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Irrigation Sciences and Engineering Vol. 41, No. 3, Fall 2018, p. 171-184

EXTENDED ABSTRACT

Critical Submergence Estimation For Horizontal Intakes Derived From Reservoir Using Intelligent and Statistical Methods

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Received: 14 March 2017 Accepted: 2 May 2017

Keywords: Critical Submergence, Nonlinear Regression, Genetic Programming, Neural Network.

Introduction

Horizontal intakes are one of the most important parts of hydraulic sets such as rivers for irrigation or reservoirs for power generation and industrial purposes. Air entrainment, by means of a free air-core vortex occurring at intake pipes, is an important problem encountered in hydraulic engineering.

Methodology

To develop and build the predictive models to estimate the critical submergence for a horizontal intake and evaluate the performance of these models, laboratory or field data are required. Gurbuzdal (2009) and Yildirim et al (2000) carried out an experimental study on critial submergence for horizontal intakes at a hydraulic laboratory. Yildirim et al (2000) experiments were performed at rectangular flume with 10m length and 0.5m width (Figure 1). Gurbuzdal (2009) was performed his experiments in a rectangular flume with 2.2m length and 0.63m width (Figure. 2).

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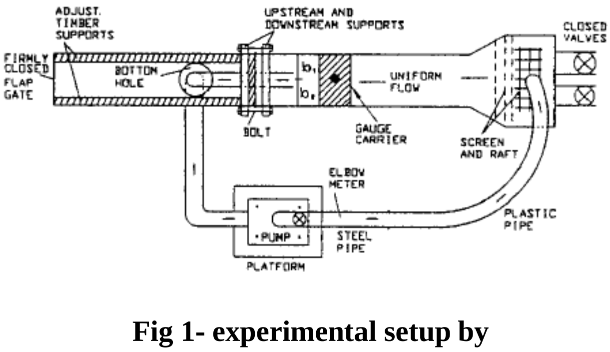

Fig 1- experimental setup by Yildirim et al. (2002)

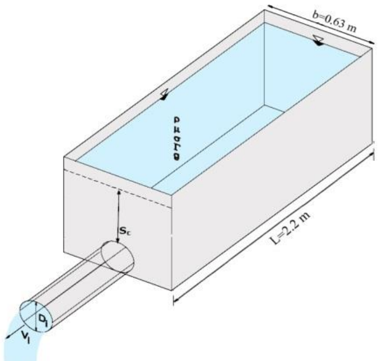

Fig 2- experimental setup by Gurbuzdal (2009)

In this study, equations for estimating critical submergence are developed using experimental data. At first, the equation of present study was determined using dimensional analysis, nonlinear regression and SPSS software. A summary of the data collected in the present study are shown in table (1). In the next step, the artificial neural network and the genetic programming models were used to investigate the accuracy of the results. At first, a functional predictors for critical submergence using nonlinear regression was proposed. The proposed model includes the effect of relative width, horizontal distance of center point of intake to impervious dead, vertical distance of intake to bottom of canal, velocity and Froude number. Then the results of the proposed model were evaluated and compared with the previous studies. As well, with development of the hydroinformatics the Artificial Neural Network model and the genetic programming model are used. The results of these models are statically compared according to the root mean square error (RMSE), mean percentage error (MPE), standard error of the estimate (SEE), modeling efficiency (EF), correlation coefficient (R^2) and The gradient of regression line between results and observations, m, is calculated for evaluating the performance of the model in a way that the intercept of the equation is zero. The results of previous research are used on this equation validation. The predicted results are close to the observations.

Table 1- Range of data collected in the present study

Parameters	Dimension	Range
Intake pipe diameter, D_i	cm	19.72, 15.32, 9.28, 6.12, 5.32
Relative width,b/D_i	dimensionless	10.29, 9.39, 6.78, 4.13, 3.19
Intake discharge, Q_i	m^3/s	0.76-38.85
Velocity of flow in intake, V_i	m/s	0.342-4.55
Froude number, Fr	dimensionless	0.47-6.25
Reynolds, Re	dimensionless	18125.86-29624
Weber number, We	dimensionless	85.357-14896.33

Results and Discussion

Nonlinear regression is a method of finding a nonlinear model of the relationship between the dependent variable and a set of independent variables. Unlike traditional linear regression, which is restricted to estimating linear models, nonlinear regression can estimate models with arbitrary relationship between independent and dependent variables. In this study, the statistical analysis was performed using nonlinear regression on critical submergence results using a statistical package for social sciences (SPSS). The below equation is yielded from nonlinear regression:

$$\frac{S_c}{D} = 4.6 + \left[\frac{-39.828 \left(542987 \quad \frac{L}{D_i} + \frac{C}{D_i} + \frac{b}{D_i} + \frac{V_i}{U} \right)^{-0.028}}{\left(1 + exp\ \left((Fr + 21.73\ \right)\right))^{0.104}} \right] \tag{1}$$

In this study, the critical submergence of intakes was investigated for horizontal intakes in the Reservoir. Five different methods for estimating critical submergence were developed using experimental data. The results of these experimental studies were used to compare with presented the equation in this study, the equation presented by Gurbuzdal (2009), the CSSS I and CSSS II approaches, the artificial neural network (ANN) model and the genetic programming model. The error functions which are used for evaluating the performance of the equation (1) are summarized in Tables 2,3,4 and 5

Table 2- Statistical error functions of the equation presented in this study to estimate S_c/D_i

Parameters	RMSE	MPE	SEE	EF	m
S_c/D_i	0.3487	20.60	0.2913	0.8363	0.9833

Table 3- Statistical error functions of various approaches to estimate S_c/D_i

Approach	Parameters	RMSE	MPE	SEE	EF	m
CSSS I	S_c/D_i	0.6643	49.01	0.4034	-0.8150	1.258
CSSS II	S_c/D_i	0.4208	33.96	0.7706	0.4817	1.075
Gurbuzdal	S_c/D_i	0.9068	-36.53	0.1117	-0.2762	0.5691

Table 4- Statistical error functions of Artificial Neural Network for estimating S_c/D_i

Parameter	Training stage				Testing stage			
	MPE	RMSE	EF	R^2	MPE	RMSE	EF	R^2
S_c/D_i	0.175	0.0089	0.9968	0.9997	0.911	0.0218	0.995	0.9997

Table 5- Statistical error functions of the genetic programming model for estimating S_c/D_i

Parameter	Training stage				Testing stage			
	MPE	RMSE	EF	R^2	MPE	RMSE	EF	R^2
S_c/D_i	0.1038	0.0287	0.9984	0.9984	-2.92	0.0323	0.9986	0.9988

All the results was compared and Gurbuzdal(2009) in comparison with experimental results predicted the depth of critical submergence 41% less; even though experimental results of CSSSI and CSSSII predicted it 25% and 7% less respectively and the proposed equation of this research predicted the value 1.5% less. However, the artificial neural network predicted the depth of critical submergence 0.15% less in comparison with experimental results, while the genetic programming model estimates the depth of critical submergence 0.52% more.

Conclusions

The analysis of the results showed that the artificial neural network (ANN) and genetic programming model performed better in error functions than the proposed equation. As well, the ANN model was developed in compared with experimental results predicted the critical submergence 0.15% more, while genetic programming model and the proposed equation in compared with experimental results estimates the critical submergence 0.52% and 1.5% less, respectively.

The results showed that equation presented by Gurbuzdal (2009) estimated the critical submergence 41% less, while the CSSS I and CSSS II approaches estimated the critical submergence 25% and 7% more respectively. This study shows that there is better agreement between the presented equation and experimental results than the equation presented by Gurbuzdal (2009), the CSSS I and CSSS II approaches. Therefor the presented equation as a simple, general and precise equation is recommended to estimation the critical submergence

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