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Verification of filter efficiency of horizontal roughing filter by Weglin's design criteria and Artificial Neural Network

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Abstract

The general objective of this study is to estimate the performance of the Horizontal Roughing Filter(HRF) by using Weglin's design criteria based on 1/3–2/3 filter theory. The motive is to reduce the Slow Sand load in the raw water by using HRF as the pretreatment unit, but the main objective is to verify the Weglin's design criteria for HRF with respect to raw water condition. A model was also built with the help of neural network which tries to predict the filter efficiency of the HRF. Three results achieved from the three different models were compared to find whether the experimental HRF output conforms to the other two models. According to the results the results from experimental setup is coherent with the neural model but incoherent with the results from Weglin's formula. As neural models are known to learn a problem with utmost efficiency, the model verification result was taken as positive.

1 Introduction

Water is essential for life. Basically all human communities grow up centering some kind of water source. Apart from ground-water most of the people of the world depend on surface water as one of the main sources for drinking purposes. As surface water is unprotected and exposed to the weather, there is possibility of feacal contamination. The main target of water treatment is the removal of chemical and bacteriological contamination and inactivation of disease causing organism. In conventional treatment of surface water plain sedimentation and even prolonged storage are often used to separate the suspended solid concentration which is followed by flocculation by using chemicals to destabilize the suspended solids of smaller magnitude. In rural area water supply system horizontal roughing filtration is used to treat the surface water of high turbidity and in this process relatively coarse grain is used to filter water. Horizontal

roughing filters are operated at filtration rates ranging from 0.3 to 1.5 m/h. And it could also remove the turbidity ranging from 50 to 1000 NTU. The using of horizontal

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roughing filter as a pre-filter is to reduce the solids load on succeeding Slow Sand Filter or Rapid Sand Filter (RSF). The main objective of research is being carried out for investigation the bacteria removal efficiency of Horizontal roughing filters. The work also incorporates the system of horizontal roughing filter in isolation and in combination with polished filtration system (SSF) with respect to removal of solids and pathogenic organism (Barman et al., 2008). For Hydraulic design of the filtration process in case of Horizontal roughing filters different theories have been developed in the laboratories based on various field studies at different conditions. But for the rural area water supply by the multistage filtration, use of Horizontal roughing filter system before the slow sand filtration is commonly practiced. Now the conceptual filter theory for evaluating the efficiency of the filter in case of HRF is still based on the filtration theory described by Weglin (1996). When a particle in the water passes through a gravel bed filled up with gravel there is a chance to escape the particle either on the left or the right or a chance to fall in the surface of the gravel and settles. Hence the probability of chance of the success of removal and the failure is 1/3 and 2/3. This is the basic of the Weglin's 1/3–2/3 theory. However, as the process of filtration continues to the multiple chambers the more of the particles settle down. So, along the flow path the quantity of the settleable particles reduced in the multistage layers when it enters in the filter. This theory has been practiced to formulate the models for describing the filter efficiency as well as the removal efficiency of the HRF. According to the available filter theories and the Fick's law the filter efficiency can be expressed by the filter coefficient λ or,

$$dc/dx = -\lambda c \qquad (1)$$

Where
c = Solid concentration,
x = Filter depth,
λ = Filter coefficient or coefficient of proportionality.

From the above equation it can be stated that the removal of the suspended particles is proportional to the concentration or the particles present in the water.

The total length of the filter can be described as the number of parallel plates and act as a multistage reactor so the performance of the HRF can be ascertained on the basis of the results obtained from the small filter cells. The total suspended solid concentration after a length of Δx of the filter cell can be expressed,

$$C_{\text{outlet}} = \sum C_{\text{inlet}} e^{-\lambda_i \Delta X} \tag{2}$$

Where,
λ_i = Filter efficiency of each filter cell,
Δx = Length of experimental filter cell,
C_{inlet} and C_{outlet} = Concentration of particles in the inlet & outlet of the filter.

From the Eq. (2) it is to be stated that after evaluating the filter depth (length) and the filter coefficient and the SS (suspended solids) concentration, the performance efficiency of the filter can be predicted.

According to Weglin (1996), the effluent quantity for the n number of compartments is given by, $Ce{=}C_0 * E_1 * E_2 * E_3 * E_4 * \ldots\ldots\ldots\ldots E_n$
C_0 = Concentration of the HRF influent,
Ce = Concentration of the HRF effluent
$E_1,\ E_2,\ E_3,\ E_4 \ldots\ldots\ldots\ldots E_n$ = Filtration efficiency for the each compartment (1,2,3 respectively).

The basic expression for the above relationship is given by,

$$Ce = Coe^{-\lambda L} \tag{3}$$

Where,
λ = Coefficient of filtration
L = Length of the filter.

The Filter efficiency is given by,

$$E = Ce/C_0 = e^{-\lambda L} \tag{4}$$

$$Ce = Co * E \tag{5}$$

E_i = Filter efficiency for $(i-1,2,3...n)$ compartments.

The values are obtained either from the table or graphical nomo-gram developed by Wegelin.

2 Methodology

A pilot plant was constructed in the Dept.of Water resources Engineering, Jadavpur University to investigate the objectives of the research study (Fig. 1). The structure of the plant was made up from the Fiber glass sheeting which consisted of three chambers of each 450 mm×300 mm.

The filter medium namely gravel was placed in the three separate chambers starting from the coarse size to the finer ones in the direction of flow and the whole system was operated in series. The first compartment was filled up of gravel size 15 mm–10 mm having the average size 12.5 mm the second compartment consisted of average gravel size 7.5 mm and the third one of average size 2.5 mm. Each compartment was being separated by the perforated fiber glass partition to avoid mixing of the gravels of different chambers. The filter bed was provided with the under drainage system to enable flushing after a certain running period of interval for hydraulic sludge extraction by observing the filter resistance (Fig. 2). A constant flow rate of 0.75 m/h was maintained through all the compartments by the help of a peristaltic pump. The suspended solids (SS) concentration of raw water for all the chambers at the inlet and the SS concentration at the out let was measured by the help of standard procedure describe in the Standard methods. Sampling from the investigation was done at least three times of week for a period of 70 days. The experiment was carried out both in low flow (dry season) and high flow (rainy season) periods during the scan of 70 days. The local pond water was used as raw water which has the concentration of suspended solids ranges from 40 mg/l to 150 mg/l. According to Weglin's design guide line this range is medium range of concentration (100–300) mg/l for which filtration rate is 0.75 m/h–1.0 m/h are recommended. So a constant flow 0.75 m/h was chosen in carrying out the experiment.

By using Eq. (5) and the total E-value of the whole filter, Table 2 was generated for predicted HRF effluent (Ce) for every recorded raw water suspended solids concentration (C_0). From table it is observed that the HRF effluent has met the required level of SS concentration.

2.1 Artificial Neural Network

Artificial Neural Network is a distributed information processing system that has certain characteristics that resemble with the biological neural network of the human. The development of an artificial neural network as prescribed by ASCE (ASCE, 2000), must follow the following basic rules,

1. Information must be processed at many single elements called nodes.

2. Signals are passed between nodes through connection links and each link has an associated weight that represents its connection strength.

3. Each of the nodes applies a non-linear transformation called as activation function to its net input to determine its output signal.

Advantage of ANN lies in its adaptive nature where "learning by example" replaces "programming" in solving problems. ANN is very appealing when very little or incomplete understanding of the problem to be solved is achieved. The intrinsic parallel architecture of ANN allows fast computations of solutions. ANN is widely applied in various fields of engineering and science due to its ability to recognize patterns, clustering complex dataset, accurate approximation and process based forecasts (Hassoun,1995).The development of the ANN model is discussed next,

2.1.1 Building the ANN

Neural network can be of different type, like feed forward, radial basis function, time lag etc.The type of the network is selected with respect to the knowledge of input and output parameters and their relationship. Once the type of network is selected, selection of network topology is the next concern. Trial and error method is generally used for this purpose but many studies now prefer the application of genetic algorithm (Ahmed and Sarma, 2005). Genetic algorithms (GA) are search algorithms based on the mechanics of natural genetic and natural selection. The basic elements of natural genetics – reproduction, crossover, and mutation – are used in the genetic search procedure. A GA can be considered to consist of the following steps:

1. Select an initial population of strings.
2. Evaluate the fitness of each string.
3. Select strings from the current population to mate.
4. Perform crossover (mating) for the selected strings.
5. Perform mutation for selected string elements.
6. Repeat steps 2–5 for the required number of generations.

2.1.2 Training the ANN

To encapsulate the desired input output relationship, weights are adjusted and applied to the network until the desired error was achieved. This is called as "training the network" (Bhatt et al., 2007). There is innumerable number of "training the network" algorithms available, among which, back-propagation is mostly prescribed (ASCE, 2000). In the present study, Quick Propagation (QP) and Conjugate gradient descent (CGD), both derived from basic backpropagation algorithms, were used as the training algorithm.

2.1.3 Testing the ANN

Some portion of the available historical dataset is used and known output is estimated and compared with the actual dataset to find an Mean Square Error (MSE). If the values found in this way are less than 1% then the networks are selected for forecast. Few part of the dataset is used for cross-validation so that the network is not over-trained.

2.1.4 Evaluation of the ANN

The accuracy of results obtained from the network can be assessed by comparing its response with the validation set. The commonly used evaluation criteria include percentage MSE, correlation coefficient (r), coefficient of efficiency (C.E.) and Standard Deviation (STDEV).

$$\%\mathrm{MSE} = \left((Tp - Op)/Tp\right) \times 100 \tag{6}$$

$$r = [\sum((Tp - Tm)(Op - Om))/(\sum_{1}^{n}(Tp - Tm)^2 \sum_{1}^{n}(Op - Om)^2)^{1/2}] \tag{7}$$

$$\mathrm{C.E.} = 1 - (\sum_{1}^{n}(Tp - Op)^2 / \sum_{1}^{n}(Tp - Tm)^2) \tag{8}$$

$$\mathrm{STDDEV} = \frac{\sum_{1}^{n}(Tn - \bar{T}n)^2}{n} \tag{9}$$

Where, Tp is the target value for the pth pattern; Op is the estimated value for the pth pattern, Tm and Om are the mean target and estimated values respectively and n is the total number of patterns. MSE shows the measure of the difference between target (Tp) and estimated (Op) value, r defines the degree of correlation between two variables. C.E. Criterion has the basis of standardization of the residual variance with initial variance (Nash and Sutcliffe, 1970).

In this criterion, a perfect agreement between the observed and estimated output yields an efficiency of one. A negative efficiency represents lack of agreement and zero agreement means all the estimated value is equal to the observed mean. STDDEV is the measure of deviation of the estimated value from the target output. A perfect match between observed data and model simulations is obtained when STDDEV approaches 0.0 (Yitian and Gu, 2003).

3 Results and discussion

The input and output was selected with the help of correlation and co-validation coefficients in between the related parameters and only the most related parameter with the output is selected. Runtime and filtration efficiency of the input chamber was taken as input and filtration efficiency at the output chamber was taken as output.

70% of the available dataset was used as training, 15% for testing and rest was used for cross validation .Four feed forward neural network is built. Two of which was trained with QP and other two by CGD. The genetic algorithm was applied to select the topology of all the four networks with population size of forty patterns. Sixty generation was forced from those patterns with 90 % cross over rate and 20 % mutation capability. The training was stopped whenever MSE on training subset drop below 1% .Each of the network was trained for 100 times with 100 000 iterations per training. After the training, average absolute error achieved from the four networks named QP1 and QP2 for the 2 networks trained in QP and CGD1 and CGD2 for the networks trained in CGD were 0.08921, 0.0921, 0.07721 and 0.08721 respectively. The average absolute MSE from the training of these networks were 0.09, 0.097, 0.00993 and 0.0978 respectively which indicates that all the networks had sufficiently learned the present problem.

The networks were tested with two patterns and the average MSE and average absolute error was found out to be 0.79, 0.77, 0.5, 0.65 and 0.87, 0.86, 0.75, 0.85 respectively for QP1, QP2, CGD1 and CGD2.

The details of the network were as given in Table 3. CGD1 was selected as the best performing network due to the least absolute and mean square error achieved from this network during training and testing procedures.

In order to compare the performance of the model with ANN and Weglin's MSE, r, C.E, STDDEV were calculated between computed and the model values. These values helped to select the best performing network (Nash and Sutcliffe, 1970). According to the results of the performance validating criteria, CGD1 was found to be better than the Weglin's Model if only the predicted values were considered (Table 4). The MSE values obtained were 0.63 and 3.32 respectively for ANN and the Weglin's model.

CGD1 showed an improvement of 5.27 times (MSE) over the Weglin's model .Estimated values from ANN gave high model efficiency of 98% and that of Weglin's Model equals to 40.8% i.e. ANN model was 2.4 times more efficient than the Weglin's Model. The STDDEV of CGD1 was found to be as 0.095 where as the same for the ANN model was 1.78.

This again showed that the ANN model was 18.7 times closer than the Weglin's Model. Observed values from the CGD1 were found to be 98% related with the target value and Weglin's Model was found out to be 14% related with the target value.

Hence, CGD1 was 7 times more related than the regression model. CGD1 model supports the results of the HRF filter but the results from the Weglin is not coherent with the model results.

4 Conclusions

Filtration efficiency of a horizontal roughing filter was estimated with a laboratory developed filter model. The efficiency of the HRF was compared with a neural model and the model developed by Weglin. From the performance validation criterions it was found that filter efficiency achieved from the experimental model was supported by the neural model but it was highly deviated in case of Weglin's. Weglin's model had considered some parameters and constants which changes with change in climatic and experimental conditions. The neural network model considered no such parameters but it simply follows the pattern of the input with output in the problem domain.

Neural network models are nowadays hugely used in different hydrologic estimation and are popular for their accuracy and efficiency. Many papers have been published in this regard. Hence, as the results from the present experimental HRF was supported by neural network model the verification of its efficiency was taken as positive.

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Table 1. E-value for different compartment and efficiency value for the total filter.

Effective size (dg)	Filtration rate (m/h)	Length of compt.	E-value (%)	Total E-value (dec)
5mm	0.75 m/h	0.45 m	E1=21.3	0.026
10mm	0.75 m/h	0.45 m	E2=19.6	
15mm	0.75 m/h	0.45 m	E3=26.0	

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Table 2. Summary table of the results of the HRF model.

Run time (Days)	$C0$ (mg/l)	Predicted Ce (mg/l)	Ce (mg/l)
3	12.50	0.33	4.02
5	9.80	0.25	4.38
7	14.60	0.38	4.62
10	18.80	0.49	4.89
12	20.70	0.54	4.86
14	25.80	0.67	4.65
17	16.70	0.43	3.89
19	19.60	0.51	3.02
22	21.65	0.56	4.02
24	22.80	0.57	4.63
27	38.80	1.00	4.56
30	24.40	0.63	2.80
32	30.10	0.78	3.80
35	48.80	1.27	3.62
38	42.40	1.10	2.80
40	48.00	1.25	4.60
42	58.60	1.52	4.32
46	72.00	1.87	5.20
48	84.00	2.18	6.00
51	116.00	3.01	3.80
53	67.00	1.34	4.30
54	98.00	2.55	3.90
55	47.00	1.22	2.60
58	50.00	1.30	3.43
60	50.40	1.31	7.00
61	33.80	0.88	4.26
62	22.50	0.59	4.36
64	33.60	0.87	2.90
67	48.60	1.26	4.80
68	47.70	1.24	5.60
70	33.20	0.86	3.10

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Table 3. Summary table of the inputs and outputs of the neural models.

Network Name	QP1	QP2	CGD1	CGD2
		Network Topology		
Network type	feed-forward fully connected network	feed-forward fully connected network	feed-forward fully connected network	feed-forward fully connected network
Number of inputs	1	1	1	1
Number of hidden layers	2	1	2	2
Hidden units in the 1st hidden layer	6	1	6	6
Hidden units in the 2nd hidden layer	8	0	8	8
Number of outputs	1	1	1	1
All the topology was created using genetic algorithms with following parameters				
Population size	40	40	40	40
Number of generations	60	60	60	60
Network size penalty	5	5	5	5
Crossover rate	0.9	0.9	0.9	0.9
Mutation rate	0.2	0.2	0.2	0.2
		Training Algorithm and Parameters		
Training algorithm	Quick Propagation	Quick Propagation	Conjugate gradient descent	Conjugate gradient descent
Training Iteration	100	100	100	100
		Stop Training Conditions		
MSE on training subset must drop below: –	0.01	0.01	0.01	0.01
Maximum allowed number of iterations: –	100000	100000	100000	100000
Training stop reason: –	Maximum iteration was reached	Maximum iteration was reached	Desired error level was achieved	Maximum iteration was reached
		Training Results		
Average MSE (Training)	0.09	0.097	0.00993	0.0978
Average MSE (Testing)	0.87	0.86	0.75	0.85
Average Absolute Error (Training)	0.08921	0.0921	0.07721	0.08721
Average Absolute Error (Testing)	0.79	0.77	0.5	0.65

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Table 4. Comparison of the neural and Weglin's Model in respect to the HRF model.

	MSE	r	C.E	STDDEV
CGD1	0.63	0.98	0.988	0.095
Weglin's Model	3.32	0.14	0.408	1.78

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Fig. 1. Model of horizontal roughing filter used in the experiment.

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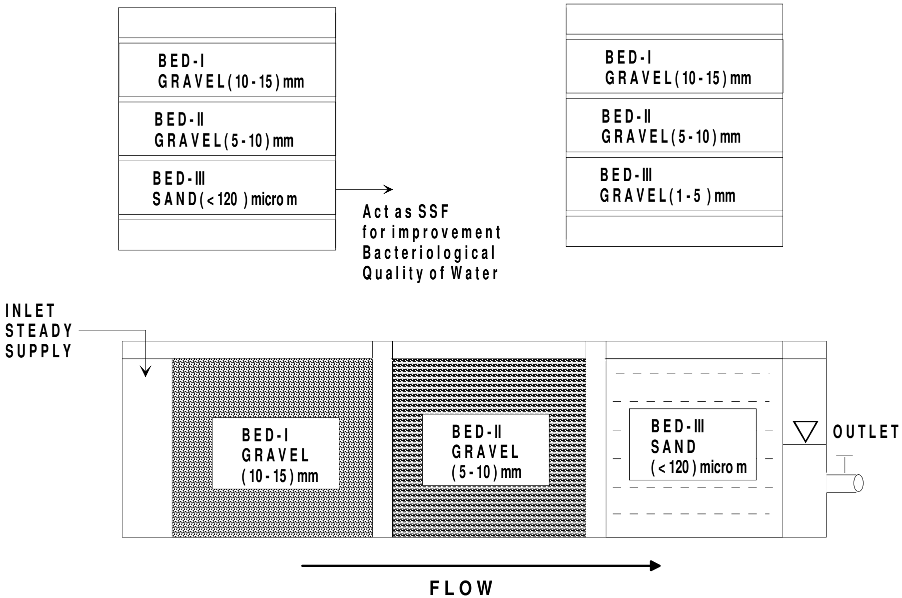

Fig. 2. Basic layout of the HRF and HRF filterbed that was used in the experiment.

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