ESTIMATION OF SCOUR DEPTH DOWNSTREAM THE SKEW V-NOTCH WEIRS USING ARTIFICIAL NEURAL NETWORK AND GENE EXPRESSION PROGRAM

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ABSTRACT

Local scour in bed materials downstream weirs is viewed as the most undesirable process which impedence the Weir's overall stability. Weirs with a skew edge in the horizontal plane will influence the scour profile downstream the structure and may minimize it. Study of local scour downstream hydraulic structures is so complex to the point that it makes it hard to build up a general exact model to give precise estimation to scour depth. The objective of this study is to establish different models by using Artificial Neural Network (ANNs) and Gene Expression Program (GEP), to estimate the scour depth downstream the skew V-notch weirs. The experimental data sets were collected from a previously published paper for scour downstream skew V-notch weir through a rectangular channel. The (ANN), (GEP) and Multiple Linear Regression modeling (MLR) results were compared with the experimental data sets. The effectiveness of the (GEP) model is more satisfactory than (ANN) and (MLR) modeling to estimate the scour depth downstream the skew V-notch weirs.

Keywords: V-notch, Weirs, Scour, ANN, GEP.

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1 INTRODUCTION

1.1. Local scour

Scour is a natural phenomena process which caused by removing sediments and submerged drags from the base of a structure by currents and waves. Every year an extensive measure of cash is spent for repairing or replace the hydraulic structures and protect them from failures. At the point when the silt rate transported into a specific zone is not as much as that shipped out of this region, a scour hole will occur. Likewise when a hydraulic structure is set in the pathway of a water current, the structure will change the pattern of the flow in its prompt neighborhood, generally causes an expansion in the neighborhood silt transport limit causing a local scour. In case of Weirs, the scour affects the downstream reach of the channel owing to the turbulence results due to changing the flow state from supercritical flow to subcritical flow downstream the weirs.

Scour properties depend on many factors such as bed material properties around the structure (particle shape, particle size, layering, grading, alluvial or cohesive), properties of flow and structure foundation geometries (Raudkivi, 1986). As indicated by numerous investigators, the scour depth around the structure is identified with intensity or velocity of flow. Melville and Chiew 1999, mentioned that local scour can be either live-bed or clear-water. Live-bed scour occurs when mean flow velocities, \( V \) is greater than the limit velocity of the bed sediment movement, \( V_c \), i.e. \( V>V_c \). While clear-water scour occurs for \( V \leq V_c \).

Many researchers considered scour downstream apron by examining the scour hole topography produced by various
hydraulic conditions for example: [Abo-Zeid 2004 & 2006; Ali, 1996; Hassan & Narayanan, 1986; Hemaid, 2000; Kamil, 2002; Negm et al., 2002; (Raudkivi et al., 1983); Youssef, 2004]. A theoretical study for the scour downstream spillways was done by Nasr and Nagy (1997). A theoretical equation for estimating the scour hole depth was obtained. Scour downstream bent weirs were studied and compared with straight ones by Ashour et al. (2008). It was found that a specific course of the arrangement of a bent weir together with two gatherings of sills situated on the solid apron gave a minimum scour depths.

1.2. Artificial neural networks (ANNs)

The (ANNs) technique is one of the most prevalent computing tools and has been utilized in a wide range of engineering problems. (ANNs) are taking into account as an adaptable modeling tool equipped for learning the mathematical relations between variables of the nonlinear systems (input, hidden and output layers) with each neuron acting as an independent computational element "Fig. 1". The outcomes from the hidden layer are exchanged to the output layer by multiplying the product of every neuron in the hidden layer by the considerable connection weight between hidden and output layers. The output layer creates the network output for additionally handling of the data. At this step, the network output is contrasted to the target output to calculate the error. If the error is reasonable, then the output is assumed to be exact. Else the weights of the layers connection are changed beginning from the output layer and propagating in reverse.

Figure 1. The developed neural network of 3-11-1 for the present application.

It utilized to examine its probability as a simulating device for reproduction of tidal flow in 2-dimensional flow field (Dibike et al., 1999). In addition, it was used to predict the scour depth downstream hydraulic structures (Mohamed, 2007). Also, it was employed to estimate the local scour downstream culvert outlet (Liriano and Day, 2001) and (Azamathulla and Haque, 2013). Furthermore, it was utilized to predict the scour depth downstream ski-jump bucket and spillway (Azmathullah and Deolalikar, 2005) and (Azmathullah et al., 2008). Moreover, this technique is employed to predict scour depth around semicircular bridge abutments (Begum, 2012). Kheireldin (1999) utilized ANN to predict the maximum scour depth nearby bridge abutments. It was concluded that the ANN has a good performance for some set of data and not favorable for another set of data.

Elkiki (2008) developed an (ANN) model to predict the drawdown depth in narrow navigation channels. The correlation coefficient between the measured and predicted drawdown using (ANN) model are 0.995907 for training data sets which was an excellent method to predict the drawdown depth. Also, Elkiki (2008) built an artificial neural network model to predict the scour parameters downstream the skew siphon pipes. It was concluded that the (ANN) model was capable of predicting all output variables of the problem with an excellent correlation coefficient (0.997066). Furthermore, Hamed et al. employed a model to predict groundwater elevations in four wells south of Riyadh City.
for a future 20-year period. Simulation results agreed well with observations.

### 1.3. Gene expression programming (GEP)

Gene expression programming (GEP) is a developmental algorithm that makes PC programs or models. These PC programs are complicated tree structures that learn and adjust by changing their sizes, shapes, and structure, just like a living organism. Furthermore, such as living life forms, the PC projects of GEP are likewise encoded in simple linear chromosomes of settled length. The (GEP) makes a PC program contain variables and function sets composed of arithmetic operations (+, −, /, *) and function calls (such as exp, sin, cos, log, ln, sqrt, power). “Fig. 2” shows the flow chart of a gene expression programming. The process begins with a random generation of chromosome of the initial population. Then, the chromosomes are expressed, and fitness of each individual is estimated. If the stopping criterion is satisfied then the results are designated and the program is ended. Else, chromosomes are selected and the fittest are kept for the next generation. After that genetic modification are performed via genetic operators and gene recombination. Then a new generation of chromosomes are reproduced and the process is repeated until the required accuracy is reached or for a certain number of iterations.

**Figure 2. Flow chart of a gene expression algorithm.**

(GEP) was utilized by many researchers, to study the characteristics of hydraulic jump (Eldrandaly and Negm, 2008), to predict characteristics of a hydraulic jump over a rough bed (KarbasI and Azamathulla, 2016), as an alternative approach to modeling of flood routing in natural channels (Bagatur and Onen, 2016) and investigate combined run-off (Fernando et al. 2009). Also, it was used to predict the pier scour depth (Mujahid, 2012 and Chuan-Yi et al., 2013), scour at a bridge abutment and scour depth at bridge abutments in cohesive bed (Azamathulla, 2012 and Danish, 2014), Estimation of dimension and time variation of local scour at short abutment (Mohammadpour, 2013) and prediction of scour at vertical bridge abutment (Begum et al., 2013). Furthermore, it was used for prediction of circular pile scour (Guven et al., 2009) and Moreover, this technique is used for prediction of scour depth downstream sills (Azamathulla, 2012), and prediction of scour depth at culvert outlet (Azamathulla and Haque, 2012).

Dorado et al. (2003) used (ANN) and (GEP) for prediction and modeling of the transformation of rainfall-runoff of an urban basin. Furthermore, the (GEP) and radial basis function neural network (RBF-NN) methods are developed in order to find a continuous spatial velocity description using discrete experimental measurements (Sharifipour, 2016). Also, Onen (2014), employed the (ANN) and (GEP) to estimate the scour depth at a Side-Weir. It is found that the execution of (GEP) is more performed than (ANN) approach. In addition, the two techniques were used for modeling the scour depth downstream hydraulic structures in a trapezoidal channel (Moussa, 2013).

### 2 THEORETICAL & EXPERIMENTAL BACKGROUND

The dimensional analysis technique was being used to derive an expression for the scour depth \(d_s\) "Fig. 3" (Hamed et al., 2009) and the following relation is obtained:

\[
\frac{d_s}{H_{ds}} = f(\theta, \alpha, F_r)
\]  
(1)
Where: $H_{ds}$ is downstream water depth, $\theta$ is V-notch angle, $\alpha$ is skewness angle of the weir in plan and $F_r$ is downstream Fraude No.

![Figure 3. Definition sketch of the experimental model](image)

The experimental work for determining the scour downstream skew V-notch weir through a rectangular channel of this study was conducted at the hydraulic laboratory of Faculty of Engineering, Port Said University. A closed operating system flume with a total length of 13.25 m is used. The flume is consisting of three parts, the inlet, the testing part and the outlet of lengths 1.7 m, 10 m and 1.375 m respectively. The side walls of the testing part are made from a glass while its bed is made of a cold rolled steel sheets welded to each other. Four sharp-edged V-notch weirs with different angle ($\theta$) (30°, 60°, 90° and 120°) were used for different Fraude No. ($F_r$) ranges from 0.05 to 0.13 and the test was repeated with four oblique angles ($\alpha$) (0°, 5°, 10° and 15°). A solid apron of length 27 cm was placed downstream the weir models. The apron was followed by 6 m long of a mobile bed which has $d_{50}$=0.76mm and thickness of 15 cm. Both of the apron and the sand have the same level.

By comparing the experimental used data in this study with a study concluded by Ibrahim (2015), where experimental results were used for developing an empirical formulae for predicting the scour depth downstream compound sharp crested V-notch weir. Eq. (2) was performed to estimate the scour depth and a very good agreement was observed between the experimental data of the current study and the previously mentioned study as shown in "Fig. 4". "Fig. 4" shows the comparison between the two studies in case of $\theta = 90^\circ$ and $\alpha = 0^\circ$ for different values of $F_r$.

$$\frac{d_s}{H_{ds}} = 0.448 + 0.968F_r + 0.00955\alpha_{r}$$ $$- 0.0021\theta + 7.423\frac{d_{50}}{H_{ds}}$$ $$+ 0.273 \frac{H}{H_{ds}}$$ (2)

![Figure 4. Comparison the values of $ds/H_{ds}$ between current study data and Ibrahim (2015) data in case of $\theta = 90^\circ$ and $\alpha = 0^\circ$ for different values of $F_r$](image)

3 BUILDING THE (ANN) MODEL

Neural connection software has the possibility to detect and build the best (ANN) based on the pre-specified training parameters through the conversation of the MLP module. PC runs are performed in order to get the perfect size of the neural network. The network parameters had been selected carefully after executing many runs using various combinations. The performance of each network was evaluated through observing and comparing the validation errors. In the present study the MLP tool is used to specify the following parameters:

1 - The initial values of the weights are obtained by trial and error with a seed number of 5 within a range of ± 0.1and are uniformly distributed.

2 – The learning algorithm is the conjugate gradient.
3 – The maximum number of weights updates are 300 per each learning stage with a total of 1200.
4 – Stopping criterion; RMSE < 0.0001.
5 – The input and target data vector are normalized according to the standard normal distribution which has a zero mean unit standard deviation.

6 – 11 for the number of neurons in hidden layer which is obtained by trial and error so that the best size of the network is 3-11-1 as shown in “Fig. 1”. To ensure the number of neurons of the hidden layer, this number is changed several times and the errors from the network are investigated. "Fig. 5" shows the relation between the root mean square error (RMSE) of the different outputs and the number of neurons of the hidden layer. The best size of neurons in the hidden layer is 11 as shown in the figure.

7 - The experimental data are investigated several times with different percentages to study the effect of training data on the variation of validation errors (RMSE) of the output variables. The data divided into 60% for training, 30% for validating and 10% for testing. "Fig. 6" shows that a network 60-30-10 is the most convenient percentage which gives a minimum (RMSE) for the data occurs.

8 – The most suitable activation function had been selected from three different functions (Tanch, Sigmoid and linear functions). The effect of activation functions on the resulting error from the best network is studied by performing three computer runs using the best (ANN) of 3-11-1 utilizing different activation function assuming other parameters unchanged. "Fig. 7" shows that the least (RMSE) is from the tanh function which is more suitable to predict the outputs of the problem.

Estimated scour depth downstream skew V-notch weir obtained with (ANN) model are graphically compared with the measured one in "Fig. 8". As seen from figure, (ANN) model prediction is well agreed with the experimental data.

4 BUILDING THE (GEP) MODEL

GeneXpro Tools 5.0 program is used in the present study. 67% of the data set is used to build (GEP) model and the rest is used to check the test data set. After this division, the following 5-major steps are applied to choose the different parameters for the (GEP) model:

Step 1 Multi-genic chromosomes (consisting of five genes) were utilized for the initial population of individuals. After many trials, a population size of 30 chromosomes was chosen as the ideal size and was in this way utilized as a part of all GEP-based models.

Step 2 The individuals were evaluated and their fitness function computed using the (RMSE) as the fitness function.
Step 3 The linking function was selected among the arithmetic operators (+, −, *, /) and the addition operator was appropriate to set. Also, some basic mathematical functions were chosen like (Exp, Pow 2, Inv., Ave., Hyp., Tang., Log, Atan, Cube root).

Step 4 The number of Genes and the length of the head and tail of every Gene in a chromosome were chosen. In this study, the No. of Genes were 3 and the head and tails sizes were 9 and 10 respectively.

Step 5 After finishing the chromosome architecture, genetic operators and rates were chosen. Genetic operators such as mutation, inversion, transposition (IS, RIS and gene transposition), recombination (one-point, two-point and gene recombination), and Dc-mutation operators were used. The rates of the genetic operators are given in "Table 1".

<table>
<thead>
<tr>
<th>Table 1 Parameters of the Genetic operators of the GEP model</th>
</tr>
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<tbody>
<tr>
<td>Mutation: 0.001</td>
</tr>
<tr>
<td>Inversion: 0.005</td>
</tr>
<tr>
<td>IS Transposition: 0.005</td>
</tr>
<tr>
<td>RIS Transposition: 0.005</td>
</tr>
<tr>
<td>Gene Transposition: 0.003</td>
</tr>
<tr>
<td>One-Point Recombination: 0.003</td>
</tr>
<tr>
<td>Two-Point Recombination: 0.006</td>
</tr>
<tr>
<td>Gene Recombination: 0.003</td>
</tr>
<tr>
<td>Dc Mutation: 0.002</td>
</tr>
</tbody>
</table>

After all parameters were defined, the model were simulated. The explicit formulation of the (GEP) for the scour depth downstream the skew V-notch weirs has been obtained as:

\[
\frac{d_s}{H_{ds}} = \frac{2(\alpha_r \times e^{\theta_r}) - (F_r - \alpha_r + \theta_r) + 2\tan^{-1}(\frac{(\alpha_r \times c_1) \times c_2 \times F_r + (3\alpha_r + \theta_r)}{4})}{\frac{1}{2} \tanh\left(\frac{(F_r + 3\alpha_r + 2\theta_r)}{e^{(\alpha_r + c_2)}}\right)}
\]

The prediction of the proposed (GEP) formulation versus actual experimental values for training sets is given in "Fig. 10". It is shown from the figure that the (GEP) model shows how good (GEP) learned the nonlinear relation between parameters and it is well agreed with the experimental data.

5 BUILDING THE (MLR) MODEL

The (MLR) technique by using Microsoft Excel with the same data set used previously in (ANN) and (GEP) were used to obtain a prediction equation for the scour depth downstream the skew V-notch weirs. The three input variables representing the $F_r$, $\alpha_r$, and $\theta_r$ are used as regressors. The following equation is obtained:

\[
\frac{d_s}{H_{ds}} = 0.414891 + 2.939977F_r + 0.000955\alpha_r - 0.07818\theta_r
\]

6 RESULTS AND DISCUSSIONS

The performance of (GEP), (ANN) and (MLR) models in training and testing sets are validated in terms of root mean square error (RMSE), correlation coefficient ($R^2$), mean absolute error (MAE) and mean percentage error (MPE). The statistical results of different model predictions for training and testing sets are given in "Table 2". From the table, it is clear that (GEP) model predicted the scour depth for both training and testing sets with relatively lower error (RMSE) (0.028826 and 0.041556), and higher accuracy ($R^2$) (0.955074 and 0.894229) respectively. Also, the values of (MAE) and (MPE) for both training and testing sets are (0.03954 and -0.21%) for training data and (0.055647 and 0.17%) for testing data respectively. The results indicate that the (GEP) model (eq. (2)) performance is the best among all scour depth prediction models.
The scatter diagram between experimental and predicted non-dimensional scour depth has been shown in figures from "Fig. 11" to "Fig. 16". "Figs. 11 & 12" show a comparison between the experimental and predicted dimensionless scour depth by the (MLR) model for the training and testing data. It is indicated by the figures that the (MLR) model are not always suitable for effectively predicting scour depth downstream the skew V-notch weirs.

"Fig. 13" shows a comparison between the experimental and predicted dimensionless scour depth for the training data by using (ANN) model. Moreover, a scatter plot of the (ANN), illustrated in Fig. "14", displays the performance of the (ANN) in the prediction of the value of $d_s/H_d.s$ for the validation and testing data. It is clear that the (ANN) gives a good performance in the prediction of non-dimensional scour depth.
The prediction of the proposed (GEP) model with eq. (3) versus experimental data for training and testing sets are given in "Figs. 15 & 16". "Fig. 15" shows the quality of (GEP) model to learn the nonlinear relation between different parameters in training data set and "Fig. 16" proves the high performance of the proposed (GEP) model for the testing data.

In summary, the (MLR) model equation is of low execution and are not appropriate for completing design purposes. (GEP) performs superior over (ANN) with respect to different statistical parameters and also the scatter plots. (GEP) gives a very good ability to provide a specific empirical equation that should be helpful for designing purposes.

7 SUMMARY AND CONCLUSIONS

Scour downstream the skew V-notch weirs is a complex phenomenon and scour depth need to be predicted accurately. The use of new AI-based models for scour modeling adds to the limited applications that exist in this area. In this study, the use of (MLR) and AI-based models such as (ANN) and (GEP) for predicting the relative scour depth downstream the skew V-notch weirs by using previously experimental data are investigated. The study investigated the benefit of different data-driven modeling technique range, from ordinary (MLR) to complicated (AI-based models). Specifically, the AI-based computer program, (GEP), was applied for the prediction of the scour depth and its effectiveness was compared with (MLR) and (ANN) models. The (MLR) has the minimum ability within other models to provide an explicit and compact empirical expression. (ANN) model having single hidden layer has been carried in the present study and it is concluded that the suitability of (ANN) model for prediction of scour depth downstream the skew V-notch weirs. The (GEP) tree and the mathematical expression generated by the best case of (GEP) model are also presented. From the results, it is observed that the predicted scour depth of the (GEP) model was found to be encouraging better than (MLR) model developed in the current study and somewhat better than the (ANN) model in terms of statistical measures. The testing achievement of proposed (GEP) model showed a very high performance for both training and testing sets with relatively lower error (RMSE) (0.028826 and 0.041556), and higher accuracy (R²) (0.955074 and 0.894229) respectively. The advantage of the model results (smaller (RMSE) and greater (R²)) indicates that the present model can be applied to varied conditions.

REFERENCES


