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Artificial neural network approaches for prediction of backwater through arched bridge constrictions

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ABSTRACT

This paper presents the findings of laboratory model testing of arched bridge constrictions in a rectangular open channel flume whose bed slope was fixed at zero. Four different types of arched bridge models, namely single opening semi-circular arch (SOSC), multiple opening semi-circular arch (MOSC), single opening elliptic arch (SOE), and multiple opening elliptic arch (MOE), were used in the testing program. The normal crossing ($\phi = 0$), and five different skew angles ($\phi = 10°, 20°, 30°, 40°$, and $50°$) were tested for each type of arched bridge model. The main aim of this study is to develop a suitable model for estimating backwater through arched bridge constrictions with normal and skewed crossings. Therefore, different artificial neural network approaches, namely multi-layer perceptron (MLP), radial basis neural network (RBNN), generalized regression neural network (GRNN), and multi-linear and multi-nonlinear regression models, MLR and MNLR, respectively were used. Results of these experimental studies were compared with those obtained by the MLP, RBNN, GRNN, MLR, and MNLR approaches. The MLP produced more accurate predictions than those of the others.

1. Introduction

The bridges constrict the flow in flood events and increase the water level at the upstream region of the bridge structure. This increase in water level above the normal unobstructed level due to constricton is defined as the backwater and shown in Fig. 1. In Fig. 1, *dh* represents bridge backwater, D_3 represents flow depth at section 3 where the flow returns to its normal depth, and D_1 represents flow depth at section 1 where the flow reaches its maximum depth. The accurate estimation of bridge backwater is still problematic [1–7] due to its physical nature and it is vital in flood defence schemes and in the economic development of floodplain areas for agricultural and park land.

Although several studies have investigated the bridge backwater problem for modern straight deck bridges, the traditional medieval arch bridges have received less attention [8].

Several studies [9–18] have defined that the blockage ratios at sections 1 and 3 in Fig. 1, as J_1 (area of blockage of bridge at depth D_1/area of flow) and J_3 (area of blockage of bridge at depth D_3/area of flow) respectively, and Froude number at section 3 (Fr_3) are effective parameters in estimation of bridge backwater through arched bridge constrictions in rivers.

In current work, these parameters were experimentally obtained and modeled to predict bridge backwater. In modeling, different artificial neural network approaches, namely multi-layer perceptron (MLP), radial basis neural network (RBNN), and generalized regression neural network (GRNN), and multi-linear and multi-nonlinear regression models, MLR and MNLR, respectively were used. These artificial intelligence methods have been successfully applied to the civil engineering problems like rainfall–runoff modeling [19], streamflow prediction [20], suspended sediment modeling [21–23], break water damage ratio estimation [24], prediction of local scour around bridge piers [25,26], modeling combined open channel flow [27], groundwater level estimation [28], predicting the long-term compressive strength of silica fume [29] and bridge backwater estimation [6,30]. These models were trained and tested on experimental data. The outputs of the MLP, RBNN, GRNN, MLR, and MNLR were compared with experimental values.

2. Experimental apparatus and procedure

Experiments were performed in a large-scale water channel located in the Fluid Mechanics Laboratory at Cukurova University

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Nomenclature

ζ	spread factor for GRNN	N	total number of data
a, b	scaling factors	p	number of elements of an input vector for GRNN
b	width of bridge opening	r	radial distance
c_n	connection weight between hidden and output layer nodes for RBNN	U	cross-sectional mean velocity
D_1	total depth at the section of maximum backwater	w_{ij}	connection weight between nodes i and j
D_3	normal flow depth of unconstricted channel	w_{jk}	connection weight between nodes j and k
dh	bridge backwater	x_i	input variable
Fr	Froude number of the flow in the unconstricted section	x_{max}	maximum value of input and output parameters
g	gravitational acceleration	x_{min}	minimum value of input and output parameters
J	blockage ratio	y_n	connection weight between pattern and summation layer nodes for GRNN

in Turkey. The water channel test section which has the following dimensions: a length of 800 cm, a width of 100 cm, and a depth of 75 cm was constructed of transparent Plexiglas with upstream and downstream fiberglass reservoirs as shown in Fig. 2. It also has honeycomb screen arrangement, which is located at the entrance of contraction. Honeycomb screen arrangements are used to maintain the turbulence intensity below 0.1%. Water flow velocity was controlled by an axial flow pump and pump rotation speed was controlled by an ABB controller unit.

At the end of the flume an adjustable tailgate was located to produce equal flow depths at each section along the 8 m test length. When equal flow depth conditions were achieved at each section the water surface profiles were measured using pointer gauges, these measurements provided the average flow depth.

Velocity measurements were made using a Particle Image Velocimetry (PIV) technique to determine Froude number (Fr) for a given flow depth. PIV technique is one of the most reliable methods for flow velocity measurement in modern fluid mechanics. The principle of PIV measurements is that taking images of the flow field containing special particles shining in the laser light exposure. With the help of a synchronizer, the time between the images to be taken and the laser pulses is synchronized and the velocity vectors

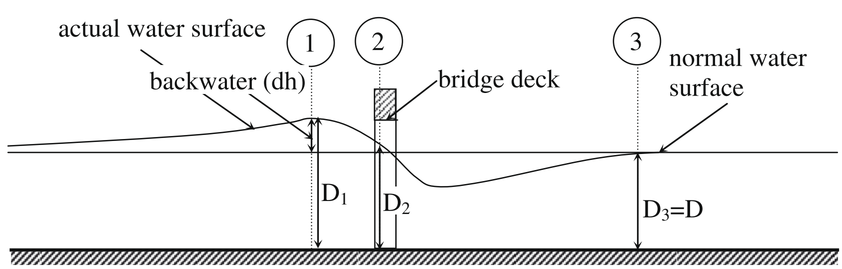

Fig. 1. Definition sketch of a flow profile through a bridge constriction.

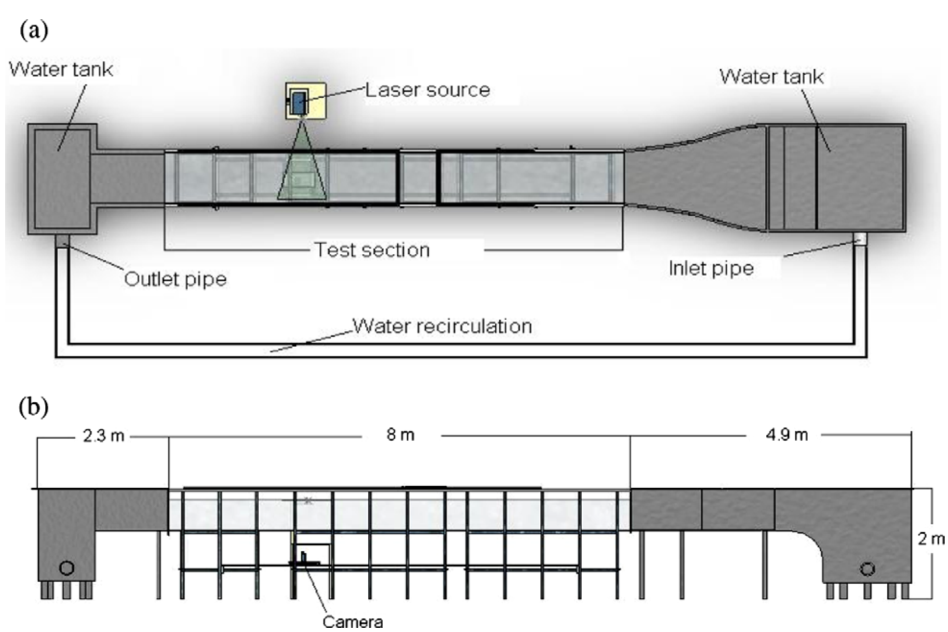

Fig. 2. Experimental setup (a) plan-view and (b) side-view.