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ESTIMATION OF IMPACT OF IMPURITIES ON RECHARGING RATE OF MEDIUM-SAND FILTER SYSTEM

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ABSTRACT

The paper highlights the potential of Adaptive Neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and Multi Linear regression (MLR) approaches to estimate the recharging rate of Medium-sand filter system. A dataset consists of 678 experimental measurements were selected. Out of 678 observations randomly selected 462 observations were used for training, whereas remaining 216 were used for testing the model. Input variables consist of cumulative time (T), thickness of medium sand bed (B), size of medium sand (S) and concentration of impurities (Conc.), whereas the recharging rate (R) was considered as output. Correlation coefficient (C.C), coefficient of determination (R^2), root mean square error (RMSE) and Nash-Sutcliffe efficiency model (NSE) were used to compare the performance of these modeling approaches. The result of evolution suggests that ANN approach works better than ANFIS and MLR models. Sensitivity analysis suggests that size of medium sand (S) is an important parameter for predicting the recharging rate of storm water filter system.

Keywords: *Medium-sand filter system; Adaptive neuro-fuzzy inference system; artificial neural network; Multi Linear regression.*

INTRODUCTION

Groundwater plays a very important role in fulfilling the basic demands like drinking and irrigation. Although, groundwater plays an essential role in agriculture, over-exploitation of groundwater has resulted in fast exhaustion and deterioration of this key natural water resource. Storm water filtering systems refer to recharge the ground water. The most serious issue with regard to the efficiency of the filtering unit is clogging, i.e. decrease in permeability of filtering medium. Past studies have shown that a filter medium consisting of concrete sand provided a good balance between the flow-through rates and filtering efficiency (Farooq and Al-Yousef, 1993; Le Coustumer and Barraud, 2007; Siriwardene et al., 2007; Kambale et al., 2009). Storm water filters which use gravel as a filter medium are liable to clogging. It takes place due to the migration of fine sediments through the medium and formation of a layer of low permeability at the bottom of the filter reducing the hydraulic efficiency of the filter (Siriwardene, 2007) and can be cleaned by removal and replacement of the whole filter medium.

The entry of sediments and suspended solids in recharging water is prevented by using filter pit. The performance of the recharge tube wells was very good without any reasonable change in recharge rates. An average recharge rate of 10.5 l/s due to individual recharge tube well was observed (Kaledhonkar et al., 2003). The effect of variable thickness of coarse sand (CS), gravel (G) and pebble (P) layers of the filtration unit of the recharge shaft on the Infiltration rate and the sediment concentration of effluent water were evaluated. In a column study of 60 cm length and 31 cm diameter, provision of CS, G and P in the ratio 1.5 : 1 : 3, i.e. 15 : 10 : 30 cm was found to be most efficient in filtration unit for a recharge shaft (Thomas, 1968; Kambale et al., 2009). Finer medium system such as medium sand (MS) achieving acceptable recharge rates but also gets clogged at the top of filter but it can be conveniently scrapped-off and managed (Coustumer and Barraud, 2007). Recharging rate is one of the most important parameters of storm water filter system (Kumar et al., 2012). Thus, indirect methods using predictive approaches have been developed for estimation of recharging rate of storm water filter system (Mohanty et al., 2013). However, predictive approaches of the recharging rate have gained considerable attention and efforts have been made by researchers to improve the power of predictability (Sadiq et al., 2004; Singh and Jain, 2015).

Within last few decades, soft computing approaches like neural network, Gaussian process, support vector machines, ANFIS and ANN have been used in environment and hydraulics applications (Singh et al., 2017, Sihag et al., 2017(a), Tiwari et al., 2017) and found to be very effective. ANFIS is new developed methods which probably can be used for the forecast the soil properties (Minasny et al., 2004; Azamathulla et al., 2009). This study was, therefore, conducted to examine the usefulness of ANFIS technique in developing model for estimating recharging rate of storm water filter system. However, ANFIS has shown capability in modeling of nonlinear functions. Data features learn by ANFIS and transforms the system characteristics relative to a given error criteria Jang (1993).

ANFIS: It uses reasoning of fuzzy logic and algorithms of neural network to generate output. Figure 1 shows the structural design of first order Sugeno fuzzy model of ANFIS having 2 inputs (a and b), 4 rules and 1 output (c).
First-order model of Sugeno fuzzy type (Sugeno and Takagi, 1985) have four fuzzy rules (if-then), given as:

Rule 1: if a is X_1 and b is Y_1, then $f_{11} = m_{11}a + n_{11}b + q_{11}$, (1)

Rule 2: if a is X_1 and b is Y_2, then $f_{12} = m_{12}a + n_{12}b + q_{12}$, (2)

Rule 3: if a is X_2 and b is Y_1, then $f_{11} = m_{21}a + n_{21}b + q_{21}$, (3)

Rule 4: if a is X_2 and b is Y_2, then $f_{22} = m_{22}a + n_{22}b + qc_{22}$, (4)

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Where X_1, X_2, Y_1 and Y_2 are fuzzy sets of input a and b, f_{ij} ($i, j = 1,2$) are the outputs within the fuzzy specified region by the fuzzy rule, for input a and b, m_{ij} , n_{ij} and q_{ij} ($i, j = 1,2$) are the design parameters that are evaluated during the training process.

Figure 1 contain five layers, each layer executes different function explained below:

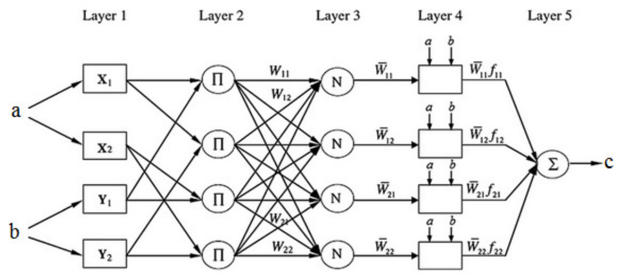


Fig. 1: Structural Designing of Fuzzy Metal

Layer 1(Input nodes): Every node is adaptive nodes and produce membership grade of input and output given by this layer are:

$O^1_{Xi} = \mu_{Xi}(a), \quad i = 1,2,$ (5)

$O^1_{Yi} = \mu_{Yj}(b), \quad j = 1,2,$ (6)

where a and b are crisp inputs, and X_i and Y_j are fuzzy set, low, medium, high class size membership function is applied, which could any shape such as triangular, bell-shaped, Gaussian function etc.

Layer 2 (Rule nodes): All nodes are fixed nodes and labeled as Π, which plays a role of a simple multiplier and output is given as below:

$O^2_{ij} = Wij = \mu_{Xi}(a)\, \mu_{Yj}(b), \quad i, j \ldots\ldots\ldots = 1,2,$ (7)

Layer 3(Average nodes): Every node are again fixed node and labeled as N and plays a normalization role in the network, output is give below as:

$O^3_{ij} = \bar{W}_{ij} = \frac{W_{ij}}{W_{11}+W_{12}+W_{21}+W_{22}} \quad , \quad i, j \ldots\ldots = 1,2,$ (8)

Layer 4 (Consequent nodes): Every node is adaptive nodes and output is product of normalized firing strength and first order polynomial and is given as below.

$O^4_{ij} = \bar{W}_{ij} f_{ij} = \bar{W}_{ij}(m_{ij}a + n_{ij}b + q_{ij}), \quad i,j \ldots = 1,2.$ (9)

Layer 5 (Output nodes): The only node output in the layer is the summation output of the system.

$O^5_1 = \sum_1^2 \sum_1^2 \overline{W_{ij}}\, f_{ij} = \sum_1^2 \sum_1^2 \overline{W_{ij}}\,(m_{ij}a + n_{ij}b + q_{ij})$

$= \sum_1^2 \sum_1^2 [(W_{ij}a)m_{ij} + (W_{ij}b)n_{ij} + (W_{ij})q_{ij}]$ (10)

Choice of membership function: Membership function may be of many shapes for example trapezoidal, triangular, generalized bell shaped, Gaussian functions and many more. In present study, performances of generalized bell-shaped and Gaussian function have been compared. All three Membership functions (MFs) are defined below:

Gaussian (gaussmf)**:** $\mu_X(a) = e^{\frac{-(a-m)^2}{2\sigma^2}}$, (11)

Where a is a function of a vector and depends on the parameters σ is the Standard Deviation and m is the mean used in gaussmf.

Bell shaped (gbellmf)**:** $\mu_{Xi}(a) = \frac{1}{1+\left(\frac{a-C_j}{A_j}\right)^{2B_j}}$ $i = 1,2,\ldots\ldots$(12)

The generalized bell function depends on three parameters A, B, and C, where the parameter B is usually positive. The parameter C locates the center of the curve. Enter the parameter vector prams, the second argument for gbellmf, as the vector whose entries are A, B, and C respectively.

Artificial neural networks (ANN): The artificial neural network (ANN) is a machine learning method widely used for numerical prediction of hydrology problems (Kia et al., 2012; Sihag et al., 2017(b)). It is inspired by the functioning of the nervous system and brain architecture. ANN has one input, one or more hidden and one output layers. Each layer consists of the number of nodes and the weighted connection between these layers represents the link between the nodes. Input layer having nodes equal to the number of input parameters, distributes the data presented to the network and does not help in processing. This layer follows one or more hidden layers which help in the processing of data. The output layer is the final processing unit. When an input layer is subjected to an input value which passes through the interconnections between the nodes, these values are multiplied by the corresponding weights and summed up to obtain the net output (P_j) to the unit

$P_j = \sum_i X_{ij} \times y_i$ (13)

Where, X_{ij} is the weight of interconnection from unit i to j, y_i is the input value at input layer, P_j is output obtained by activation function to produce an output for unit j. The detailed discussion about ANN is provided Haykin (1999).

Multi-linear regression (MLR): Multi-linear regression (MLR) is applied on more than one predictor's parameters. The common structure of the MLR model is

$Z = c_0 x_1{}^{c_1} x_2{}^{c_2} x_3{}^{c_3} x_4{}^{c_4} \ldots\ldots\ldots\ldots\ldots\ldots x_n{}^{c_n}$ (14)

The non linear relation of recharging rate of medium sand storm filter system is as follow:

$R = 2.2326\ \frac{B^{1.1279} S^{0.7714}}{T^{0.1179} C^{0.1090}}$ (15)

Where independent variables are cumulative time (T), thickness of medium sand bed (B), concentration of impurities (C), and size of medium sand (S) whereas the recharging rate (R) is dependent variable.

METHODOLOGY AND DATA SET

A laboratory experiment was conducted using rectangular column (Figure 1) of 20×16×120 cm. Inlet was provided in the upper portion of the column to retain a constant head. Outlet was provided at the base of column to drain out filtrate water. A measuring cylinder was used to collect the water. Recharging water was recorded at regular interval. The detail of the experiment program listed in Table 1.

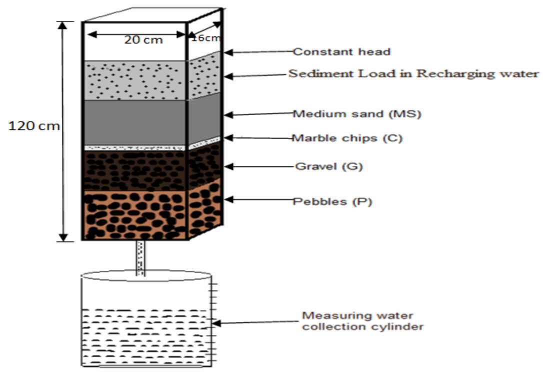


Fig. 2: Experimental setup of storm water filter.

Detail of ANFIS and ANN for recharging rate of medium sand storm water filter system prediction

In the current study, ANFIS was used to model the relationship between inputs and output. The model was executed using MATLAB based fuzzy logic, a Sugeno-type approach shown in Figure 3 (Sugeno and Takagi, 1985). There are no fixed criteria for generating an ANFIS model (Cui et al., 2010) gbellmf and gaussmf MFs for input are used in ANFIS model. The "gaussmf" membership functions were the best for each input.

A hybrid learning algorithm was employed to train the ANFIS model. In the ANFIS training process, forward pass and a backward pass is composed by each epoch. In the forward pass, a training set of input patterns (an input vector) is presented to the ANFIS, neuron output is planned on the layer-by-layer basis, and rule resulting variables are recognized. As soon as the rule resultant variables are recognized, an authentic network output vector, y_1, is determined and the error vector (e) is computed as ($e = y_1 - y_2$) as y_2 is actual output. This process finishes at desired epochs (Jang, 1993).

Table 1: Detail of the Experimental Programme.

	Boulders/pebbles (P)		Gravel (G)		chips	Medium sand (MS)			Sediment concentration (ppm)
	Thickness of bed (cm)	Diameter (cm)	Thickness of bed (cm)	Diameter (cm)	Thickness of bed (0.475-0.8) (cm)	Thickness of bed (cm)	Diameter (mm)	Mean diameter (mm)	
1	20	2–4	22	0.8- 2.0	3	25	0.150-0.300, 0.300-0.425, 0.425-0.600	0.212, 0.357, 0.505	250, 500, 1000, 1500, 2000, 2500, 3000
2	20	2–4	22	0.8- 2.0	3	30	0.150-0.300, 0.300-0.425, 0.425-0.600	0.212, 0.357, 0.505	500, 1000, 1500, 2000, 2500, 3000
3	20	2–4	22	0.8- 2.0	3	35	0.150-0.300, 0.300-0.425, 0.425-0.600	0.212, 0.357, 0.505	500, 1000, 1500, 2000, 2500, 3000

Dataset used in this study consists of 678 experimental observations. Out of 678 observations arbitrarily selected 462 observations were used for training, whereas remaining 216 were used for testing the model. Input variables consist of cumulative time (T), thickness of medium sand bed (B), concentration of impurities (C), and size of medium sand (S) whereas the recharging rate (R) was considered as output. The detail of the training and testing data set characteristics are listed in Table 2.

Table 2: Detail of the training and testing data set

Parameters	Training				Testing		
	units	**Range**	**Mean**	**Std. deviation**	**Range**	**Mean**	**Std. deviation**
T	minutes	1-90	29.84	21.05	1-90	29.56	23.15
S	mm	0.21- 0.51	0.36	0.12	0.21- 0.51	0.36	0.12
Conc.	ppm	250- 3000	1679.65	891.89	250- 3000	1692.13	889.93
B	cm	25-35	30.45	4.28	25-35	30.83	4.18
R	l/s	1.16- 6.45	3.16	1.36	1.20-6.50	3.22	1.33

The training error was 0.0855 when membership function was "gaussmf" and linear membership function was used for output. A plot of the Actual and predicted values of recharging rate of filter system (Figure 4) for the training data set shows that the model obtained the relationship between input parameters and recharging rate of filter system (R). Figure 5 shows the surface diagram of recharging rate of medium sand storm filter system from ANFIS for Gaussian MFs) focuses on three dimensional surface diagram of two input and output (R), and it can be concluded that there are non linear relationship between the input parameters and recharging rate.

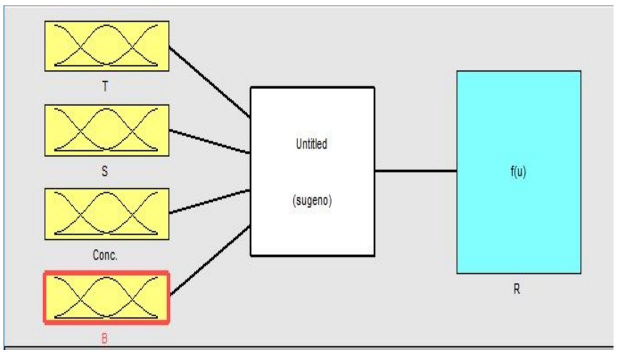


Figure 3: Sugeno type approach of ANFIS

Specifications of the developed ANFIS model are as follow:

Number of nodes: 193 nodes, 81 linear parameters, 24 non linear parameters, 216 training data pairs and 81 fuzzy rules.

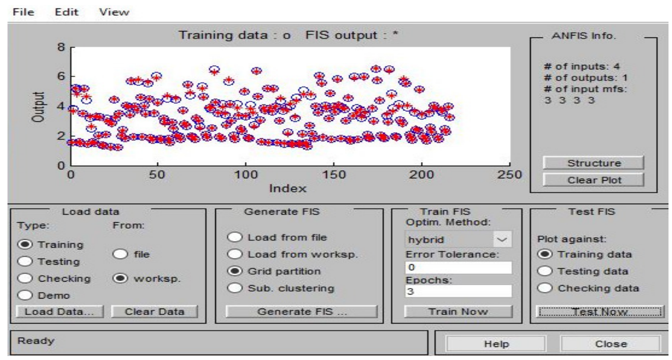
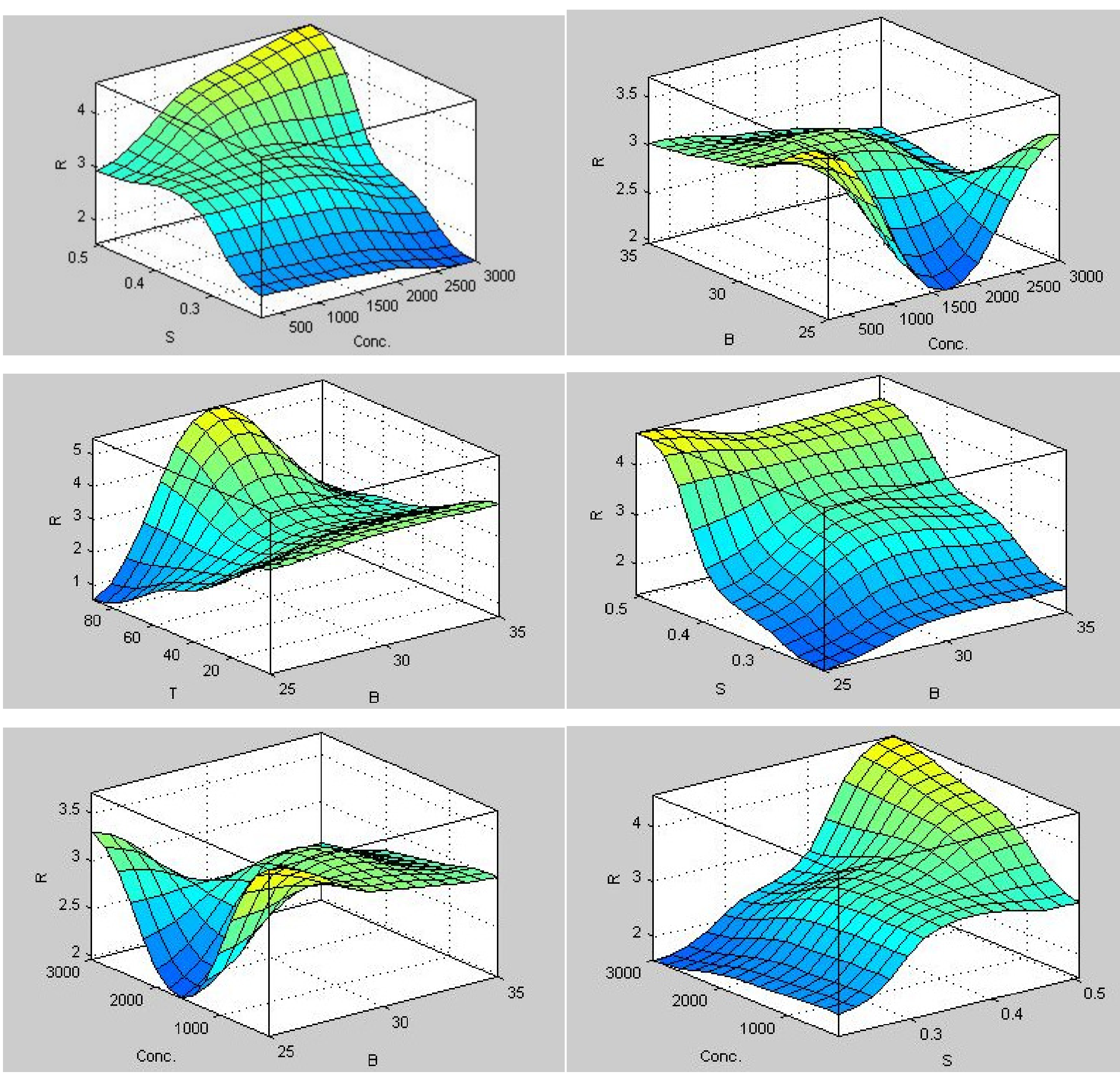


Fig. 4: Actual and predicted values of recharging rate of medium sand storm water filter system for the training data set.



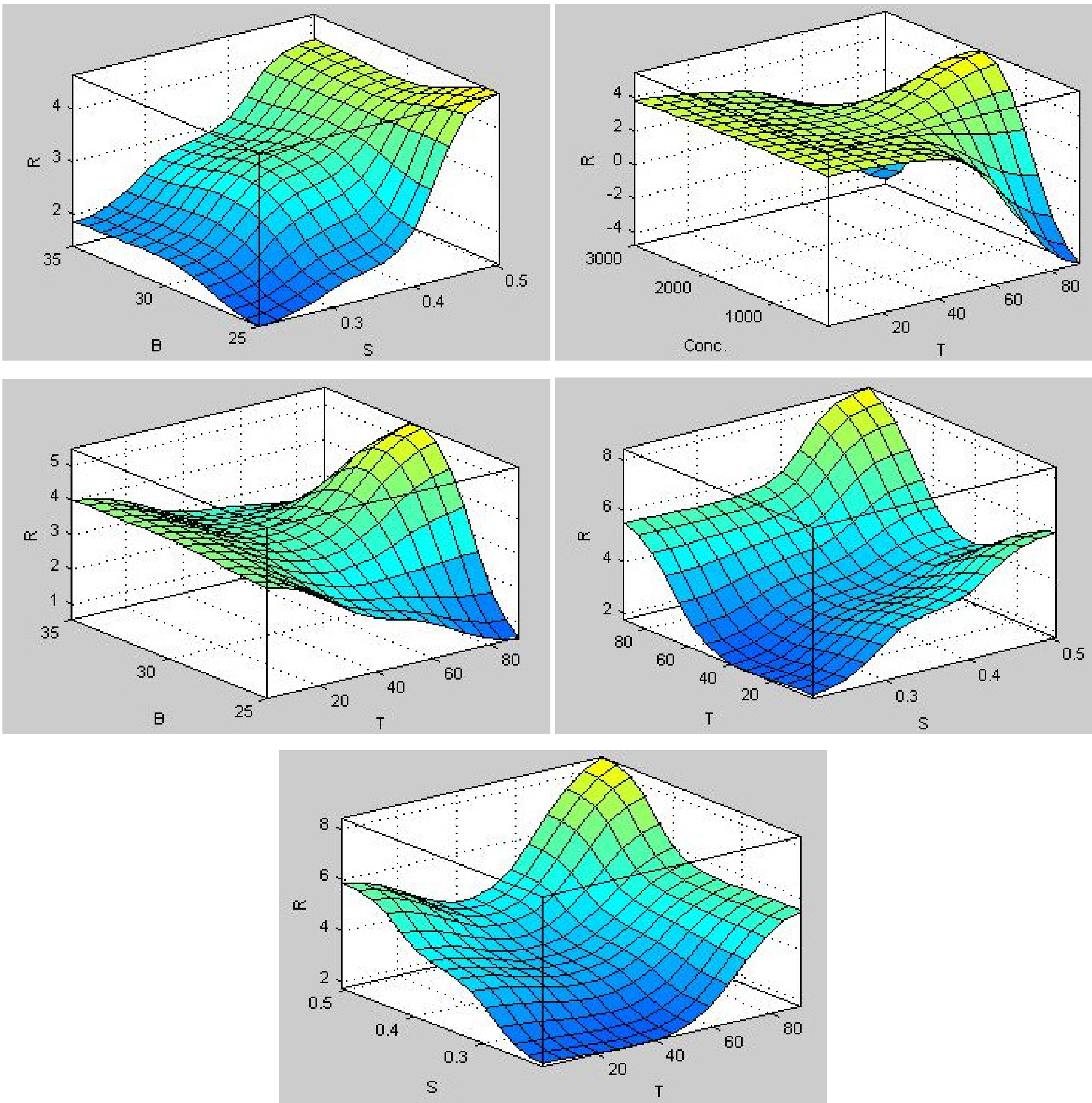


Fig. 5: Surface diagram of relationship between different input variable and output (R)

ANN modelling was conducted using WEKA (3.9) and various trial suggest, Learning rate =0.2, momentum=0.1, hidden nodes=7, no. of iteration=1500 gives best results.

Table 3. Optimal value of user-defined parameters used in this study

Algorithm	Structure	user-defined parameters
ANN	4-7-1	Learning rate =0.2, Momentum=0.1, Hidden nodes=7, No. of iteration=1500

RESULT AND DISCUSSION

Correlation coefficient (CC), coefficient of determination (R^2), root mean square error (RMSE) and Nash-Sutcliffe efficiency coefficient (NSE) were used to compare the performance of ANFIS, ANN and MLR models. Table 4 provides the values of performance evaluation parameters by ANFIS, ANN and MLR models. Figure 6 provides the graph plotted between actual and predicted values of recharging rate by using Gaussian and Gaussian bell shape MF based ANFIS with the test dataset. A higher value of CC, R^2, NSE and lower value of RMSE with Gaussian MF confirms that this MF works well in comparison to Gaussian bell MF in predicting the recharging rate of medium sand filter system by ANFIS.

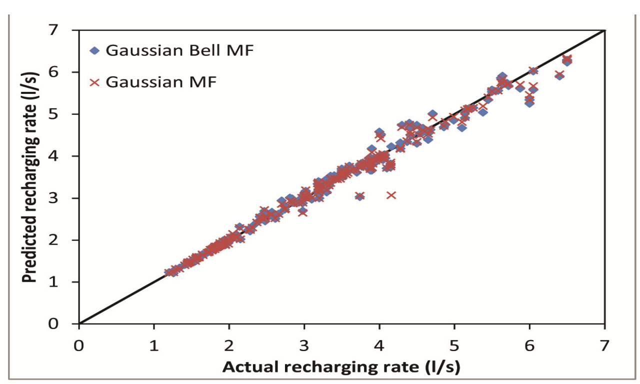


Fig. 6: Actual vs. Predicted values of recharging rate of storm water filter using ANFIS of testing data set.

Figure 7 and 8 provides the graph plotted between actual and predicted values of recharging rate by using ANN and MLR with the test dataset respectively. Optimal value of user-defined parameters of ANN is listed in Table 3. For ANN, user-define parameters i.e. hidden nodes, number of iterations need to be determined for given dataset. After several number of trials hidden nodes = 7, number of iterations = 1500 were found working well with this dataset. CC value of 0.9966, R^2 value of 0.9932, RMSE value of 0.1231 and NSE value of 0.9915 and CC value of 0.9525, R^2 value of 0.9072, RMSE value of 0.4259 and NSE value of 0.8978 were achieved using ANN and MLR with test dataset respectively.

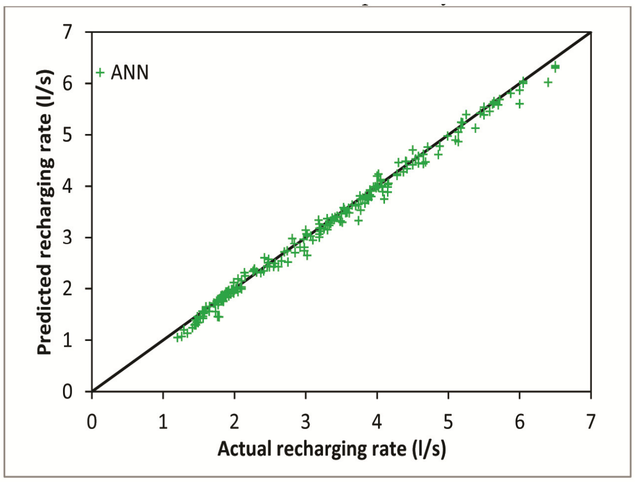


Fig. 7: Actual vs. Predicted values of recharging rate of storm water filter using ANN of testing data set.

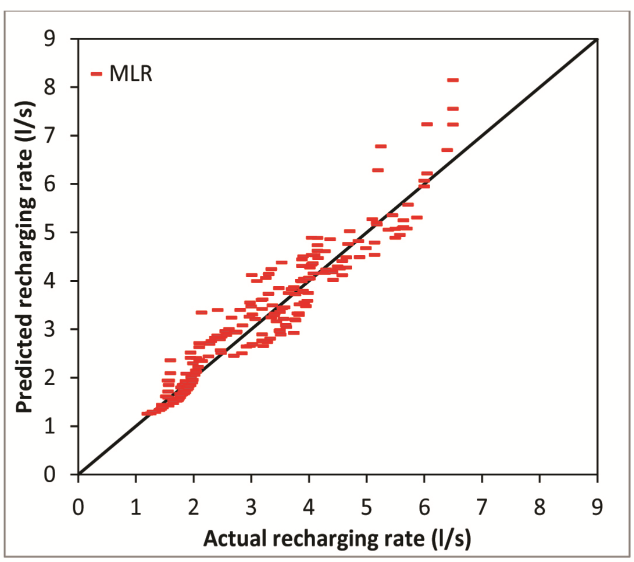


Fig. 8: Actual vs. Predicted values of recharging rate of storm water filter using MLR of testing data set.

Table 4: Detail of Performance evaluation Parameters using ANFIS, ANN and MLR of testing dataset.

Approaches	CC	R^2	RMSE (l/S)	NSE (%)
Gaussian Bell MF	0.9925	0.9850	0.2336	0.9845
Gaussian MF	0.9931	0.9863	0.1584	0.9858
ANN	0.9966	0.9932	0.1231	0.9915
MLR	0.9525	0.9072	0.4259	0.8978

Figure 9 gives the comparison graph plotted between observed and predicted values of recharging rate of medium sand storm filter system obtained using Gaussian MF and Gaussian bell MF based ANFIS, ANN, MLR models for test dataset. Statistical comparison of results (Table 4) suggests that ANN shows improved performance than any other discussed models. Further, results in terms of C.C, R^2, RMSE and NSE suggest a better performance by Gaussian MF based ANFIS model in comparison to the Gaussian bell MF based ANFIS and MLR model. Single factor ANNOVA results show that *F*-values (0.1899) was less than *f*-critical (2.3802) and *P*-values (0.9437) was greater than 0.05 suggest that difference in predictive and observed values for all above discussed models is insignificant. A graph between test data set number and recharging rate was plotted (Figure 10). It could be inferred from the figure that the predicted values of recharging rate by ANN were in very close proximity to the observed recharging rate of medium sand storm filter system.

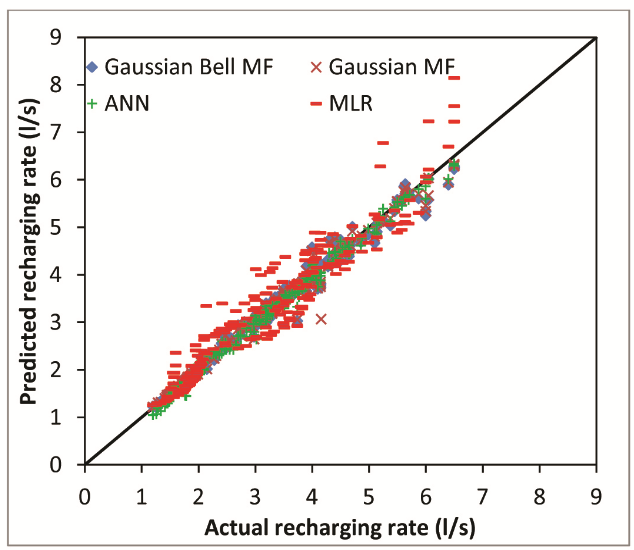


Fig. 9: Observed vs. Predicted values of recharging rate of storm water filter using ANFIS, ANN and MLR of testing dataset.

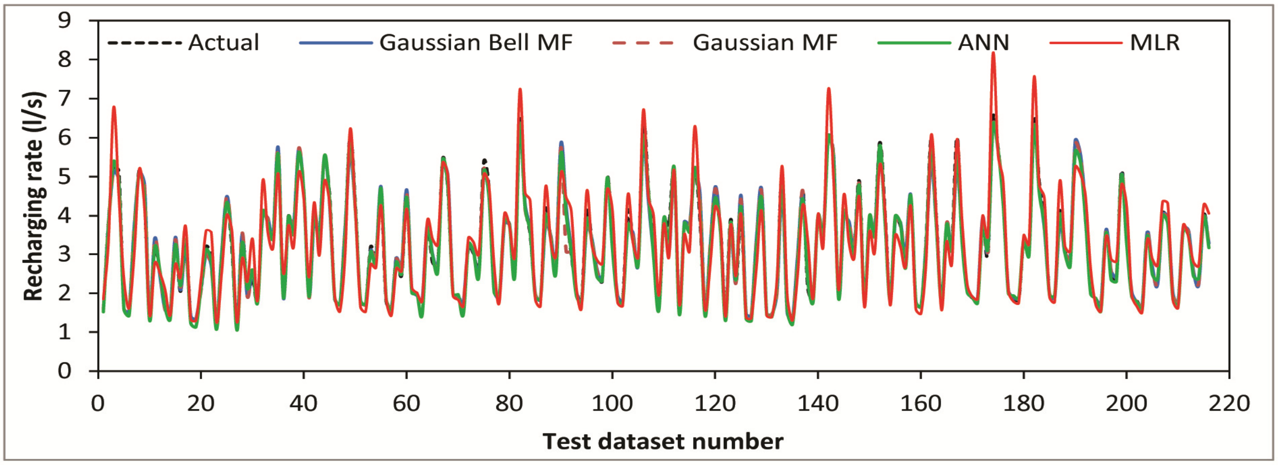


Fig. 10: Variation in predicted values of recharging rate of storm water filter using ANFIS, ANN and MLR approach in comparison to actual values

SENSITIVITY ANALYSIS

Sensitivity tests were performed using ANN to decide the relative significance of every input parameter on the recharging rate of medium sand storm filter system. Several factors including the cumulative time, concentration of impurities, thickness of bed and size of sand affect the recharging rate. Various input combinations as provided in Table 5, were considered by extracting one input variable in each case and its influence on predicted cumulative infiltration was evaluated in terms of C.C and RMSE considered as major performance criteria. Table 5 compares the performance of ANN model with different input combinations using same user-defined parameters as shown in Table 3. Results from Table 5 suggest that the size of medium sand (S) has most influence input parameter in predicting the recharging rate of storm water filter system with ANN in comparison to other input parameters and extracting of any other input parameter has no major influence on the prediction potential of ANN.

Table 5: Sensitivity analysis using ANN.

Input combination	Input parameter removed	ANN	
		Coefficient of correlation	Root mean square error (m^3/min.)
T,B,S, Conc.		0.9966	0.1778
B,S, Conc.	T	0.8975	0.6001
T, S, Conc.	B	0.9533	0.412
T, B, Conc.	S	0.4148	1.2964
T,B,S	Conc.	0.9713	0.4361

CONCLUSION

The accurate prediction of recharging rate directly affects the budget allocation for the maintenance and rehabilitation of the storm water filter system. In this paper, the ANFIS, ANN and MLR methods were applied to predict the recharging rate of storm water filter. To the end, four effective variables of medium sand storm water filter were considered and used in ANFIS, ANN and MLR approaches. The results show that ANN is capable of predicting accurate recharging rate of storm water filter system. ANN kernel function works well than other above discussed methods. In comparison of Gaussian MF and Gaussian bell shape MF based ANFIS approach, Gaussian MF works better than Gaussian bell shape MF based ANFIS approach for this data set. Sensitivity analysis suggests that size of medium sand (S) is an important parameter for predicting the recharging rate of storm water filter system.

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