), $H_w$ is water depth (cm), $H_S$ is the sediment height (cm) and $d_{50}$ is the medium size of particles (mm).**

## 2.5. Adaptive Neuro-Fuzzy System (ANFIS)

ANFIS was proposed by Jang (1993) in the early 1990s. It combines the fuzzy qualitative approach with the neural networks adaptive capabilities to achieve a desired outcome. ANFIS model is one of the implementation of a first order Sugeno fuzzy inference system (Kulkarni, 2001). ANFIS model make a map between inputs and output, even if our processes are complicated. The detailed algorithm and mathematical background of the hybrid-learning algorithm can be found in Jang (1993).

## 2.6. Implementation of ANFIS

This ANFIS models was implemented by using MATLAB software package (MATLAB version R2009a with neural network and fuzzy logic toolboxes). The performance of ANFIS was assessed based on three error measures namely, correlation coefficient square ($R^2$), root mean square error (RMSE), and mean absolute error (MAE). Expressions for these measures are given as follow:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - t_i| \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - t_i)^2}{N}} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(O_i - t_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{5}$$

Where $O_i$ and $t_i$ are respectively the observation data and model output for the ith output, $\overline{O}$ is the average of target output and N is the total number of events considered.

## 3. RESULTS AND DISCUSSIONS

### 3.1. Assessing the normalized flushing half-cone volume

For the all of dimensionless parameters at the right side of Eq. (2), was assigned a two number of fuzzy set. The number of fuzzy set is determined by trial and errors and by developing various models and studying the rules and their results. Note that it is inappropriate for choose three or more member function set for each input because the total parameter needing to be learned in that case will be greater than the number of training pairs. Different types of fuzzy membership function were used in this study and the best performance is obtained with general Bell-shaped function as Eq. (6):

$$\mu_{Ai}(x) = \frac{1}{1+\left(x-\frac{c_i}{a_i}\right)^{2b_i}} \qquad (6)$$

Where x is input to the node i, μ is the membership function, $A_i$ and $B_i$ are fuzzy sets associated with nodes and $\{a_i,b_i,c_i\}$ are changeable parameters set that changes the shapes of the membership function. In Table 3 the ANFIS model structure presented in details. The number of Epoch was set 300 for the training phase. After the training process, the trained ANFIS system could be used for volume flushing half-cone prediction. The prediction of flushing half-cone volume was achieved by using the "evalfis" function of MATLAB Software.

**Table 3 The ANFIS model structure for general Bell-shaped function**

| Parameters of ANFIS model | Number |
|---|---|
| Nodes | 55 |
| Linear parameters | 80 |
| Non-linear parameters | 24 |
| Total parameters | 104 |
| Training data pairs | 107 |
| Number of fuzzy rules | 9 |

To assess the performance of the ANFIS model, the observed values for flushing half-cone volume are plotted versus the predicted ones. Figure 3 depict the observed normalized flushing half-cone volume values versus the predict ones for training phase. This figure clearly indicate a very close fit during the training (calibration) phase.

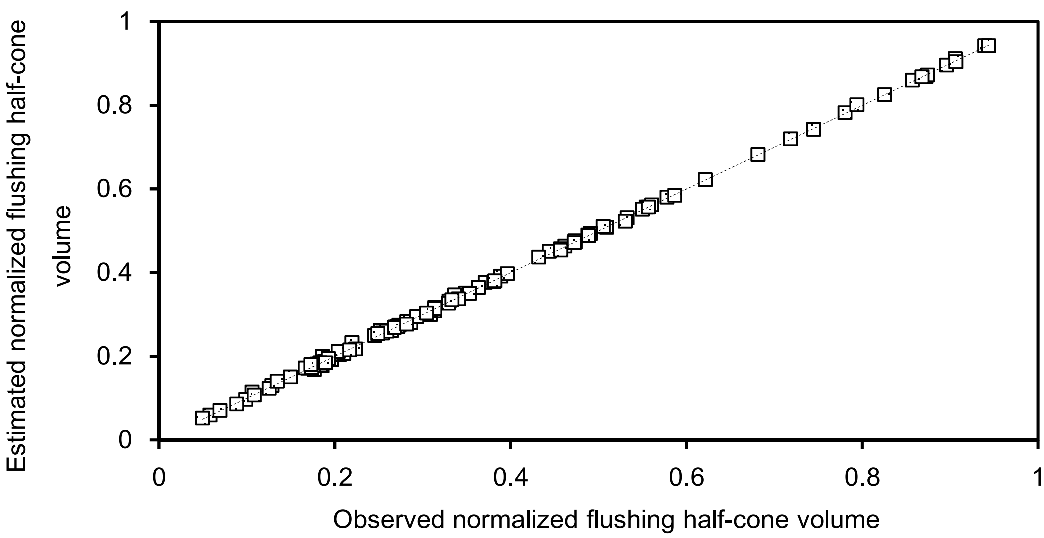


**Figure 3 observed and estimated normalized flushing half-cone volume for training data set**

## 3.2. Comparison of ANFIS model with regression equation

To evaluate the capability of applied model in this study (ANFIS), a comparison between the ANFIS model and a regression model was developed. The regression model was applied for the same inputs and output parameters with ANFIS (training set). A multiple regression model (MRM) aims to estimate single parameters (normalized flushing half-cone volume) by means of a set of other explanatory parameters, which is defined in section 2.2. The MRM implemented in this paper is presented as Eq. (7), where K, a, b, c and d are calibration parameters.

$$\frac{\sqrt[3]{V_{Scouring}}}{H_w} = K(Fr)^a (Re)^b \left(\frac{H_S}{H_w}\right)^c \left(\frac{D_O}{d_{50}}\right)^d \tag{7}$$

This model is calibrated by minimizing the distance between calculated and measured value by using least square error approach. In this approach minimizing the sum of squared errors is the main criteria used for calibration. Correlation coefficient square ($R^2$), root mean square error (RMSE), and mean absolute error (MAE), Eq. (3-5), were used as measure of goodness of calibration. The obtained equation is as Eq. (8):

$$\frac{\sqrt[3]{V_{Scouring}}}{H_w} = 0.66\left(\frac{Fr}{Re^{0.2}}\right)^{0.1} \left(\frac{H_S}{H_w}\right)^{0.9} \left(\frac{D_O}{d_{50}}\right)^{0.1} \tag{8}$$

Prediction accuracy using Neuro-fuzzy and multiple linear regression analysis is summarized in Table 4. Figure 4 shows normalized flushing half-cone volume values using the ANFIS, and the multiple linear regressions for the same 46 test data set. As can be seen in Figure 4 and 5 and Table 4, it is very clear that ANFIS has smaller RMSE and MAE as well as bigger $R^2$ for both the training and testing datasets than the regression model. For instance in ANFIS model results the values of RMSE and MAE respectively were reduced 2 times and 2.6 times for training data set in compare to regression model.

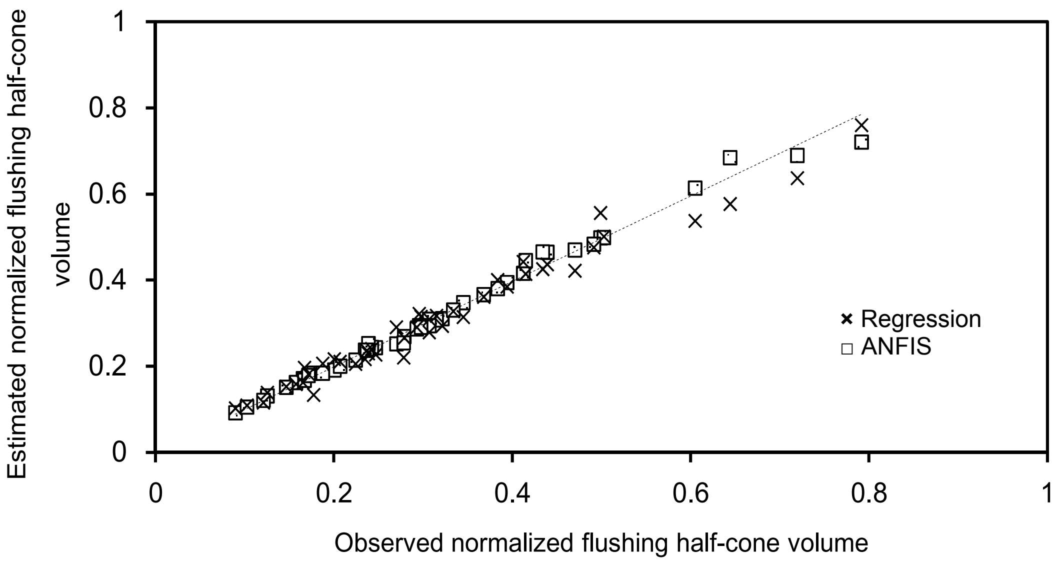


**Figure 4 Compare of prediction results with regression and ANFIS model for testing data set**

**Table 4 The Performance of models during the training and testing**

| Performance index | Neuro-fuzzy | | Multiple linear regression | |
|---|---|---|---|---|
| | Training | Testing | Training | Testing |
| $R^2$ | 0.999 | 0.989 | 0.97 | 0.95 |
| MAE | 0.002 | 0.009 | 0.026 | 0.024 |
| RMSE | 0.004 | 0.016 | 0.034 | 0.032 |

## 3.3. Sensitivity analysis

To assign the relative significance of each independent parameters (input parameter), on volume of flushing half-cone (output), a sensitivity analysis was applied with the best ANFIS model, which described above. Sensitivity of the presented model was evaluated for training data set and without considering all of inputs. It was found that the Ratio of height, $H_s/H_w$, is the most effective parameter on flushing half-cone volume, while the Reynolds number maybe has the least influence on flushing volume cone (Table 5). This subject is very important to find and select the most important parameters affected on volume of flushing half-cone. The effects of the parameters on normalized flushing half-cone volume are seen to be ranked (from higher to lower) in the order: $H_S/H_W$, Froude number, $D_O/d_{50}$ and Reynolds number.

**Table 5 Sensitivity analysis for the non-dimensions data set**

| Model | $R^2$ | RMSE | MAE |
|---|---|---|---|
| ANFIS model with all of inputs | 98.92 | 0.016 | 0.009 |
| ANFIS model without Froude number | 86.99 | 0.05 | 0.03 |
| ANFIS model without Reynolds number | 98.9 | 0.017 | 0.013 |
| ANFIS model without Ratio of height ($H_s/H_w$) | 59.1 | 0.126 | 0.1 |
| ANFIS model without Ratio of diameter ($D_O/d_{50}$) | 95.59 | 0.04 | 0.02 |

As above mentioned, the ratio of height (sediment height to water depth $H_s/H_w$) has a dominant contribution in the ANFIS model and were in good agreement with the experimental results. Sediment flushing processes commence when the bottom outlet was opened. Soon after, a small scouring hole appeared on the surface of the deposited sediment located above bottom outlet and near the dam wall. Sediment were flushed in a vertical column most affected to the gravity and finally out through the bottom outlet. Then, a small scouring hole was gradually developed due to the vertical vortex. When the depth of this small scoured hole was deepened sufficiently, the adjacent sediment layers became unstable and then slide down into the small scouring hole. Abrupt slide down of sediment to the hole start the process of surface extension flushing which is always occurs at the angle of submerged sediment repose.

After sediment slides into the small hole, vertical scouring resumes and a new hole was created. This new hole has larger dimensions in contrast to the pervious hole. Likewise, the vertical scouring process will recur until the depth of the new hole causes surrounding layers of sediment to become unstable. This will cause more unstable sediment to slide into an even larger hole. The vertical scouring and surface extension phenomena will reoccur repeatedly until the sediment height has sufficiently decreased to the point at which the sediment level is equal with the lower edge of the bottom outlet and In addition that slope of flushing half-cone bank reached to angle of submerged sediment repose. The flushing hole at the equilibrium condition called flushing half-cone.

On the whole, the greater the sediment height ($H_s$), the greater the amount of sediment removal volume and bigger flushing half-cone dimensions. Releasing sediment from reservoir in this technique (pressure flushing) is more dependent to the gravity acceleration and angle repose of sediment in contrast to other hydraulic criteria ($Q_o$, $H_w$, $D_o$, $d_{50}$). As can be seen in Figure 2(d), variation of sediment height ($H_s$) causes to great changes in value of sediment removal volume $V_{\mathrm{Scouring}}$, while variation of water depth ($H_w$), sediment grain size ($d_{50}$) and bottom outlet diameter ($D_o$) in the reservoir are not effective on normalized flushing half-cone volume as much as sediment height ($H_s$). Therefore maybe sediment height behind the dam ($H_s$) is one of the main parameter in this research.

## 4. CONCLUSION

In this paper first by using schematic shapes and dimensional figures the main parameters affected on dimensions and volume of flushing half-cone was introduced. And then ANFIS model was used to predict of the flushing half-cone volume. Between the main parameters that introduced above, outlet discharge, sediment height and diameter of bottom outlet have direct effects on dimensions of flushing half-cone. By increasing of these parameters flushing cone volume will increase.  while the water depth in reservoir has indirect effect. It means by increasing the water depth in model, the amount of sediment release from reservoir was decreased. Sensitivity analysis demonstrates the Ratio of height ($H_s/H_w$) has the most effect on volume of flushing half-cone in compare to other dimension-less parameters.

There are three reasons to use such intelligent models as ANFIS, first for their friendly operation features, second their high accuracy and finally their rapid responses. The ANFIS model developed by using almost all of main parameters affected on sediment removal from reservoir. Comparing between the results of ANFIS model both in training and testing phases indicate the capability and workability of ANFIS to predict the volume of flushing half-cone. Moreover ANFIS model provides the more accurate result compare to regression formula.

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