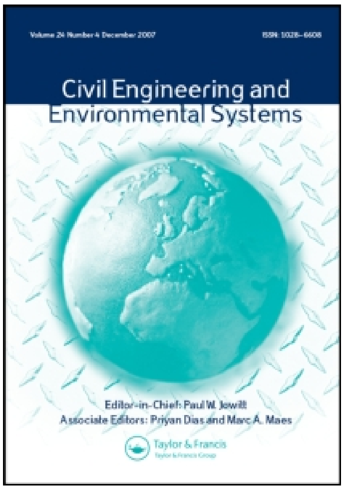

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An artificial neural network model for the prediction of critical submergence for intake in a stratified fluid medium

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Density differences may occur because of temperature differentials, suspended sediments, dissolved salts or other chemicals. Most of the large surface reservoirs are stably stratified throughout most, or all, of the year. One of the means of assisting the management is to allow a selective withdrawal from the reservoir. And while an intake is used for withdrawal (from the lower layer), a maximum discharge is required not allowing the uptake of the upper layer fluids. The value of the intake's vertical distance from the upper layer elevation (submergence) when the upper layer fluids begin to be drawn into the intake is known as 'critical submergence'. In this study, the critical submergence for a circular intake pipe in a stratified body (which has different layer thickness) is investigated. Experiments were conducted on a vertically flowing downward intake pipe in a still-water reservoir. Artificial neural network (ANN) models and formulas, which are found by the theoretical analysis of critical spherical sink surface (CSSS), are used for the analysis of experimental results. The CSSS has the same centre and discharge as the intake. The ANN model and CSSS results are compared with the experimental results.

Keywords: critical spherical sink surface; critical submergence; intake; artificial neural networks; stratified fluid medium

1. Introduction

Reservoirs and natural lakes are density stratified almost throughout the year. In a reservoir, vertical density gradients may arise from variations in temperature, dissolved salt content and suspended sediments. In practice, mostly the density stratification is because of the temperature variation within the reservoir. The use of thermal stratification, which exists in tropical seas, as a source of energy has raised the question of the degree of selectivity that exists during intake of a vertical density gradient fluid. The reduction of reservoir sedimentation by the removal at the dam of water containing large amounts of suspended sediment has been suggested as a means of prolonging the useful life of major structures. A common feature of the applications described is the fact that, in all cases, the fluids are miscible and the density differences are small. For the purpose of selective withdrawing, various intake structures have been studied and used. These structures may be broadly classified as fully or partially submerged (Sharp and Parchure 1991,

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1993). In the former, the intake structure is simply a circular pipe projecting vertically from the bed, with or without a horizontal cap (Harleman *et al.* 1959). Fully submerged intakes are usually less costly. In locations where the bed is soft, intakes set level with the bed may suck the sediment into the cooling system. Therefore, a fully submerged intake is constructed at some distance above the bed level. This raised intake can reduce the sediment intrusion but needs deeper water. Sharp and Parchure (1991, 1993) have investigated the effect of the clearance, c (vertical distance of the intake to the bed), on the critical submergence. Their studies were performed on simple vertical intakes set flush with bed and raised above the bed level. They showed that the critical submergence decreased as the intake was raised.

The maximum discharge (from the lower layer) without simultaneous withdrawal from the upper layer is investigated. Investigations have been made to determine the critical value of the withdrawal rate in terms of known quantities, such as distance from the interface (critical submergence), diameter of the intake pipe and density (Davidia and Glover 1956).

If the gravitational acceleration is reduced by the factor $\Delta\rho/\rho$, then it is designated by a prime, $g(\Delta\rho/\rho) = g'$. It follows that the Froude number remains as the primary similitude parameter for the stratified flows. The results of the analysis of the earlier investigators can be generalised as

$$\frac{S_c}{D_i} = a \cdot \mathrm{Fr}^b \tag{1}$$

where S_c is the critical submergence, D_i the internal diameter of the intake pipe, a and b the constants, $\mathrm{Fr} = V_i/\sqrt{g' \cdot D_i}$ denotes densimetric Froude number, V_i the average intake velocity, $g' = g(\Delta\rho/\rho)$ denotes reduced gravitational acceleration, g the gravitational acceleration, $\Delta\rho = \rho - \rho_0$ the difference in the density of the two fluids, ρ the density of the lower layer, and ρ_0 the density of the upper layer. For the case in which the lower fluid is a liquid and the upper fluid is air $\Delta\rho \cong \rho$.

Yıldırım and Kocabaş (1995, 1998, 2002) and Yıldırım (2004) investigated the critical submergence for an air-entraining vortex at an intake. They show that the critical submergence for an intake can be predicted by means of a potential flow solution. Theoretical results of these investigators show that the critical submergence for an intake is equal to the radius of a critical spherical sink surface (CSSS).

In this study, experiments on a circular intake sited in water and water–oil reservoirs are conducted. When the fluids are at rest, the interface will be horizontal. A sharp interface is desirable to determine the critical submergence in a stratified fluid medium. For this purpose, oil (specific gravity is 0.91) was used to obtain the stratification in this study. CSSS is utilised to determine the theoretical S_c/D_i. Also, artificial neural network (ANN) model is developed to estimate the value of S_c/D_i for intakes in a stratified fluid medium. The experimental results are compared with those of CSSS and ANN model.

2. Experiment

The experimental tests were carried out at the Hydraulics Laboratory of the Faculty of Engineering and Architecture at Bozok University, Yozgat, Turkey.

2.1. *Equipment and test program*

Laboratory studies were conducted in an $80 \times 80 \times 50\,\mathrm{cm}^3$ rectangular prism tank. One side and the bottom of the tank were made of 3.5 mm-thick steel plate. The other sides were made of 6 mm-thick glass. The tank was elevated 1 m above the floor. A massive concrete cylindrical floor was

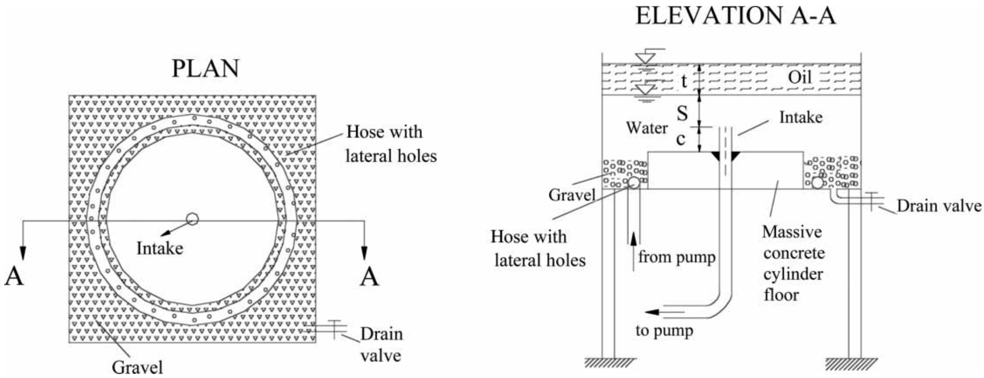

Figure 1. Experimental set-up.

constructed at the centre bottom of the tank. Experiments were performed on a vertically flowing downward intake pipe in a still-water reservoir. Steel intake pipe of internal diameter 27.5 mm was used in the experiment. The intake was located in the centre of the concrete cylinder bottom and connected to the pump which re-circulated the water. For uniform and silent distribution, the returned water is sent through a plastic pipe-ring having lateral holes. This plastic pipe-ring is embedded in a fine gravel packing placed within the circumferential gap between the massive cylindrical floor and the inner wall of the tank as shown in Figure 1.

The discharge of the intake was measured by a calibrated venturimeter on the intake outlet line. The intake pipe was changeable and connected to the outlet line with a threaded coupling. The procedure for the experiment is as follows. After placing the intake, the tank is filled with sufficient water. Stratification was then simulated using oil of thickness $t_i/D_i = 0.73$ or 1.82. Here, t is the thickness of the oil layer. The pump is started and the valve on the pump line is opened and the discharge is slowly increased to a desired value. When the conditions became steady, a small amount of the valve on the drain pipe (Figure 1) was opened (i.e. submergence was decreased). The experiment was continued until the upper layer fluid enters the intake. When the air-entraining vortex or the upper layer fluid reaches the intake, the draining was stopped to keep the water level constant and then the measurements were related to the intake discharge, Q_i, and critical submergence, S_c. This experiment was conducted for calculating clearances, when $c/D_i = 0, 1, 2$ and 3 (Ülker 2005, Kocabaş and Ülker 2006).

3. Methods of analysis

3.1. *Analysis by CSSS*

Theoretical results of Yıldırım and Kocabaş (1995, 1998, 2002) show that the critical submergence for an intake is equal to the radius of a CSSS, where the critical velocity, V_s, is constant for a given flow and geometry. The CSSS has the same centre and discharge as the intake. On the basis of continuity and potential flow solution, Yıldırım and Kocabaş derived the following formulas for the critical submergence during intakes:

$$\text{for } c \leq S_c \quad \frac{S_c}{D_i} = \frac{-(c/D_i) + \sqrt{(c/D_i)^2 + V_i/(2V_s)}}{2} \tag{2}$$

and

$$\text{for } c > S_c \quad \frac{S_c}{D_i} = 0.25\frac{(V_i/V_s)^{1/2}}{\sqrt{1-(D_0/D_i)^2(V_s/V_i)}} \tag{3}$$

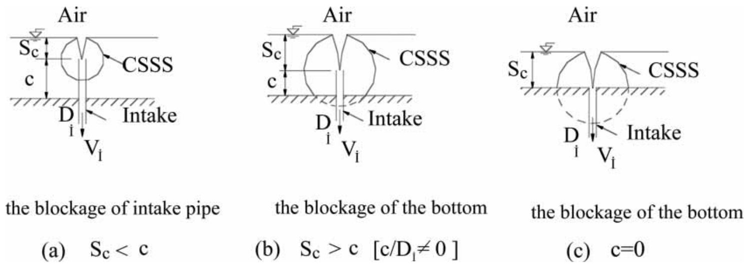

Figure 2. Effect of blockage on critical spherical sink surface.

where c is the clearance (vertical distance of the intake to bottom), V_s the critical radial velocity at CSSS, and D_0 the outer diameter of the intake pipe.

V_s is a constant for a given flow and its geometry can be determined by conducting a few experiments. It can be computed from the continuity equation, $V_s = Q_i/A_c$, where A_c is the net total working surface area of the CSSS after subtracting the blockage of all the impervious boundaries and intake pipes. Blockage means loss in the surface area of a complete CSSS. It is attributable to impervious flow boundaries or structures through which no flow is supplied to the intake (Figure 2).

Yıldırım *et al.* (2000) show that the blockage of intake pipe is equal to the surface area of the spherical sector (cap) of the CSSS remaining inside the outer boundaries of the intake pipe, where no flow is supplied to the intake. The blockage of the intake pipe is present for $c > S_c$ (Figure 2a) and the net total working surface area of CSSS is equal to

$$A_c = 2\pi S_c^2 \left(1 + \sqrt{1 - 0.25\left(\frac{D_0}{S_c}\right)^2}\right) \tag{4}$$

The blockage of the tank bottom is present for $c \leq S_c$ (Figures 2b and c), and the total net working surface area of CSSS is equal to

$$A_c = 2\pi S_c(S_c + c) \tag{5}$$

A_c is calculated for each flow and geometry. If Q_i is plotted against A_c, the critical radial velocity at CSSS, V_s, should be equal to the slope of the linear line. The values of Q_i, c/D_i and t_i/D_i were known for each experiment. Thus, for a given Q_i, c/D_i and t_i/D_i, the value of A_c can be computed by using the measured value of S_c. In total, 88 experiments were performed, in which 64 were used to determine the critical radial velocity, V_s. Figure 3 indicates that the relationship between Q_i and the area of CSSS, A_c, is linear as mentioned earlier. The value of V_s should be equal to the slope of this linear line. Figure 3 shows the values of V_s for different c/D_i and t_i/D_i. The determined V_s for the given flow and geometry was used to calculate S_c/D_i from Equations (2) and (3) for CSSS by the results of 24 experiments. The observed and calculated values of S_c/D_i by CSSS are given in Table 2.

3.2. *Neural networks*

ANNs are based on the present understanding of the biological nervous system, though much of the biological detail is neglected. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. Of the many ANN paradigms, the multi-layer back-propagation network is by far the most popular (Lippman 1987). The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the preceding layer by interconnection strengths or weights, W. Figure 4 illustrates

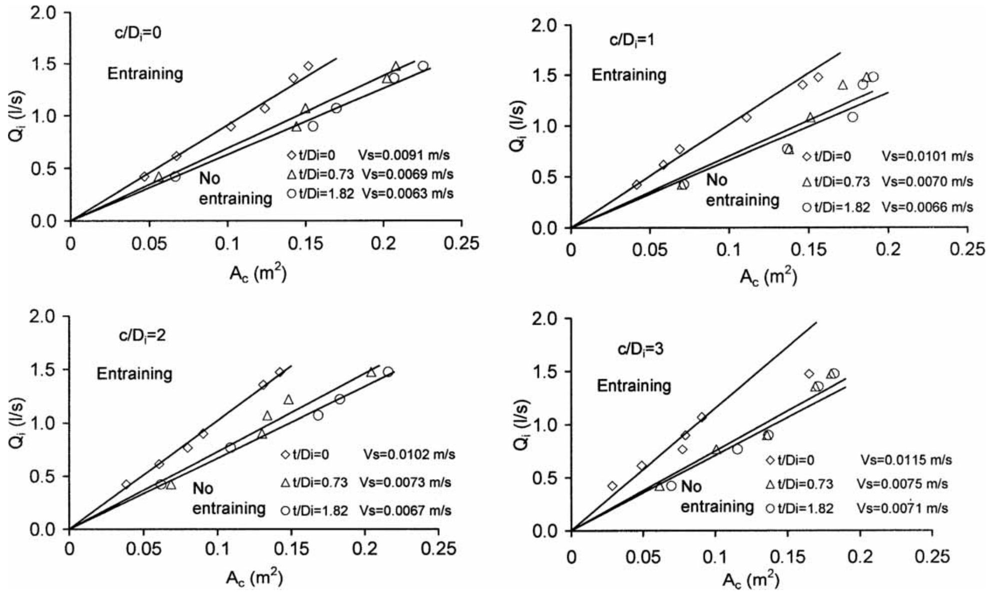

Figure 3. Determination of V_s values.

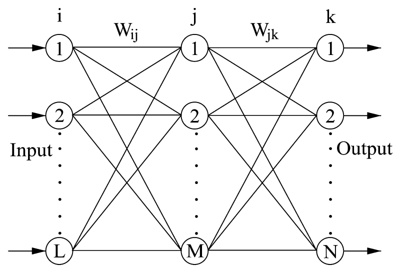

Figure 4. A three-layer neural network structure.

a three-layer neural network consisting of layers i, j and k, with the interconnection weights W_{ij} and W_{jk} between layers of neurons. Initial estimated weight values are progressively corrected during a training process that compares predicted outputs to known outputs and back-propagates any errors (from the right to left in Figure 4) to determine the appropriate weight adjustments necessary to minimise the errors.

The Levenberg–Marquardt training algorithm was used here for adjusting the weights. The adaptive learning rates were used for the purpose of faster training speed and solving local minima problem. For each epoch, if performance decreases towards the goal, then the learning rate is increased by the factor learning increment. If performance increases, the learning rate is adjusted by the factor learning decrement. The number of hidden layer neurons was found using simple trial-and-error method.

4. Application and results

A program code, including neural networks toolbox, was written in MATLAB language for the ANN simulation. Different ANN architectures were tried using this code and the appropriate model structure was determined.

A difficult task with ANN involves choosing parameters such as the number of hidden nodes, the learning rate and the initial weights. Determining an appropriate architecture of a neural network for a particular problem is an important issue, because the network topology directly affects its computational complexity and its generalisation capability. The optimum network geometry is obtained using a trial-and-error approach, in which ANNs are trained with one hidden layer. It should be noted that one hidden layer could approximate any continuous function, provided that sufficient connection weights are used (Hornik *et al.* 1989). Here, the hidden layer node number of ANN model was determined after trying various network structures, as there is no theory yet to tell how many hidden units are required to approximate any given function. In the training stage, same initial weights were used for each ANN. The sigmoid activation function was used for the hidden and output nodes.

The parameters considered in the study are the c/D_i, V_i, t_i/D_i and S_c/D_i. The parameters c/D_i, V_i and t_i/D_i are used as inputs to the ANN for the estimation of S_c/D_i. Of the 88 experimental data sets, 64 data are used to train the ANN and the remaining data are used for validation. The remaining 24 data sets are randomly selected among the whole data. The model results are evaluated using mean square errors (MSEs) and determination coefficient (R^2) statistics.

Before applying the ANN to the data, the training input and output values were normalised using the equation

$$a\frac{x_i - x_{min}}{x_{max} - x_{min}} + b \tag{6}$$

where x_{min} and x_{max} denote the minimum and maximum of the data, respectively. Different values can be assigned for the scaling factors, a and b. There are no fixed rules as to which standardisation approach should be used in particular circumstances (Dawson and Wilby 1998). Herein, the values of a and b were taken as 0.6 and 0.2, respectively.

Different ANN structures are tried in terms of iterations and hidden layer numbers. The test MSE statistics of the ANN models are given in Table 1. As can be seen from this table, the ANN (3, 7, 1) model comprising three inputs, seven hidden and one output layer neurons has the lowest MSE (0.0136).

The observed and calculated values of S_c/D_i by CSSS and ANN are given in Table 2. The absolute relative errors for CSSS and ANN model are also presented in Table 2. These are defined as

$$\text{Relative error}(\%) = \left|\frac{(S_c/D_i)_{observed} - (S_c/D_i)_{calculated}}{(S_c/D_i)_{observed}}\right| \times 100 \tag{7}$$

As seen from this table, the ANN generally gives smaller relative errors than the CSSS. The ANN has a mean absolute relative error of 2.04%, which is smaller than that of the CSSS (3.11%).

Table 1. The mean square error statistics obtained after different trials.

	Iteration number									
MSE	10	20	30	40	50	60	70	80	90	100
Number of hidden layer nodes										
1	0.0777	0.0772	0.0765	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767	0.0767
2	0.0455	0.0333	0.0332	0.0333	0.0337	0.0342	0.0346	0.0348	0.0346	0.0345
3	0.0606	0.0181	0.0167	0.0147	0.0146	0.0145	0.0144	0.0144	0.0144	0.0144
4	0.038	0.0337	0.0318	0.0281	0.027	0.0318	0.0342	0.0346	0.0348	0.0345
5	0.0172	0.0168	0.0168	0.0168	0.0168	0.0167	0.0167	0.0168	0.0168	0.0169
6	0.0203	0.0201	0.0262	0.0255	0.0262	0.0256	0.0309	0.0312	0.0311	0.0311
7	0.026	0.0136	0.0151	0.0185	0.0219	0.036	0.0376	0.0383	0.0418	0.0458
8	0.0222	0.0248	0.0543	0.0611	0.0704	0.0828	0.0842	0.091	0.0998	0.1005
9	0.0433	0.0506	0.0553	0.0568	0.0582	0.0596	0.0609	0.0725	0.0876	0.1305
10	0.0277	0.0385	0.044	0.0556	0.1185	0.1233	0.0595	0.0704	0.0686	0.0697

Table 2. Test results and calculated S_c/D_i by critical spherical sink surface and artificial neural network.

Number of test	c/D_i	t_i/D_i	V_i (m/s)	S_c/D_i Observed	CSSS	ANN	Absolute relative error % CSSS	Relative error % ANN
1	0	0	2.05	5.29	5.30	5.22	0.14	1.40
2	0	0	1.29	4.27	4.20	4.14	1.63	3.10
3	0	0.73	2.05	6.24	6.08	6.11	2.51	2.00
4	0	0.73	1.29	5.11	4.82	5.10	5.60	0.19
5	0	1.82	2.05	6.49	6.38	6.38	1.75	1.68
6	0	1.82	1.29	5.18	5.06	5.36	2.37	3.40
7	1	0	2.05	4.56	4.57	4.76	0.17	4.24
8	1	0	1.53	3.95	3.89	4.04	1.45	2.40
9	1	0.73	2.05	5.42	5.59	5.55	3.18	2.40
10	1	0.73	1.53	4.95	4.77	4.96	3.60	0.35
11	1	1.82	2.05	5.67	5.76	5.77	1.56	1.76
12	1	1.82	1.53	4.95	4.92	5.05	0.69	2.13
13	2	0	2.05	4.09	4.10	4.17	0.31	2.05
14	2	0	1.80	3.73	3.80	3.83	1.82	2.77
15	2	0.73	2.28	5.42	5.33	5.15	1.66	4.86
16	2	0.73	1.29	4.00	3.81	4.00	4.86	0.12
17	2	1.82	2.28	5.51	5.58	5.43	1.29	1.40
18	2	1.82	1.51	4.71	4.39	4.56	6.85	3.15
19	3	0	2.28	4.33	3.69	4.18	14.62	3.30
20	3	0	2.05	3.89	3.45	3.83	11.37	1.54
21	3	0.73	2.05	4.40	4.55	4.42	3.46	0.55
22	3	0.73	1.80	4.22	4.20	4.07	0.55	3.40
23	3	1.82	2.05	4.58	4.71	4.60	2.85	0.50
24	3	1.82	1.80	4.36	4.34	4.35	0.43	0.21

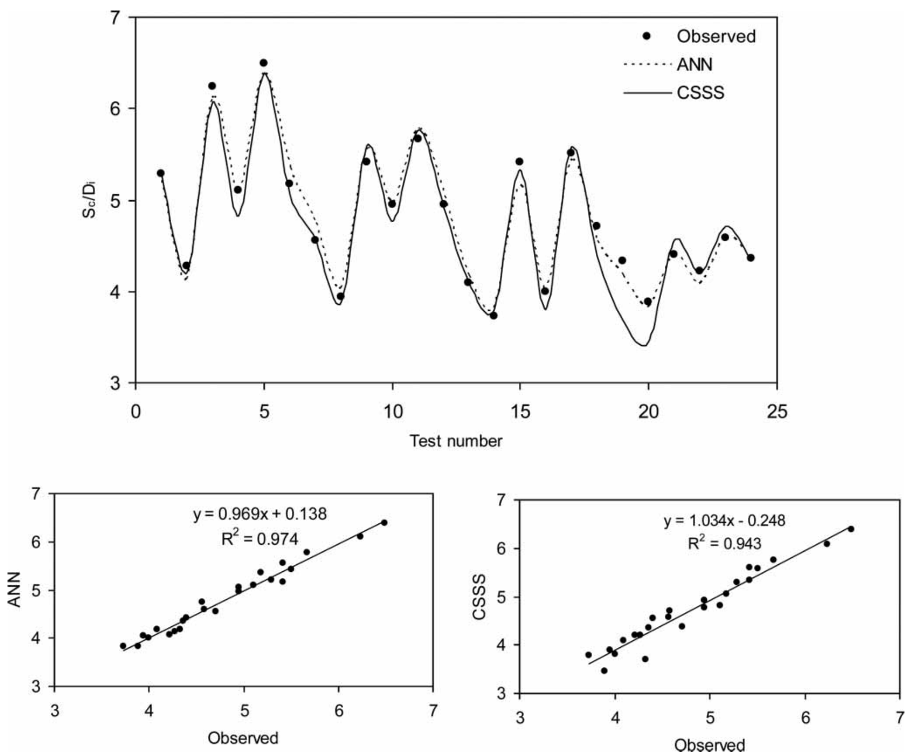

Figure 5. Plot of observed and estimated S_c/D_i by (a) artificial neural network and (b) critical spherical sink surface.

The ANN estimates are compared with those of the CSSS in Figure 5 in the form of hydrograph and scatter plots. As can be seen from the hydrographs, the ANN estimates catch the observed values with a high accuracy. The fit line equation coefficients of the ANN model, 0.969 and 0.138, are closer to 1 and 0, respectively, with a higher R^2 value of 0.974 than those of the CSSS.

5. Conclusions

ANN models and CSSS formulas, which are found by theoretical analysis, were used for the analysis of experimental results in the present study. The optimum ANN models were obtained after trying different structures in terms of iterations and hidden layer numbers. The estimates of the selected ANN models were compared with the CSSS and experimental results. Based on the comparison results, the ANN was found to perform better than the CSSS model in the prediction of critical submergence for an intake in a stratified fluid medium. The experimental results cannot be used for prototype design purposes, because of the fact that the model is very small.

Nomenclature

A_c	total net working surface area of CSSS
c	clearance (vertical distance of intake to the bottom of tank)
D_i	internal diameter of intake pipe
D_0	outer diameter of intake pipe
Fr	densimetric Froude number $= V_i/(g' \cdot D_i)^{0.5}$
g	gravitational acceleration
Q_i	intake discharge
S_c	critical submergence (critical value of S)
t	depth of the upper layer
V_i	average intake velocity
V_s	critical radial velocity at CSSS
$g' = g\frac{\Delta\rho}{\rho}$	reduced gravitational acceleration
ρ	density of the lower layer
ρ_0	density of the upper layer
$\Delta\rho = \rho - \rho_0$	difference in density of the two fluids

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