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Performance evaluation of two different neural network and particle swarm optimization methods for prediction of discharge capacity of modified triangular side weirs

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ABSTRACT

Technical design of side weirs needs high accuracy in predicting discharge coefficient. In this study, discharge coefficient prediction performance of multi-layer perceptron neural network (MLPNN) and radial basis neural network (RBNN) were compared with linear and nonlinear particle swarm optimization (PSO) based equations. Performance evaluation of the model was done by using root mean squared error (RMSE), coefficient of determination (R^2), mean absolute error (MAE), average absolute deviation (δ) and mean absolute relative error (MARE). Comparison of the results showed that both neural networks and PSO based equations could determine discharge coefficient of modified triangular side weirs with high accuracy. The RBNN with RMSE of 0.037 in test data was found to be better than MLPNN with RMSE of 0.044 and multiple linear and nonlinear PSO based equations (ML-PSO and MNL-PSO) with RMSE of 0.043 and 0.041, respectively. However, due to their simplicity, PSO based equations can be sufficient for use in practical cases.

1. Introduction

Side weirs are extensively being used in hydraulic engineering applications to control and divert the overflow from the channels. Flood control and flow deviation from dam reservoirs and irrigation and drainage systems are among the main functions of side weirs. Side weirs are constructed along the side of the main channel to direct the overflow to a tributary channel when the water level increases. Calculating side weir equations through a mathematical method, De Marchi [1] assumed that the specific energy before and after the weir are equal and calculated per unit length discharge over the side weir by using Eq. (1).

$$-\frac{dQ}{dx}=\frac{2}{3}C_M\sqrt{2g}(y-w)^{1/5} \tag{1}$$

where C_M is De Marchi coefficient, dQ/dx upstream main channel discharge/distance from the beginning of weir, y flow depth, w weir height, and g gravity acceleration. Many studies have been done on rectangular side weirs and some equations have been introduced to estimate discharge coefficient [2–11]. Triangular and circular are other kinds of side weir and many researchers have investigated the efficiency of such side weirs [12–19]. An increment in the length of the side weir can reduce the risk of channel side edge overflow and erosion. One way to increase weir length is to increase the width of tributary channel, but while this widening seems impossible, a practical way seems to be using labyrinth side weir in which the weir crest is not straight. This very geometrical change can increase discharge coefficient from 1.5 to 4.5 times [20]. Borghei and Parvaneh [21] designed a new modified labyrinth triangular side weir. The authors found that this modified side weir is up to 2.33 times more efficient than the rectangular side weir. Discharge coefficient equation for modified triangular side weir as a function of geometrical and upstream flow parameters was presented by using nonlinear regression method as follows.

$$C_M=\left[-0.18\left(\frac{Fr_1}{\sin(\theta/2)}\right)^{0.71}-0.15(Fr_1)^{0.44}+\left(\frac{w}{Y_1}\right)^{0.7}\right]\times\left[-2.37+2.58\left(\frac{w\,\sin(\theta/2)}{Y_1}\right)^{-0.36}\right] \tag{2}$$

where Fr_1, Y_1 and θ are upstream Froude number, upstream flow depth, and side weir included angle.

Due to the high capacity of soft computing methods such as artificial neural network (ANN) and particle swarm optimization (PSO) to analyze complex problems, these methods have been used in various hydraulic problems such as discharge coefficient of lateral weirs [20,22–26], scour depth prediction [27], flow characteristics in different open channels [28–30], rainfall modeling [31,32], combined open channel flow [33], and sediment transport [34,35].

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The goal of this study is to provide a reliable method to predict the discharge coefficient of modified triangular side weir. Two different artificial neural network (ANN) models, multi-layer perceptron neural network (MLPNN) and radial basis neural network (RBNN) were developed and compared with two different particle swarm optimization (PSO) based formulation, multiple linear particle swarm optimization (ML-PSO and multiple nonlinear particle swarm optimization (MNL-PSO). Four dimensionless parameters, w/L (weir height/weir length) $Fr_1/\sin(\theta/2)$ (upstream Froude number/sin (weir included angle/2)), w/Y_1 (weir height/upstream flow depth) and $w \times \sin(\theta/2)/Y_1$ (weir height × sin(weir included angle/2)/upstream flow depth) were used to develop the ANN and PSO models as input data and discharge coefficient C_M is used as output data. To assess the accuracy of the methods, the experimental results of Borghei and Parvaneh [21] were used. The results of this study showed that radial basis neural network is a suitable method to compute discharge coefficient of modified triangular side weir.

2. Experimental results

The experimental results of Borghei and Parvaneh [21] were used in this research. Fig. 1 shows a schematic representation of experimental set-up consisting of main channel, modified labyrinth triangular side weir and discharge collection system.

A no-slope rectangular channel with 11 m length and 0.4 m width is used as the main channel. Channel side wall has 0.66 m height and is made of glass. The experiments were done at 0.3 m, 0.4 m, and 0.6 m weir length (L), and at 50 mm, 75 mm, 100 mm, and 150 mm weir height (w). In addition, the weir included angle (θ) is taken as 60°, 90°, 120° and 140°. In all cases, upstream Froude number (Fr_1) ranges from 0.19 to 0.96 and the ratio of weir height to water depth in side weir upstream (w/Y_1) changes between 0.46 and 0.83.

Two hundred experiment runs were conducted in different geometrical conditions to obtain discharge coefficient C_M of modified labyrinth triangular side weir. The details of these experiments are given in Table 1.

Water head measurement accuracy and discharge measurement accuracy were ±1 mm and ±0.0001 m^3/s respectively.

3. Methods

To estimate discharge coefficient of modified labyrinth side weir, four different soft computing methods, MLPNN, RBNN, ML-PSO and MNL-PSO have been used. In ANN models, 60% of experimental data is used for training. ANN training data were also used to perform PSO models. Then the accuracy of each model was investigated by test data. The characteristics of RBNN, MLPNN, and PSO-based equations are given in the following sections.

3.1. Multi-layer perceptron neural network

One of the most applicable neural networks is multi-layer perceptron (MLP) [36]. A feed forward MLP consists of an input layer or one or more hidden output layers. Every layer comprises of a number of neurons. The number of neurons in input layers equals the number of inputs and outputs of the given issue, respectively. In the neural networks made in this study for hidden-layer and output neurons, sigmoid and linear activation functions are used, respectively. Function $f(x)$ is a sigmoid type if it is bounded and is increased by increasing x value [37]. However, diverse functions can be regarded as sigmoid function. In the present study, hyperbolic tangent was used in hidden layers as activation function. To train ANN, Levenberg–Marquardt method was applied. In this method, back-propagation algorithm is used to find the weights and bias of neural network. It is one of the most useful algorithms in MLP neural network [38]. This algorithm quantifies the difference between the outputs observed in laboratory studies and outputs of ANN model by determining weights and bias with high velocity.

3.2. Radial basis neural network

Radial basis neural networks (RBNN) [39,40] are formed of two layers. The output nodes consist of a linear combination of the radial basis function. A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin [41]. Input transformation is necessary to reduce the curse of dimensionality in experimental modeling; then a non-linear projection is used in RBNN. After that, the output layer plays the role of a linear regressor. Adjustable parameters of this regressor are the weights that can be determined using the linear least squares method. In RBNN method, a nonlinear radial basis function $\varphi(x,c)$ was used, where x is the input variable and c is the center of function. φ only depends on the radial distance, $r=\|x-c\|$. The RBNN goal is choosing a function from a linear space of dimension N, depending on the data points [42]. The basis of

Table 1
Range of variable tested [21].

θ	L (m)	w (mm)	w/Y_1	Q_1 (m^3/s)	Fr_1	Number of runs
60	0.3	50,75,100,150	0.46–0.83	0.019–0.030	0.19–0.96	40
	0.4	50,75,100,150				
90	0.3	50,75,100,150	0.46–0.83	0.019–0.030	0.19–0.96	55
	0.4	50,75,100,150				
	0.6	50,100,150				
120	0.3	50,75,100,150	0.46–0.83	0.019–0.030	0.19–0.96	50
	0.4	50,100,150				
	0.6	50,100,150				
140	0.3	50,75,100,150	0.46–0.83	0.019–0.030	0.19–0.96	55
	0.4	50,75,100,150				
	0.6	50,100,150				

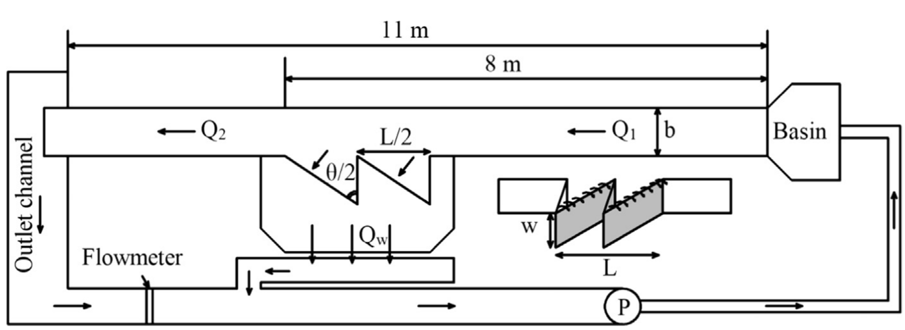

Fig. 1. Plan view of a modified oblique weir and the parameters used [21].