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Estimation of Phosphorus Reduction from Wastewater by Artificial Neural Network, Random Forest and M5P Model Tree Approaches

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ABSTRACT: This study aims to examine the ability of free floating aquatic plants to remove phosphorus and to predict the reduction of phosphorus from rice mill wastewater using soft computing techniques. A mesocosm study was conducted at the mill premises under normal conditions, and reliable results were obtained. Four aquatic plants, namely water hyacinth, water lettuce, salvinia, and duckweed were used for this study. The growth of all the plants was inhibited in rice mill wastewater due to low pH, high chemical oxygen demand, high conductivity, and high phosphorus concentration. Subsequently, a 1:1 ratio of mill water to tap water was used. A control was maintained to assess the aquatic plant technology. In this study, the aquatic plants reduced the total phosphorus content up to 80 % within 15 days. A comparison between three modeling techniques e.g. Artificial neural network (ANN), Random forest (RF) and M5P has been done considering the reduction rate of total phosphorus as predicted variable. In this paper, the data set has been divided in two parts, 70 % is used to train the model and residual 30 % is used for testing of the model. Artificial neural network shows promising results as compared to random forest and M5P tree modelling. The root mean square error (RMSE) for all the three models is observed as 0.0162, 0.0204 and 0.0492 for ANN, RF and M5P tree, respectively.

KEYWORDS: *Aquatic plants; rice mill; modelling; water hyacinth; Total phosphorus.*

INTRODUCTION

Phytoremediation is a plant-based technique used to remove, transfer, stabilize or degrade contamination from soil and water. It is a solar energy-driven technique and is currently very popular in the field of nutrient removal from water and wastewater. These nutrients, if unattended, ultimately cause eutrophication of water bodies. Eutrophication is a process in which the algal blooms cover the whole or part of a water body and block the transfer of oxygen from the atmosphere to the water. Nitrogen and phosphorus are the major nutrients that support the eutrophication of the water body. Improving the quality of a waterbody through physical and chemical methods could be expensive and strenuous. Phytoremediation is a suitable alternative for removing nutrients from water and wastewater, which requires availability of aquatic plants and some maintenance. Phytoremediation is very effective in tropical and subtropical regions but it is less effective in cold areas. In cold climate, plants face special growth challenges (Wang et al., 2017). Several researchers have studied the removal efficiency of various aquatic plants

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and found the results satisfactory. Aquatic plants can decrease different types of wastewater contaminants, including nitrogen, phosphorus, nitrate, potassium, calcium, magnesium, sodium, heavy metals and organic matter (Hadiyanto et al., 2013; Kamal et al., 2004). Daud et al. (2018) used duckweed to treat landfill leachate, Rahman & Hasegawa (2011) used floating plants to reduce arsenic from water, Singh et al. (2012) used duckweed to eliminate lead from wastewater, Favas & Pratas (2013) studied the potential of aquatic plants to remove uranium from water, Axtell et al. (2003) studied the removal of lead and nickel from wastewater by using aquatic plants, Abu Bakar et al. (2013) used phytoremediation to remove arsenic, zinc, and aluminum from gold mine wastewater, Tanhan et al. (2007) used phytoremediation for the removal of cadmium, zinc, and lead from wastewater, Azeez & Sabbar (2012) used Lemna minor L to remove pollutants from oil refinery wastewater, Saha et al. (2017) studied removal of chromium from mine wastewater by using water hyacinth. Sri et al. (2015) studied pollutant removal from sugar industry wastewater by using floating aquatic plants. Mishra et al. (2013) studied heavy metal removal from paper mill wastewater by using aquatic plants. Ajayi & Ogunbayio (2012) studied pollutant removal from textile, metallurgical, and pharmaceutical wastewaters by using water hyacinth.

In this paper, phosphorus reduction efficiency of four aquatic plants, namely water hyacinth, water lettuce, salvinia, and duckweed, is compared. Phosphorus is eliminated through various mechanisms such as direct uptake by plants, assimilation by microbes, filtration by rhizosphere, adsorption on roots, and precipitation with the help of metal ions. Phosphorus removal depends on the growth rate and phosphorus content of plants. It is faster when the phosphorus concentration of water is lower than a specific limit. Water lettuce can tolerate up to 50 mg/L phosphate, and the accumulation rate was 6.12 ± 0.95 mg/g dry weight of plant after 35 days of investigation under greenhouse condition (Ready et al., 1999).

The objective of this study was to compare the phosphorus reduction capabilities of four aquatic free floating plants, namely water hyacinth, water lettuce, salvinia, and duckweed, in parboiled rice mill wastewater. In this paper, the authors also attempt to predict the values of total phosphorus reduction with water hyacinth from rice mill wastewater by using soft computing techniques like ANN, RF and M5P. To date, most of the models on wetlands are based on the linear regression equations and first order decay, which mainly focused on input and output concentrations. No such research paper was found in which modelling of phosphorus removal by free floating aquatic plants is covered. However, some researcher used artificial neural network to predict phosphorus removal in other treatment systems. Artificial neural network shows promising results as compared to random forest and M5P tree modelling. The root mean square error (RMSE) for all the three models is observed as 0.0162, 0.0204 and 0.0492 for ANN, RF and M5P tree, respectively.

MATERIALS AND METHODS

These experiments were performed in a rice mill in Kurukshetra district, Haryana, India. Kurukshetra is located at 160 km northward to the national capital, New Delhi. It is located at 29° 58' 10.2468" N latitude and 76° 52' 41.8116" E longitude coordinates, and its elevation is 258 m above the mean sea level. A batch scale mesocosm study was performed in five identical polyvinyl chloride tubs, with dimensions of 44.25 cm in diameter, 13 cm in depth, 0.1541 m^2 in surface area, and 20 L in volume (Figure 1). The study was conducted from May 1, 2019 to May 15, 2019. During the study, the average high temperature was 38°C and average low temperature was 22°C. On May

1, the tubs were filled with rice mill wastewater diluted with tap water in a dilution ratio of 1:1. Of the five tubs, one was used as control in which no aquatic plant was placed, and the other four were planted with water hyacinth, duckweed, water lettuce, and salvinia, respectively (Figure1). On the same day, water samples were checked for total phosphorus (TP). Water samples were monitored daily. When the water level dropped due to evaporation and transpiration, tap water was used to top up the water level in the tubs.

Aquatic plants were collected from nearby wetlands and their roots washed with tap water to remove dirt. All the plants were placed in tap water for 5 days to remove soil and other materials deposited on roots. After 5 days, healthy plants were selected, and their dead leaves were chopped off. The selected plants were put in 20% diluted rice mill wastewater for 1 week to acclimatize them to the rice mill wastewater environment. Plants were selected from the 20% diluted water and finally placed in their designated tubs. Out of all plants, 15 plants of water lettuce with a total weight of 200 g, 10 plants of water hyacinth with a total weight of 300 g, 200 g of salvinia and, 50 g of duckweed selected for final experiments. Samples were collected from water tubs by using 50 mL sample bottles to obtain water from three sites; these samples were then mixed. All the parameters were analyzed in triplicate within 4 hours of the sample collection according to the American Public Health Association (APHA) methods (APHA, 2005). Table 1 shows the physicochemical characteristics of wastewater used in this study.

Fig. 1. Setup of phytoremediation experiment

Table 1. Physicochemical characteristics of wastewater

Parameter	Unit	Raw water	Diluted water
pH	-	5.04	6.8
Conductivity	µs/cm	2651	1945
Temperature	ºC	37.3	34.5
COD	mg/l	2560	1280
BOD	mg/l	1096	-
Total Phosphorus	mg/l	32.4	16.2
Total Nitrogen	mg/l	0.3	-
Dissolved Oxygen	mg/l	0.5	-

A brief overview of the modelling techniques used in this paper is discussed in the following paragraphs.

Artificial neural network (ANN) is the most common soft computing technique practicing almost in every stream. This technique is highly complex and nonlinear, based on the human nervous system (Mashaly & Alazba, 2019; Van De Moortel et al., 2010; Zare Abyaneh, 2014). It is used to model the complicated relationship between input and output There are many types of ANN network applications, and the selection of the best depends on the nature of the work and the availability of the data. The most commonly used ANN network in the field of environmental hydraulics is multilayer perceptron (MLP) (Govindaraju, 2000; R.S. Govindaraju, 2000; Kumar et al., 2018; Sihag et al., 2019). Artificial neural network with backpropagation algorithm, composed of three layers: input layer, hidden layer, and output layer is used.

The activation function used in this study as follows:

$$f(u_j) = \frac{1}{1+e^{-uj}} \quad (1)$$

Random forest is a machine learning technique used for classification, regression, and many other applications. In this technique, there are several decision trees. For a random forest regression, the number of variables used (m) and the number of trees (k) are the two parameters defined by the user. The earlier version of the random forest was invented by Tin Kam Ho using a random subspace method (Ho, 1995). Later, Leo Breiman and Adele Cutler, make the extended version of this technique (Breiman, 2001). Breiman had come up with an idea of combining two techniques, namely begging and the first version of Ho model. In this article, we applied a random forest technique to predict the reduction of phosphorus from wastewater by aquatic plants.

Model trees were first introduced by Quinlan (1992), then the concept was rebuilt and improved by Wang et al. (1997) into a program known as the M5P. M5P model is the modification and combination of conventional tree with linear regression at the terminal nodes. In this model, data is divided in subsets and all the subsets make a tree. Out of the many tree structures made with subsets, a tree structure with minimal errors is to be constructed. To eliminate the problem of overfitting, the tree must be pruned back by replacing a sub-tree with a leaf (Sihag et al., 2019). Thus, the second stage in the design of a model tree involves pruning the overgrown tree and replacing the sub-trees with linear regression functions.

To check the effectiveness of ANN, RF and M5P tree modelling, three parameters are used to evaluate the model performance:

1. Coefficient of determination (R^2)
2. Root mean square error (RMSE)
3. Mean absolute error (MAE)

All the above parameters are calculated using training and testing data sets. The formula of the above parameters as follows:

$$f(u_j) = \frac{\left(n\sum a_i p_i - \sum a_i \sum p_i\right)^2}{\left[n\sum (a_i)^2 - \left(\sum a_i\right)^2\right]\left[n\sum (p_i)^2 - \left(\sum p_i\right)^2\right]} \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(p_i - a_i)^2}{n}} \quad (3)$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}|p_i - a_i|}{n} \quad (4)$$

where *a* is actual value; *p* is predicted value and *n* is the number of observations

A detailed study on rice mill wastewater has been conducted to get credible data. There are about 106 number of data available on total phosphorus (TP) reduction. The data set is divided into two separate parts: training (70 %) and testing (30 %). Table 2 shows the features of training and testing data set, in which hydraulic loading rate (HLR), hydraulic retention time (HRT), and initial concentration of total phosphorous (C_{in}) are considered as input parameters whereas reduction rate of total phosphorous (R) is considered as output parameter. The original data set is modified according to the requirement of the paper. The reduction rate was calculated as:

$$R = \frac{C_{in} - C_{out}}{C_{in}} \quad (5)$$

C_{in}: Initial concentration of total phosphorus

C_{out}: Final concentration of total phosphorus.

Hydraulic loading rate (*HLR*) is calculated as:

$$\mathrm{HLR} = \frac{\mathrm{V}}{\mathrm{A} * \mathrm{HLR}} \tag{6}$$

V: Volume of tub (m^3)
A: Surface area of tub (m^2)
HRT is in days.

Table 2. Characteristics of the dataset used in this study

Parameter	Unit	Train data				Test data			
		Min	**Max**	**Mean**	**St. dev**	**Min**	**Max**	**Mean**	**St. dev**
R	-	0.028	0.761	0.377	0.27	0.031	0.772	0.425	0.216
HRT	days	1	13	5.342	3.465	1	14	1.5313	3.355
HLR	$m^3/m^2.d$	0.007	0.097	0.033	0.029	0.007	0.097	0.031	0.028
C_{in}	mg/l	3.872	16.2	8.907	3.934	4.115	16.2	10.583	3.95

RESULTS AND DISCUSSION

The biomass growth rate or the relative growth rate (RGR) is defined as the change of biomass with respect to the initial biomass of the plant. It was measured based on the following formula (Eq. 7). All the plants show positive biomass growth rate except salvinia (- 0.1386 g/g per day). Water hyacinth exhibit highest growth rate (0.09877 g/g/day), followed by water lettuce (0.0780 g/g/ day) and duckweed (0.0462 g/g/ day), respectively.

$$\mathrm{RGR} = \frac{\ln \mathrm{W}_2 - \ln \mathrm{W}_2}{\mathrm{T}} \tag{7}$$

W_1: Initial weight of biomass
W_2: Final weight of the biomass
ln: natural log
T: experiment time

Phosphorus removal from water column occurs through various mechanisms, which includes uptake by plants, assimilation by periphytons, adsorption, and precipitation. The effectiveness of four aquatic plants for removing phosphorus was tested, and it is evident from the results that these plants are capable of removing phosphorus. Water lettuce showed the maximum efficiency among all the plants, followed by water hyacinth, salvinia, duckweed, and control. Water lettuce showed the maximum removal efficiency of 80.06 % on Day 15, followed by water hyacinth (77.2%), salvinia (61.41% on Day 10), duckweed (70.24% on Day 13), and control (67.40% on Day 11). The growth rate of salvinia was negative; the phosphorus removal may have occurred owing to the periphyton present in the salvinia tub. After Day 15, phosphorus concentration in the water started increasing possibly owing to the decomposition of leaves and roots of these plants. Table 3 and Figure 2 shows the details of phosphorus removal by the four aquatic plants. Similar results were obtained by different researchers, Akinbile & Yusoff (2012) performed a study on aquaculture wastewater by using water hyacinth and water lettuce and found that water hyacinth reduces phosphorus by 85%, whereas water lettuce reduces phosphorus by approximately 70% in 3 weeks. Moreover, Mukherjee et al. (2015) performed a laboratory-scale experiment on parboiled rice mill wastewater by using water lettuce in a small container of 38 cm diameter and 10 L capacity and found that phosphorus removal efficiency was 73% within 2 weeks. Similarly, Kutty et al. (2009) used water hyacinth and found the TP removal was 72% in 6 days. Li et al. (2014) used livestock wastewater and found the TP removal by duckweed to be 96% in 40 days. Rezania et al. (2016) used domestic wastewater and found the results to be 70% on Day 15.

Table 3. Phosphorus concentration in each tub (mg/l)

Time (Days)	Control	Salvinia	Water lettuce	Duckweed	Water hyacinth
1	16.2	16.2	16.2	16.2	16.2
2	14.48	13.67	13.72	14.19	13.81
3	13.25	11.32	11.34	11.88	11.68
4	12.11	9.45	9.49	9.33	9.46
5	10.54	9.17	7.94	8.84	8.18
6	9.39	8.52	7.23	8.16	7.40
7	7.24	7.55	6.67	6.94	6.64
8	6.85	7.22	5.98	6.47	5.94
9	5.93	6.38	5.60	5.97	5.18
10	5.53	6.25	5.12	5.61	4.53
11	5.28	6.58	4.81	5.31	4.27
12	5.62	6.83	4.31	5.48	4.11
13	5.97	6.74	3.73	4.82	3.98
14	6.34	6.91	3.50	5.12	3.87
15	6.70	7.39	3.23	4.85	3.69
Removal %	67.40	61.41	80.06	70.24	77.22

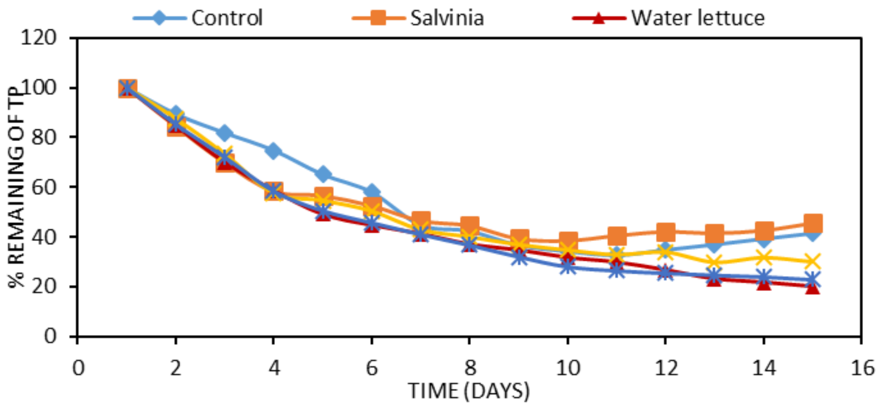

Fig. 2. Reduction of total phosphorus by aquatic plants

A comparative analysis of the data has been done by using artificial neural network, random forest and M5P techniques. The data obtained from water hyacinth plant have been considered for this analysis. WEKA 3.8 software was used to derive regression or equation coefficients using training data-set.

ANN is a trial and error method which consist of three main components viz. input layer, hidden layer and output layer. The results of the artificial neural network were checked by varying different parameters. The results obtained at momentum = 0.2, learning rate = 0.1, Iteration = 3000 and one hidden layer with 8 neurons was in the close proximity of the actual values of total phosphorus reduction. The performance of ANN model is shown in Figure 3. As shown in Table 5, the values of R^2, RMSE and MAE of ANN model are 0.9946, 0.0124 and 0.0162 for water hyacinth for testing data set. The results of ANN model show that the use of ANN model is suitable to predict the reduction of phosphorus by aquatic plants from wastewater.

The prediction of phosphorus removal from wastewater by random forest is in close proximity of the actual values. Figure 8 shows the scatter plot of prediction by RF, it can be visualise from the figure that the prediction points are closely related to prefect prediction line. The optimum results were obtained at k=4, and m=1.0. The performance of RF model is shown in Figure 4. The performance evaluation parameters obtained from this model were 0.9467 and 0.9791 (R^2), 0.0388 and 0.0492(MAE), 0.0265 and 0.0204 (RMSE) for training and testing data sets, respectively (Table 5).

M5P model is the modification and combination of conventional tree with linear regression at the terminal nodes. In this model, data is divided in subsets and all the subsets make a tree. Out of lot of trees made with subsets, the tree with minimum errors is to be constructed. The optimum results were obtained by setting the value of parameter M (instances) to 6.0. Table. 5 shows the statistical evaluation parameter of the model for phosphorus reduction. It is clear from the Figure 5 that the prediction of phosphorus reduction from water by M5P is close to the actual value. The performance evaluation parameters obtained from the model were, R^2 values (0.9757, 0.9467), MAE values (0.0256 and 0.0388) and RMSE values (0.0337 and 0.0492) for training and testing data sets, respectively (Table 5). When M5P model tree is pruned to get the results using smoothed linear models, there are two conditional linear equations best fit for different HRT values (Table 4).

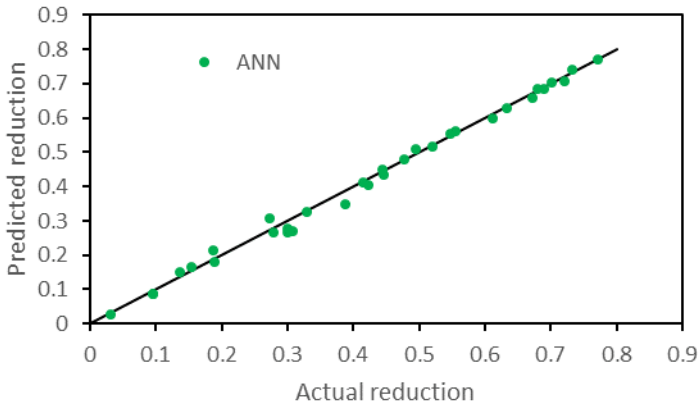

Fig. 3. Actual versus predicted values of phosphorus reduction using ANN model (testing data)

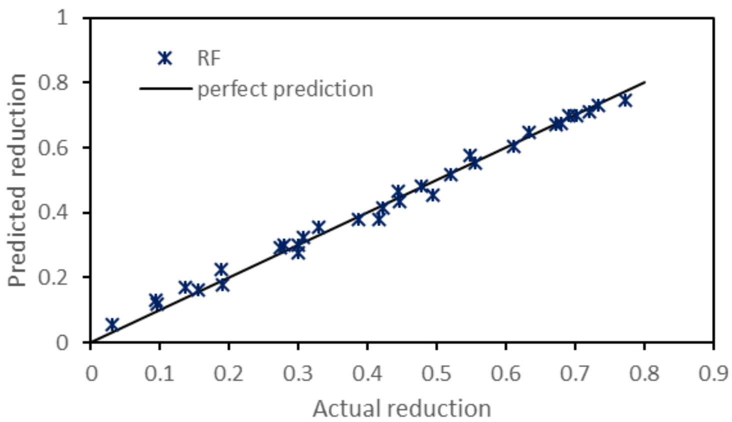

Fig. 4. Actual versus predicted values of phosphorus reduction using RF model (testing data)

Table 4. Pruned model tree equations for different conditions

Condition	Equation
HRT <= 5.5	R = 0.0667 * HRT + 0.0185 * C_{in} - 0.0905
HRT > 5.5	R = 0.0331 * HRT + 0.0196 * C_{in} + 0.0966

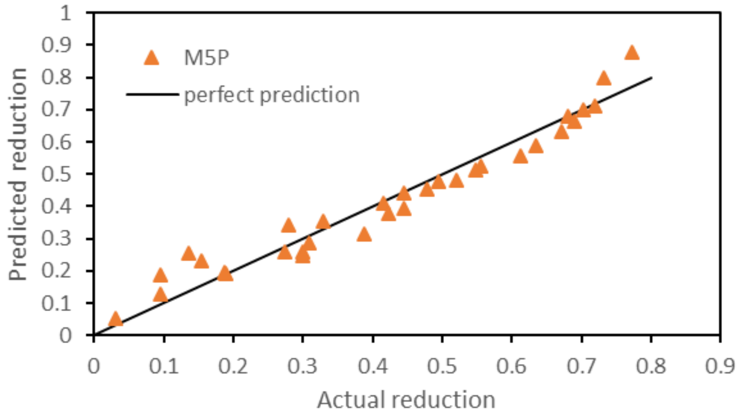

Fig. 5. Actual versus predicted values of phosphorus reduction using M5P model (testing data)

Comparison of all the modelling technique is shown in Figure 6 to Figure 8. It is evident from all the Figures that the performance of ANN model is superior to RF and M5P tree model. Figure 6 and Figure 7 shows the scattered plots of the predicted values by both training and testing data sets. It can be inferred from Figure 7 that the estimated values obtained by ANN model are closer to the actual phosphorus reduction. The estimated values of total phosphorus reduction by RF and M5P models are close to the actual values but not as much as ANN model. Table 5 shows the performance evaluation parameters of all the three models for training and testing data sets. The ANN model showed superior results followed by random forest and M5P model tree. Figure 8 shows the comparison of actual and predicted phosphorus reduction by all three model for testing data sets.

Table 5. Performance measured for various models

Model	Training data			Testing data		
	R^2	MAE	RMSE	R^2	MAE	RMSE
ANN	0.9938	0.012	0.0171	0.9946	0.0124	0.0162
RF	0.9986	0.0064	0.0085	0.9924	0.0163	0.0204
MP5	0.9757	0.0256	0.0337	0.9467	0.0388	0.0492

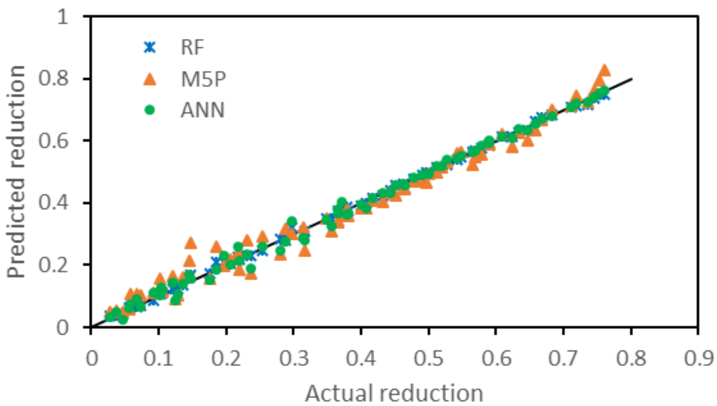

Fig. 6. Scattered diagram of actual and predicted TP reduction by water hyacinth using ANN, RF and M5P tree model in training dataset

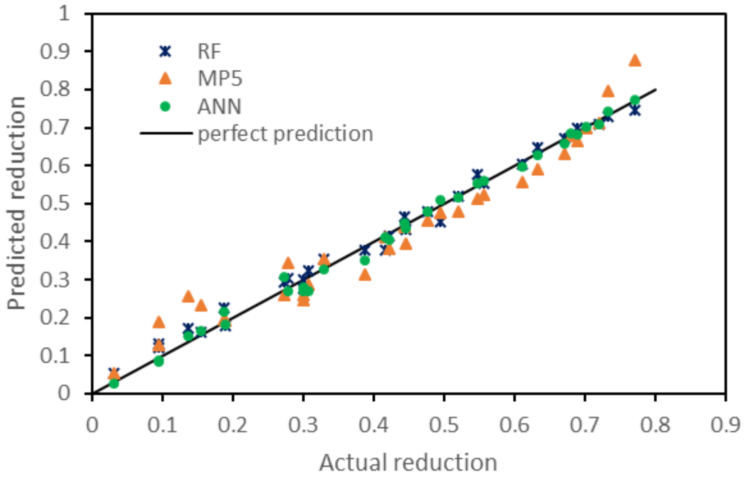

Fig. 7. Comparison of actual and estimated TP reduction by water hyacinth using ANN, RF and M5P model tree in testing dataset

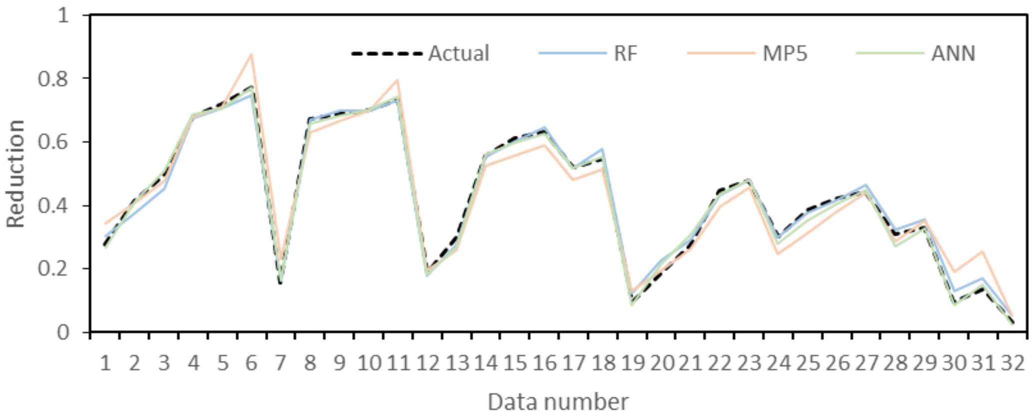

Fig. 8. Comparison of actual and estimated TP reduction by water hyacinth using ANN, RF and M5P model tree in testing dataset

CONCLUSION

In raw rice mill wastewater, the growth of all aquatic plants has been found inhibited. A dilution approach of 1:1 with tap water was adopted to perform experiments. Among the plants, water lettuce shows most promising results as it removes phosphorus content up to 80 % within 15 days. Water hyacinth reduces phosphorus content up to 77 % followed by duckweed, salvinia and control. A statistical comparison to predict phosphorus reduction has been done using three soft computing techniques i.e. ANN, RF and M5P. ANN model predicted superior values as compared to RF and M5P tree model. The root mean square error (RMSE) for all the three models is observed as 0.0162, 0.0204 and 0.0492 for ANN, RF and M5P tree, respectively. After the 15th day phosphorus content in water start rising again due to falling of dead leaves. Hence, it is advisable to harvest plant biomass after every 15 days to get optimum performance. Although this mesocosm study was successful but to verify the success and feasibility of the system, pilot-scale and full-scale field studies are required.

ABBREVIATIONS

%	Percentage
°C	Degree centigrade
A	Surface area of tub
ANN	Artificial neural network

APHA	American Public Health Association
cm	Centimeter
$CaCo_3$	Calcium carbonate
C_{in}	Initial concentration of total phosphorus
C_{out}	Final concentration of total phosphorus
Co_2	Carbon dioxide
c/p	Carbon / phosphorus
d	day
DIP	Dissolved inorganic phosphorus
DNA	Deoxyribonucleic Acid
Eq.	Equation
Fig.	Figure
g	Gram
g/L	Gram per litter
HLR	Hydraulic loading rate
HRT	Hydraulic retention time
MAE	Means absolute error
MLP	Multilayer perceptron
m^2	Square meter
Max	Maximum
mg/g	Milligram per gram
mg/L	Milligram per litre
Min	Minimum
min.	Minute
mL	Milliliter
pH	Potential of hydrogen
RRSE	Root relative squared error
R	Reduction rate
R^2	Coefficient of determination
RAE	Relative absolute error
RF	Random forest
ROL	Radial oxygen loss
RMSE	Root mean square error
St. dev	Standard deviation
T	Experiment time
Temp.	Temperature
TP	Total phosphorus
V	Volume of tub

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CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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