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Application of Improved Neuro-Fuzzy GMDH to Predict Scour Depth at Sluice Gates

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Abstract

An improved neuro-fuzzy based group method of data handling using the particle swarm optimization (NF-GMDH-PSO) is developed as an adaptive learning network to predict the localized scour downstream of a sluice gate with an apron. The input characteristic parameters affecting the scour depth are the sediment size and its gradation, apron length, sluice gate opening, and the flow conditions upstream and downstream of the sluice gate. Six non-dimensional parameters were yielded to define a functional relationship between the input and output variables. The training and testing of the NF-GMDH network are performed using published scour data from the literature. The efficiency of the training stages for the NF-GMDH-PSO is investigated. The testing results for the NF-GMDH network are compared with the traditional approaches based on regression method. A sensitivity analysis is carried out to assign the most significant parameter for the scour prediction. The results showed that the NF-GMDH-PSO network produced lower error in scour prediction than all other models.

Keywords: Neuro-Fuzzy GMDH; Particle Swarm Optimization; Apron; Scour Depth; Sluice Gate

1. Introduction

A sluice gate is a hydraulic structure commonly used to control flow and as a discharge measurement device in irrigation channels or rivers, and often applied in water treatment plants, mining, dams, rice fields, and cranberry bogs. The gates may be typically made of wood and metal. In addition, slide vertically on a frame to open or close, allowing water to flow out of a space or to be contained in it. Hence, these machines are called as a sluice gate valve. Sluice gate design is usually in the form of a vertical sliding system, but can also operate like a flap system and even in cylindrical shape.

It is a common practice to install an apron to protect and prevent the erosive effects of the flow downstream of a sluice gate. The localized scour hole can be expected to decrease considerably with a launching apron. The design and projection of an apron is based mostly on laboratory works due to the complexity of the flow conditions and the associated scour phenomena below the hydraulic structure.

Over the past few decades, many experimental investigations on scour downstream of an apron have been carried out (Breusers, 1965; Chatterjee and Ghosh, 1980; Hassan and Narayanan, 1985; Chatterjee et al., 1994; Balachandar and Kells, 1997; Balachandar et al., 2000; Kells et al., 2001; Lim and Yu, 2002; Dey and Westrich, 2003; Dey and Sarkar, 2006; Hamidifar et al., 2011).

In spite of the reported experimental datasets, it is difficult to comprehensively capture the influences of the various relevant parameters on the scour produced because of inherent limitations in the lab facilities and range of experiments that can be conducted. Hence, conventional approaches using regression-based techniques to predict the scour depth are common. The empirical equations proposed by these techniques are necessarily restricted to the range of the database used in their derivation. One noticeable fault in empirical formulas is the difficulty to quantify and validate the effects of dynamic and kinematic scaling laws on the scour profiles (Lim and Yu, 2002; Dey and Sarkar, 2006). Recently, artificial intelligence approaches have been increasingly used to solve complex problems in different fields of water, geotechnical and transportation engineering (Gandomi et al., 2013; Gandomi et al., 2013; Alavi and Gandomi, 2011; Gandomi and Alavi, 2011).

In hydraulic engineering, predictions of scour downstream of hydraulic structures have been conducted Azmathullah et al. (2005), and Azamathulla and Guven (2012b) reported works on scour downstream of ski-jump bucket spillway using the artificial neural networks (ANNs), Gene-expression programming (GEP), and non-linear regression analysis. Azamathulla et al. (2008a&b) also use the adaptive neuro-fuzzy inference systems (ANFIS) and genetic programming (GP) to predict scour downstream of ski-jump bucket based on field data. Guven and Gunal (2008a&b) proposed ANNs, GP, and GEP techniques to predict scour at grade-control structures. The general conclusion of these studies is that the artificial intelligences approaches are better in scour predictions than the traditional methods. These applications show the superiority of predictive methods based on iterative and evolutionary algorithms

Amongst the various artificial intelligence methods, the group method of data handling (GMDH) network is known for its self-organizing approach to solve complex problems in non-linear systems (Hwang, 2006; Amanifard et al., 2008). Recently, alternative GMDH networks were utilized to predict scour around hydraulic structures. Najafzadeh et al. (2012) developed the GMDH model by the back propagation algorithm to predict scour below pipelines. An improved GMDH network by the back propagation algorithm, genetic programming, and levenberg-marquardt was developed to predict scour around bridge piers (Najafzadeh and Barani, 2011; Najafzadeh and Azamathulla, 2013; Najafzadeh et al., 2013a; Najafzadeh et al., 2013b; Najafzadeh et al., 2013c; Najafzadeh et al., 2013d). The GMDH approach has been used to identify behavior of non-linear systems such as forecasting of mobile communication, explosive cutting process, tool life testing in gun drilling, construction of optimal educational test, control engineering, marketing, economics and engineering geology (Astakhov and Galitsky, 2005; Hwang, 2006; Witczak et al., 2006; Amanifard et al., 2008; Srinivasan, 2008; Jamali et al., 2009; Abdel-Aal and El-Alfy, 2009; Mehrara et al., 2009; Kalantary et al., 2009). Nagasaka et al. (1995) used a multi-stage fuzzy decision rule as neuro-fuzzy (NF) GMDH to model grinding characteristics, and Takashi et al. (1998) proposed the orthogonal and successive projection approach for the learning of NF-GMDH. Hwang (2006) applied the NF-GMDH model to forecast the unreliable mobile communication, configured through the least square training method. He found it to be excellent for forecasting problems with very high complexity. The NF-GMDH has higher flexibility and lower complexity compared to the GMDH network. The latter is a nonlinear model using a combination of quadratic polynomial of two parameters with multi-layer procedure. However, the NF-GMDH, as a multi-stage fuzzy decision networks, is more useful in nonlinear systems to identify a fuzzy feature. Moreover, the volume of calculations for NF-GMDH networks is lower compared to the GMDH, artificial neural networks (ANN), and adaptive neuro-fuzzy inference system (ANFIS). One useful feature of the NF-GMDH networks is the resulting analytical equations which can be obtained using partial descriptions based on multi-stage fuzzy rule decision (Hwang, 2006).

In this study, a computer program has been coded for modeling the Neuro-Fuzzy GMDH network, and the particle swarm optimization (PSO) algorithm is applied to improve the topology design of the NF-GMDH for scour prediction downstream of a sluice gate with an apron protection. The performance of the proposed NF-GMDH model is compared to existing empirical equations based on regression method.

2. Previous Scour Studies Downstream of Sluice Gates

Many experimental studies have been conducted to determine the scour depth downstream of a sluice gate with and without an apron. For example, Breusers (1965) studied the scour time variations and presented a power function for predicting the scour time variation. Chatterjee and Ghosh (1980) proposed empirical equations to calculate the bed shear stress in the equilibrium scour hole downstream of a sluice gate. Hassan and Narayanan (1985) proposed a semi-empirical approach to predict the rate of scour below a sluice gate. Chatterjee et al. (1994) proposed a scour time relationship based on their experiments for submerged jet issuing from a sluice opening.

Balachandar and Kells (1997 and 1998) used video recording to analyze the instantaneous variations of water surface and scour profile development for scour downstream of sluice gate. Balachandar et al. (2000) studied the effects of tail water depth on the scour depth, and Kells et al. (2001) investigated the effects of bed sediment gradations on the scour depth. Lim and Yu (2002) carried out an extensive experimental study of scouring downstream of sluice gates, with particular focus on the effects of the apron length on scour depth. They observed a cyclical jet-flipping phenomenon in the local scour under certain hydraulics conditions. Dey and Westrich (2003) presented an equation for the bed shear stress in local scour by solving the von Karman momentum integral equation. A comprehensive study by Dey and Sarkar (2006) investigated the effects of various parameters on the scour depth and proposed equation for its prediction. Hamidifar et al. (2011) found that a minimum reduction of 60% in scour can be obtained for a rough apron compared with the smooth apron. In this study, a comprehensive scour database has been compiled from these past studies and used to train and test the proposed NF-GMDH-PSO networks for scour downstream of a sluice gate with an apron.

3. Scour Modeling

Fig. 1 shows a typical definition sketch of local scour caused by a submerged jet issuing from a sluice gate with an apron. The main parameters affecting the scouring process are the characteristics of the bed sediments, apron length, sluice gate opening size, and the flow conditions upstream and downstream of sluice gate (e.g., Hassan and Narayanan, 1985; Chatterjee et al., 1994; Balachandar and Kells, 1997; Kells et al., 2001; Lim and Yu, 2002, Dey and Westrich, 2003; Dey and Sarkar, 2006). A functional relationship between the scour depth and the effective parameters can be expressed as follows:

$$d_s = f(U, b, l, h, d_{50}, \sigma_g, \mu, \rho, \rho_s, g) \tag{1}$$

where d_s, U, b, l, h, d_{50}, σ_g, μ, ρ, ρ_s, and g are the scour depth, issuing jet velocity, sluice gate opening, apron length, tail water depth, median sediment size, geometric standard deviation, dynamic viscosity of water, mass density of water, mass density of bed material, acceleration due to gravity, respectively.

Using dimensional analysis, the following function is obtained:

$$d_s / b = f(\mathrm{Re}, h/b, l/b, d_{50}/b, Fr_0, \sigma_g) \tag{2}$$

where Re and Fr_0 are the Reynolds number and densimetric Froude number, respectively. The Re and Fr_0 non-dimensional parameters are defined as follows:

$$\mathrm{Re} = \rho U b / \mu \tag{3}$$

$$Fr_0 = U / \sqrt{g.(S-1).d_{50}} \tag{4}$$

where S is the relative density of sediments defined as ρ_s/ρ. In most cases, the jet velocity is relatively high and Re is in the fully turbulent range. Hence, the influence of the viscosity on the jet hydraulics and scouring may be eliminated (Lim and Yu, 2002; Dey and Sarkar, 2006). Eq. (2) can be reduced to the following function:

$$d_s / b = f(h/b, l/b, d_{50}/b, Fr_0, \sigma_g) \quad (5)$$

In the application of artificial intelligence methods for scour modeling, it has been found that modeling using dimensionless parameters produced better scour predictions than that using dimensional parameters (Guven and Gunal, 2008a; Najafzadeh and Barani, 2011; Azamatulla and Ghani, 2011 Azamathulla, 2012).

In this study, Eq.(5) issued to develop the NF-GMDH-PSO model for scour prediction. The scour database consists of 228 datasets collected from Hamidifar et al. (2011), Dey and Sarkar (2006). Table 1 presents the ranges of datasets. We select randomly about 75% (171 datasets) and 25% (57 datasets) to perform the training and testing stages, respectively. Two empirical equations proposed by Dey and Sarkar (2006) and Lim and Yu (2002) are also selected (Table 2) to predict the scour depth based on the testing conditions in the database.

4.1. Framework of Neuro-Fuzzy GMDH

The GMDH network is a learning machine based on the principle of heuristic self-organizing, proposed by Ivakhnenko in the 1960s. It consists of a series of operations of seeding, rearing, crossbreeding, selection and rejection of seeds which correspond to the determination of the input variables, structure and parameters of the model, and the selection of model by the principle of termination (Malada and Ivahknenko, 1994). The other descriptions of GMDH network can be found in the literatures, such as Iba and de Garis, 1996; Amanifard et al., 2008; and Onwubolu, 2008. In this study, a neuro-fuzzy GMDH model based PSO algorithm has been proposed for scour depth prediction. The structure of the neuro-fuzzy GMDH is constructed automatically using heuristic self-organized algorithm (Hwang, 2006). This is a very flexible algorithm and can be easily hybridized by other iterative and evolutionary algorithms.

Furthermore, a simplified fuzzy reasoning rule is utilized to improve the GMDH network as follows (Takashi et al., 1998):

If x_1 is F_{k1} and x_2 is F_{k2}, then, output y is w_k.

Gaussian membership function is used in term of F_{kj} which is related to the *k*th fuzzy rules in the domain of the *j*th input values x_j.

$F_{kj}(x_j) = \exp(-(x_j - a_{kj})^2 / b_{kj})$	(8)

which a_{kj} and b_{kj} are constant values for each rules. Also, y parameter is defined as output that has been expressed as follows:

$y = \sum_{k=1}^{K} u_k w_k$	(9)
$u_k = \prod_j F_{kj}(x_j)$	(10)

where w_k is real value for *k*th fuzzy rules (Takashi et al., 1998; Hwang, 2006).

The neuro-fuzzy GMDH model is one of the adaptive learning network that has hierarchical structure. In this model, each neuron has two input variables and one output. A general configuration of the model is shown in Fig. 2. In this figure, the output of each neuron in a layer is considered as the input variable for the next layer. The final output is calculated using the average of the outputs from the last layer. From Fig.2, it can be said that the inputs from the *m*th model and *p*th layer are the output variables of the (*m-1*)th and *m*th model in the (*p-1*)th layer. The mathematical function for calculating the y^{pm} is ,

$y^{pm} = f(y^{p-1,m-1}, y^{p-1,m}) = \sum_{k=1}^{K} \mu_k^{pm}.w_k^{pm}$	(11)

$\mu_k^{pm} = \exp\left\{ -\frac{(y^{p-1,m-1} - a_{k,1}^{pm})^2}{b_{k,1}^{pm}} - \frac{(y^{p-1,m} - a_{k,2}^{pm})^2}{b_{k,2}^{pm}} \right\}$	(12)

where μ_k^{pm} and w_k^{pm} are the kth Gaussian function and its corresponding weight parameter, which are related to the mth model in the pth layer, respectively. In addition, the a_k^{pm} and b_k^{pm} are the Gaussian parameters for the ith input variable from the mth model and pth layer, respectively. The final output is expressed using the following function:

$$y = \frac{1}{M}\sum_{m=1}^{M} y^{pm} \tag{13}$$

The learning process of feed forward neuro-fuzzy GMDH is known as an iterative method to solve complicated systems. In each iteration, the error parameter for the network can be obtained as follows:

$$E = \frac{1}{2}(y^* - y)^2 \tag{14}$$

where y^* is the predicted value.

4.2. Development of Neuro-Fuzzy GMDH Using PSO Algorithm

In this study, the neuro-fuzzy (NF) GMDH model is developed using the PSO algorithm. The basic structure of the NF-GMDH consists of partial descriptions (neurons). As mentioned in the previous section, the grouped parameters in the form of Gaussian variables and weights related to the fuzzy rule are unknown in each partial description (PD). The PSO algorithm has been applied to optimize the grouped-unknown parameters in PDs. Performing the NF and PSO is a parallel action in each PD. Also, two fuzzy rules were used to model the neuro-fuzzy in each PD. The NF-GMDH-PSO has five input variables and one output. Through modeling the NF-GMDH-PSO, 10 PDs were produced in the first layer. The second layer was generated using 10 PDs from the first layer. This process could be continued until a minimum error of training network is obtained. The NF-GMDH-PSO model with three layers was generated through an optimization process. The training error of the optimization process was 1.024. Table 3 shows the values of the PSO properties for predicting the scour depth downstream of sluice gates.

The error values related to the PDs for each layer are shown in Fig.3. From performing the training stage, many PDs for the first layer are given as follows:

$$OUTNF_1^1 = 0.4842\exp[-\frac{(\sigma_g - 0.5214)^2}{0.5326} - \frac{(\frac{l}{b} - 0.5214)^2}{0.5326}] + 0.1\exp[-\frac{(\sigma_g - 0.5214)^2}{1.44029} - \frac{(\frac{l}{b} - 0.5214)^2}{1.44029}] \quad (15)$$

$$OUTNF_2^1 = 0.5242\exp[-\frac{(\frac{l}{b} - 0.5384)^2}{1.0855} - \frac{(\frac{d_{50}}{b} - 0.5384)^2}{1.0855}] + 1.117\exp[-\frac{(\frac{l}{b} - 1.395)^2}{0.1} - \frac{(\frac{d_{50}}{b} - 1.395)^2}{0.1}] \quad (16)$$

$$OUTNF_3^1 = 0.2207\exp[-\frac{(\frac{d_{50}}{b} - 0.1)^2}{0.9413} - \frac{(\frac{h}{b} - 0.1)^2}{0.9413}] + 0.5294\exp[-\frac{(\frac{d_{50}}{b} - 0.8705)^2}{1.327} - \frac{(\frac{h}{b} - 0.8705)^2}{1.327}] \quad (17)$$

The superscript and subscript of each parameter represent the number of pertaining layer and partial description, respectively. Fig. 4 shows the proposed structure of the NF-GMDH-PSO for scour depth modeling downstream of a sluice gate.

To reduce the volume of calculations, only three layers for the NF-GMDH-PSO model has been considered. The number of fuzzy rules in each neuron corresponds to the assumptions of the NF-GMDH-PSO model. The number of layers and properties of the PSO algorithm are also related to the limitations of the proposed model.

5. Results and Discussion

The results of scour predictions using the proposed NF-GMDH-PSO model and the 2 empirical equations are presented in this section. The correlation coefficient (R), root mean square error (RMSE), scatter index (SI), BIAS, and mean absolute percentage of error (MAPE) can be defined to evaluate the error indicators in the training and testing stages (Azmathullah et al., 2005; Najafzadeh et al., 2013b), as follows:

$$R = \frac{\sum_{i=1}^{M}(Y_{i(Actual)} - \overline{Y}_{(Actual)})(Y_{i(Model)} - \overline{Y}_{(Model)})}{\sqrt{\sum_{i=1}^{M}(Y_{i(Actual)} - \overline{Y}_{(Actual)})^2 . \sum_{i=1}^{M}(Y_{i(Model)} - \overline{Y}_{(Model)})^2}} \tag{18}$$

$$RMSE = \left[\frac{\sum_{i=1}^{M}(Y_{i(\mathrm{mod}el)} - Y_{i(Actual)})^2}{M}\right]^{1/2} \tag{19}$$

$$MAPE = \frac{1}{M}\left[\frac{\sum_{i=1}^{M}\left|Y_{i(\mathrm{mod}el)} - Y_{i(Actual)}\right|}{\sum_{i=1}^{M}Y_{i(Actual)}} \times 100\right] \tag{20}$$

$$BIAS = \frac{\sum_{i=1}^{M}(Y_{i(\mathrm{mod}el)} - Y_{i(Actual)})}{M} \tag{21}$$

$$SI = \frac{RMSE}{(1/M)\sum_{i=1}^{M}y_{i(Actual)}} \tag{22}$$

where $Y_{i(\text{model})}$ is the predicted values (network output), $Y_{i(Actual)}$ is the observed values (target), and M is the total number of events.

The proposed NF-GMDH-PSO model and traditional methods should be compared using a suitable criterion and not just using R or error functions only. For this reason, R will not change significantly by shifting the output values of a model equally, and the error functions in terms of RMSE and MAPE only indicate the error and not the correlation. In this way, the suitable criteria parameter should be a combination of R and error functions. A recent study by Gandomi and Roke (2013) suggested using ρ as a statistical parameter, to replace SI and it is defined as follows:

$$\rho = \frac{SI}{1+R} \times 100 \tag{23}$$

The statistical results of the NF-GMDH-PSO network for the training and testing stages are presented in Table 4. In the training stage, it can be seen that the NF-GMDH-PSO network predicted the scour depth with higher performance. The proposed model have 31 partial descriptions (PDs), consisting of 10 PDs for the first layer, 20 PDs for the middle layer, and one PD for the output of the network. The training result of the NF-GMDH-PSO has low error parameters (R=0.9, RMSE=1.05, and MAPE=0.129). The BIAS and ρ values for the training stage were -0.154 and 14.45, respectively.

In the testing stage, it can be said that the NF-GMDH-PSO network predicted the scour depth with low error (RMSE = 1.12 and MAPE = 0.455) and high accuracy (R=0.94, BIAS=0.454, and ρ=16.7). Fig. 5 shows the scatter plots between the predicted and observed scour depths for the training and testing of the NF-GMDH-PSO model.

In Fig. 5, the scour predictions using Eqs. (6) and (7) proposed by Dey and Sarkar (2006), and Lim and Yu (2002) are also shown. The results show that Eq. (6) produced lower error

(RMSE=10.12 and MAPE=2.25) but lower accuracy (R=-0.68), compared to the NF-GMDH- PSO model. From Table 4, it can be seen that the BIAS and ρ parameters obtained from Eq. (6) (3.95, 1271.8) has higher error than NF-GMDH-PSO. It should be pointed out that Eq. (6) was proposed for a restricted range of datasets, whilst wider ranges of input and output parameters were used in the NF-GMDH-PSO model.

The statistical results using Eq. (7) are given in Table 5. The table show that Eq. (7) predicted the scour depth with lower error (RMSE=6.16 and MAPE=1.45) and higher accuracy (BIAS=2.45 and ρ=354) than Eq. (6). It should be noted that Lim and Yu's (2002) Eq (7) also included the five non-dimensional variables that were used in the present scour model. For the empirical equations, the availability of experimental datasets and the mathematical feature of the empirical equations are the most significant factors to give accurate scour depth predictions. Practically speaking, it is evident that the lack of validation for the traditional empirical methods is related to the limitations of the effective parameters tested in a lab set-up and therefore not all the physical behavior of scour process can be captured accurately (Guven and Gunal, 2008a&b; Najafzadeh et al., 2012; Najafzadeh et al., 2013a,b,c). Fig. 6 shows the scatter plots between the predicted and observed scour depths for the NF-GMDH based models and the empirical equations.

6. Sensitivity Analysis

A sensitivity analysis is carried out for the NF-GMDH-PSO network in order to assign the most effective parameters for the model. The analysis is conducted such that one parameter from Eq.(5) is eliminated each time to evaluate the effect of that input on the output. The results indicated that the parameter, l/b (R=0.53, RMSE=1.45, MAPE=1.82, BIAS=1.105, and ρ=32.67) is the most effective parameter on the scour depth, and d_{50}/b (R=0.9, RMSE=0.87, MAPE=0.33, BIAS=0.04, and ρ=12.52) has the least influence. The other effective parameters are the Fr_0, σ_g, and h/b, which are ranked from high to low values, respectively. The statistical error parameters obtained from the sensitivity analysis are given in Table 6. The table shows the outcomes of the sensitivity analysis are in agreements with previous investigations. For instance, the experimental observations reported by Dey and Sarkar (2006), Lim and Yu (2002) also found that l/b and Fr_0 are the two main effective parameters for scour downstream of sluice gate.

7. Conclusion

In this study, the structure of a neuro-fuzzy GMDH network is developed as a self-organized method to predict the scour depth downstream of a sluice gate with an apron. An evolutionary algorithm of PSO is developed with the NF-GMDH network for the training stage. In order to avoid a network with lower complexity, the NF-GMDH-PSO model is designed using three layers with each layer having 10 partial descriptions. The empirical equations proposed by Dey and Sarkar (2006), and Lim and Yu (2002) are used to compare with the predictions using the NF-GMDH-PSO model using datasets collected from literatures for the training and testing of the networks. Five inputs and one output parameters are derived based on dimensional analysis of the most effective parameters affecting the scour processes. The performing of the NF-GMDH network for the training stage indicated that the proposed NF-GMDH-PSO network provided accurate predictions (RMSE=1.05 and MAPE=0.129). In the testing stage, the NF-GMDH-PSO network yielded better scour predictions with relatively lower error (RMSE=1.12, MAPE=0.455, and ρ=16.7) than those calculated using the empirical equations. For the latter, Eq.(6) proposed by Dey and Sarkar (2006) provided higher error (RMSE=10.12 and MAPE=2.25) and lower accuracy (R=-0.68) than the other models. The results of the sensitivity analysis indicated that l/b and Fr_0 are the most important parameters in the scour model of the NF-GMDH-PSO network. The application of the PSO algorithm as an evolutionary approach to improve the NF-GMDH network has been proven and this method can be used as a new soft computing tool for scour prediction downstream of a sluice gate with an apron.

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Table 1. Ranges of input-output parameters for the scour depth prediction

Parameter	Range
$h(m)$	0.103-0.986
$l(m)$	0.4-1
$b(m)$	2-20
$d_{50}(m)$	0.00026-0.00556
$U(m/\sec)$	0.89-2.21
$\mu(Pa.s)$	0.001
G_s	2.65
σ_g	1.06-3.92
$d_s(m)$	0-0.11

Table 2. Empirical equations for the scour depth prediction at sluice gates

Empirical Equations	Authors	Eq.no
$\frac{d_s}{b} = 2.59 Fr_0^{0.94} (\frac{l}{b})^{-0.37} (\frac{h}{b})^{0.16} (\frac{d_{50}}{b})^{0.25}$	Dey and Sarkar (2006)	(6)
$\frac{d_s}{b} = 1.04 \sigma_g^{-0.69} Fr_0^{1.47} .(\frac{d_{50}}{b})^{0.33} .\exp\{-0.004\beta(\frac{l}{b})^{1.4}\}$ $\beta = \sigma_g^{-0.5} Fr_0^{-0.35} (\frac{d_{50}}{b})^{-0.5}$	Lim and Yu(2002)	(7)

Table 3.Values of the PSO properties for predicting the scour depth at downstream of sluice gate

Parameter	Range
Omega	0.04-0.09
Number of Particles	30
Number of Variables	6
Maximum Iteration	50
error	0.00001
C_1 and C_2	2.5
x	0.1-1.5

Table 4. Results of Performances for training and testing stages of NF-GMDH-PSO

Stage	R	RMSE	MAPE	BIAS	ρ
Training	0.91	1.05	0.129	-0.154	14.45
Testing	0.94	1.12	0.455	0.454	16.7

Table 5. Resuls of Performances for NF-GMDH-PSO and empirical equations

Methods	R	RMSE	MAPE	BIAS	ρ
NF-GMDH-PSO	0.94	1.12	0.129	-0.154	16.7
Eq.(6)	-0.68	10.12	2.25	3.95	1271.8
Eq.(7)	-0.5	6.16	1.45	2.45	354

Table 6. Results of sensitivity analysis for NF-GMDH-PSO model

Functions	R	RMSE	MAPE	BIAS	ρ
$d_s / b = f(l/b, h/b, d_{50}/b, Fr_0)$	0.85	1.1	0.44	3.05	16.92
$d_s / b = f(l/b, h/b, d_{50}/b, \sigma_g)$	0.77	1.57	0.65	-0.989	24.97
$d_s / b = f(l/b, h/b, \sigma_g, Fr_0)$	0.9	0.87	0.33	0.04	12.52
$d_s / b = f(l/b, d_{50}/b, \sigma_g, Fr_0)$	0.89	1.26	0.42	0.7	17.99
$d_s / b = f(h/b, d_{50}, \sigma_g, Fr_0)$	0.53	1.45	1.82	1.105	32.67

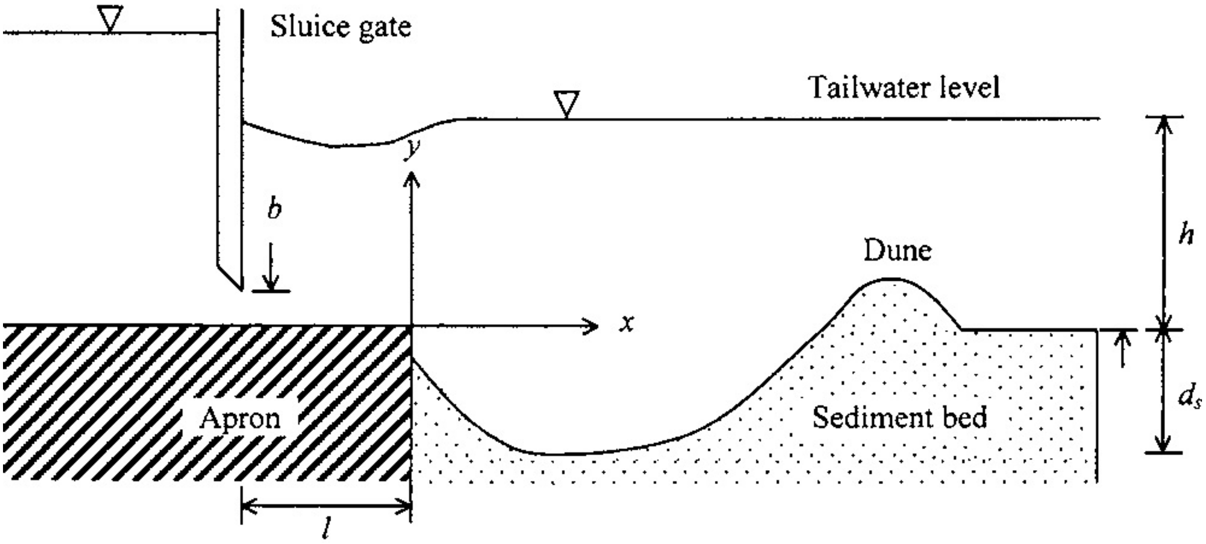

Fig. 1. Schematic sketch for scour process of an apron downstream of sluice gate (Dey and Sarkar, 2006).

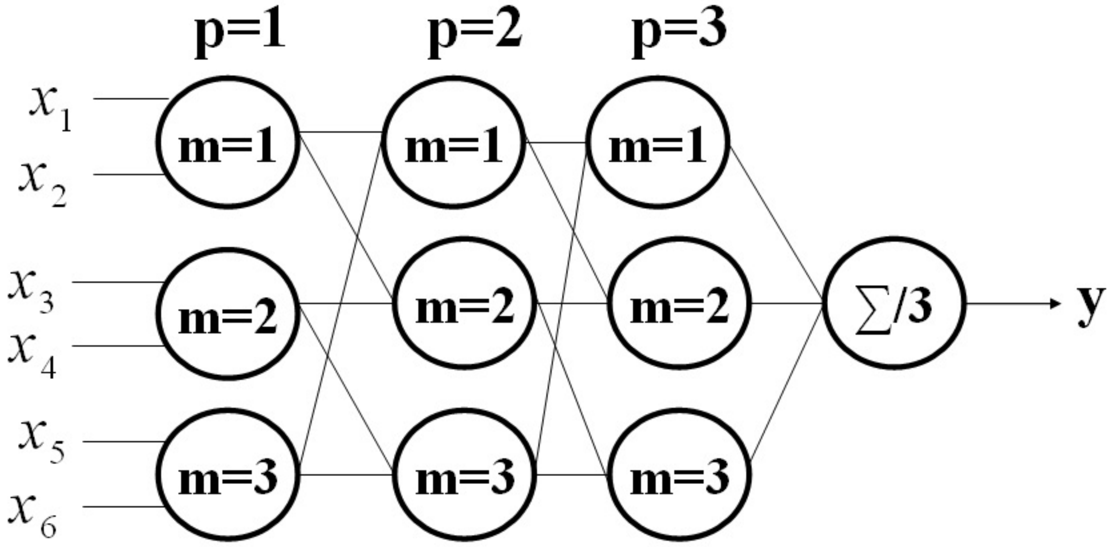

Fig.2 . A case for structure of the neuro-fuzzy GMDH

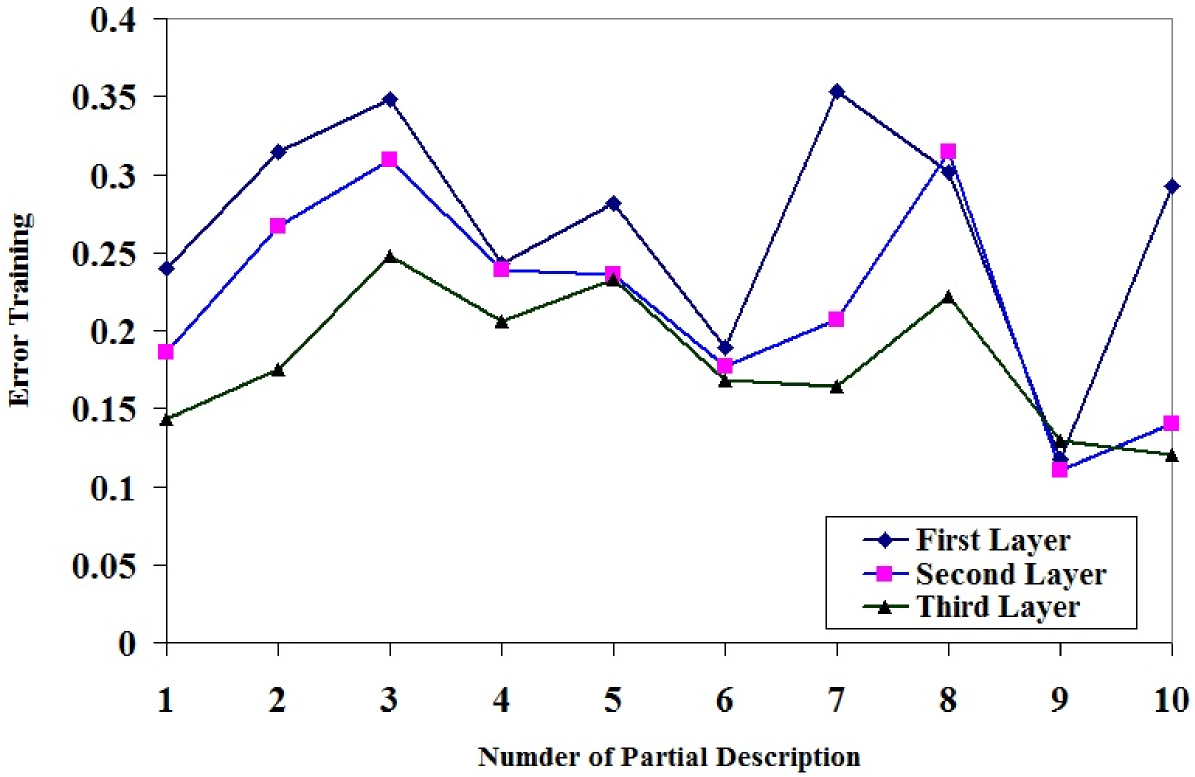

Fig.3. Values of training error for three layers of proposed NF-GMDH-PSO.

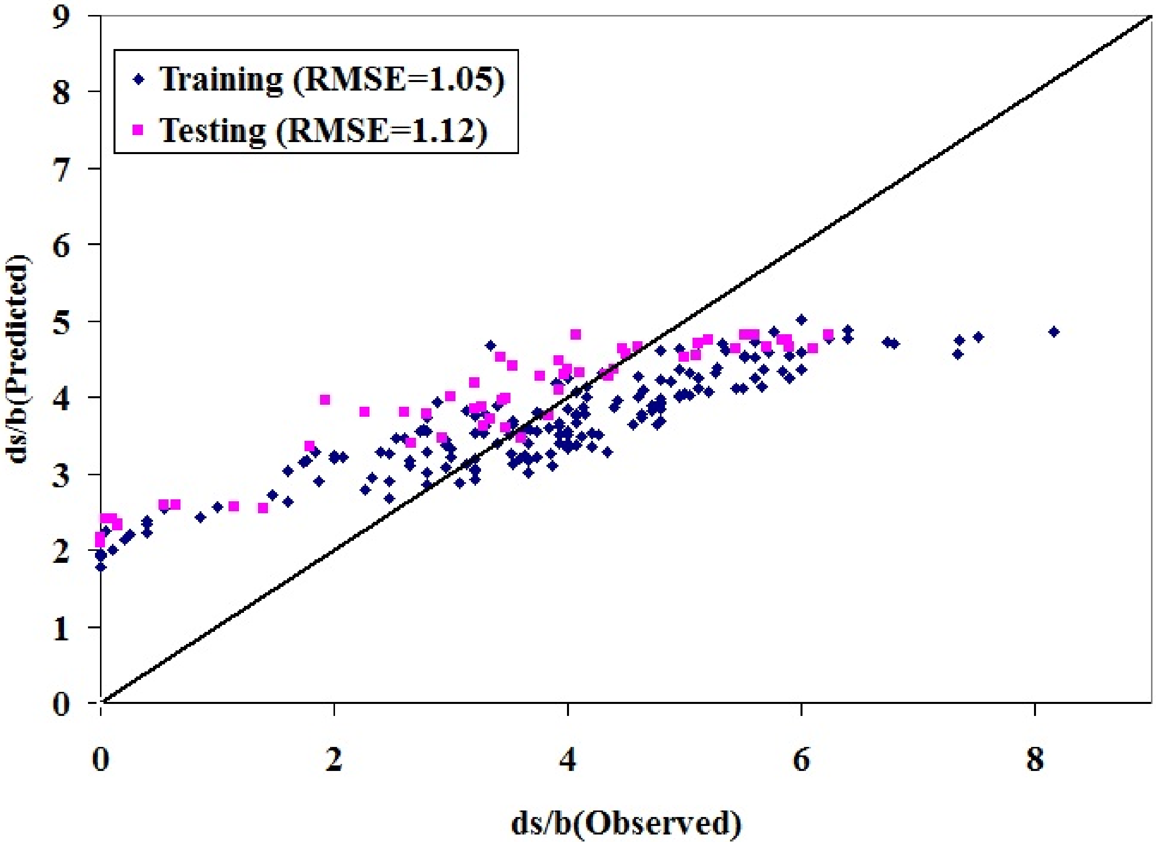

Fig. 5. Scatter plot of observed and predicted scour depth for training and testing stage of NF-GMDH-PSO

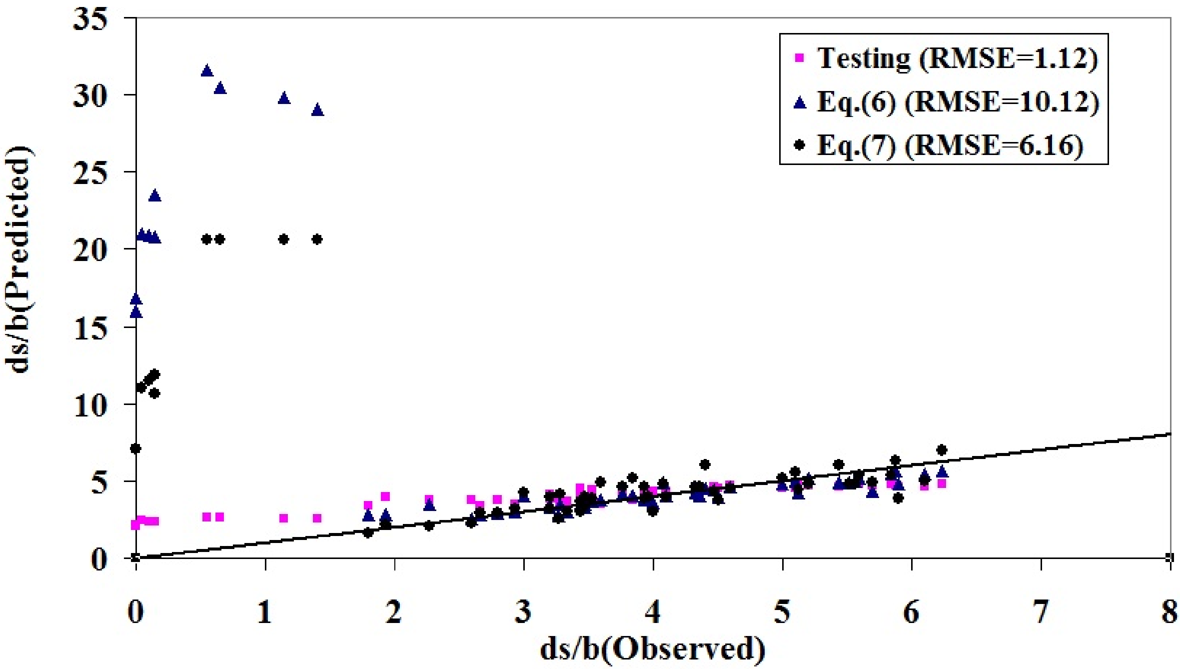

Fig. 6. Scatter plot of observed and predicted scour depth for testing stages of NF-GMDH-PSO and empirical equations.