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Pareto genetic design of group method of data handling type neural network for prediction discharge coefficient in rectangular side orifices

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ABSTRACT

The powerful method of Group Method of Data Handling (*GMDH*) was used for estimating the discharge coefficient of a rectangular side orifice. First, the existing equations for calculating the discharge coefficient were studied making use of experimental results. On the first hand, the factors affecting the discharge coefficient were determined, then five models were constructed in order to analyze the sensitivity in achieving accuracy by using different parameters. The results, obtained using statistical indexes ($MARE$=0.021 and $RMSE$=0.017), showed that one model out of the five models, on estimation using the dimensionless parameters of the ratio of depth of flow in main channel to width of rectangular orifice (Y_m/L), Froude number (Fr), the ratio of sill height to width of rectangular orifice (W/L) and width of main channel to width of rectangular orifice (B/L), presented the best results.

1. Introduction

Diversion structures are used to divert flow from a main channel to branch channels. Among various types of diversion structures side orifices, which are usually located on the side of the main channel. They are used by environmental and hydraulics engineers to control the flow surface within irrigation channels, drainage networks and wastewater collection systems. The flows passing through channels with side orifices are considered to be spatially varied flows with decreasing discharge. Numerous researches and studies have been conducted, namely on the hydraulic specifications of the flow in channels with side orifice by different researchers such as: Panda [1], Tanwar [2], Ramamurthy et al. [3,4], Gill [5], Swamee et al. [6], Ojha and Subbaiah [7], Oliveto et al. [8], Ghodsian [9], Kra and Merkley [10], Prohaska et al. [11], Bryant et al. [12], Hussain et al. [13], Lewis et al. [14] who have carried out experimental researches on the behavior of the flow passing through rectangular channels with side orifices. Hussain et al. [13] presented an equation which calculated the discharge coefficient of a circular sharp-crested side orifice. They presented their equation as a function of the Froude number and the ratio of the circular side orifice diameter to the width of the main channel. Prohaska et al. [11] studied the factors affecting the discharge coefficient of a side orifice located on the side of a circular channel. Hussain et al. [15] studied experimentally the hydraulic characteristics of a rectangular side orifice on the side of a rectangular channel, using the least square technique, they presented the following equation:

$$C_d = 0.714 - 0.062Fr - 0.347\frac{L}{B} \tag{1}$$

where C_d is the coefficient of discharge, Fr the Froude number, L the width of rectangular orifice and B the width of the main channel. Recently, Hussain et al. [16] conducted an analytical study on the discharge passing through a rectangular side orifice located on the side of a main open channel. They calculated the discharge of a flow passing through the rectangular side orifice by use of analytical equations and compared it with the experimental discharge. The analytical equations of Hussain et al. [16] predict the discharge of the flow passing through a rectangular side orifice with a $\pm 5\%$ error.

In recent years using soft computing software has been considered a powerful tool by researchers, especially in modeling, pattern recognition and solving nonlinear complex problems in different fields such as hydraulics engineering [17,18], river engineering [19] and sediment transport [20,21,22]. Different researches such as Shamseldin [23] and Giustolisi and Laucelli [24] attempted to propose an anticipating rainfall-runoff model using artificial neural networks (ANN). Jain et al. [25] and Bae et al. [26] estimated the dam inflow using different ANN algorithms. The daily floating sediment load was predicted by Kisi [27] using neuro-fuzzy models. Khorchani and Blanpain [28] presented a formula for calculating the discharge coefficient of side weirs located on the side of main open channels. Yang and Chang [29] modeled the flow within open channels by using ANN. Emiroglu et al. [30] presented an equation

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for calculating the discharge capacity of a triangular labyrinth side orifice located on a rectangular channel subcritical flow conditions through the adaptive neural fuzzy inference system (ANFIS). The discharge capacity of a triangular labyrinth side weir located on the main side of an open channel was modeled by Emiroglu et al. [31] making use of ANN. Emiroglu et al. [31] suggested an equation for the discharge of a triangular labyrinth side weir as a function of the ratios of length of the side weir to width of main channel, length of side weir to crest length, height of weir to the weir upstream flow depth, labyrinth side weir included angle and Froude number at the beginning of the side weir. Using the ANFIS model, an equation was presented by Dursun et al. [32] to calculate the discharge coefficient of semi-elliptical side weirs, located on the rectangular channels subcritical flow regime. The discharge coefficient formula suggested by Dursun et al. [32] is a function of the upstream side weir Froude number, the ratios of length of side weir to width of main channel, length of side weir to length of side weir crest, crest height of side weir to flow depth at beginning of side weir, and small radius to large radius of semi-elliptical side weir. Bagheri et al. [33] used ANN to anticipate the discharge coefficient of a rectangular sharp-crested weir located on the main side of rectangular channels. In this study, a computer program is coded for a GMDH network. The purpose of this article is to present a formula using GMDH-type neural networks to estimate the discharge coefficient of sharp-crested rectangular side orifices located on the side of a main rectangular channel in subcritical flow conditions. Therefore, the dimensionless parameters affecting the estimation of the discharge coefficient are presented first, then five different models are presented for examining each of the dimensionless parameters that have an effect on the results. The genetic algorithm is applied to optimize the design of the GMDH-type neural network structure through double targeted optimization.

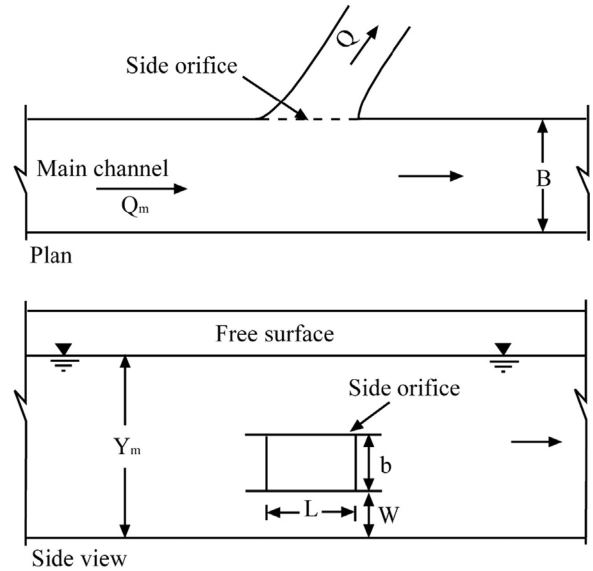

Fig. 1. Plan and longitudinal section of the rectangular side orifice in an open channel [15].

Table 1
Range of Hussain et al.'s data [15].

Parameters	Q_m (m^3/s)	Q (m^3/s)	L (m)	Y_m (m)	W (m)	Fr
Min	0.0281	0.0009	0.044	0.154	0.05	0.05
Max	0.1467	0.0288	0.1333	0.59	0.2	0.48

2. Methodology

2.1. Data collection

The experimental results presented by Hussain et al.'s [15] were used in order to estimate the discharge coefficient of sharp-crested rectangular side orifices (Fig. 1). They conducted their experiments in a rectangular channel, which were 0.6 m deep 0.5 m wide and 9.15 m long. In order to regulate the flow depth within the channel, they used a sliding gauge and also installed a square orifice on the left side of the channel. Their experiments were conducted under free flow conditions for three sizes of square side weirs of 0.044, 0.089 and 0.133 m and with crest height of 0.05, 0.1 and 0.15 m. They used sliding gauge to regulate different depths of the flow within the main channel. Acoustic Doppler flow meter was used in the experiments in order to measure velocity in the main channel and near the side weir, which was located on the horizontal plane passing through the central axis of the side orifice. The range of the data is presented in the Table 1. In this table Q_m is the discharge in the main channel, Q the discharge through orifice, L the width of rectangular orifice, Y_m the depth of approach flow in the main channel, W the sill height and Fr the Froude number.

2.2. Group method of data handling (GMDH)

Group method of data handling (GMDH) is a method based on the principles (basic) of a self-organized learning method, modeling the nonlinear systems (from the set of input and output data). GMDH- type neural networks make suitable map connections between input and output variables without the need for detailed consideration of the under-study issue, even when the number of the data is large. Imagine there is a set of m variables consisting of $x_1, x_2, \ldots, x_m$ and one y variable. For each of the related data visa vis each x_i, there is one (y) output variable. The basis of the GMDH algorithm is that it uses the expansion of Volterra series, which is defined in the form of the following formula [34]:

$$y = b_0 + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} b_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} b_{ijk} x_i x_j x_k + \ldots \quad (2)$$

where $X(x_1, x_2, ..., x_n)$ represent the input amounts and m the number of the input variables. Also $B(b_1, b_2, ..., b_m)$coefficients are obtained through regression methods for each pair of x_i and x_j input variables [35–37]; therefore GMDH algorithm utilizes a number of second- degree polynomials.

$$y_k = \beta_0 + \beta_1 x_i + \beta_2 x_j + \beta_3 x_i^2 + \beta_4 x_j^2 + \beta_5 x_i x_j \quad (3)$$

$$k = 1, 2, ..., N; i = 1, 2, ..., m; j = 1, 2, ..., m-1; \quad (4)$$

$$N = m(m-1)/2 \quad (5)$$

where y_k indicates the middle variable (middle level), and x_i and x_j are input variables. We select those input variables which affect the output variable. Divide the data into two categories, train and test (evaluation) sets. We utilize the train data to estimate the coefficients of the minor systems and the test data to estimate the accuracy of the minor systems and to prevent the divergence of the system. Complicated systems, consisting of m input variables and one output, can be broken down to a simple minor system that has two inputs and one output. Then the minor systems are combined with each other and form a united system. The number of minor ones, with r inputs and one output are found by the following formula:

$$C_m^r = \frac{m!}{r!(m-r)!)} \quad (6)$$