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Artificial Neural Network Based Model for the Prediction of Effluent from Lab-Scale Upward Flow Hybrid Anaerobic Sludge Blanket (UHASB) Reactor

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Abstract— Anaerobic processes have gained popularity over the past decade, and have already been applied successfully for the treatment of a number of waste streams. One of the most attractive options available for such a treatment is the up flow anaerobic sludge blanket (UASB) reactor, which acts as a compact system for removal and digestion of organic matter present in sewage. The hybrid reactor UHASB is an improved version of the UASB system and combines the merits of the up flow sludge blanket and the fixed film reactors. The hybrid reactor is an economical solution for the treatment of municipal sewage. This paper presents the predictions of the effluent from a UHSAB reactor using artificial neural network. Two different neural network Error back propagation network (EBPN) and Radial basis function network (RBF) are used here for prediction, the prediction results are compared. When a UHSAB reactor is put into operation, variations of the waste water quantity and quality must be predicted using mathematical models to assist in UHSAB reactor such that the treated effluent will be controlled and meet discharge standards. In this study ANN is used to predict the effluent biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspended solids (SS) and total dissolved solids (TDS) from the lab-scale upward flow hybrid anaerobic sludge blanket reactor (UHASB).The simulation results indicated that the mean absolute percentage error (MAPE) of 11.86, 15.53, 26.67 and 22.26 for BOD, COD, SS and TDS respectively could be achieved in case of testing. Prediction result suggests that EBPA tuned neural network (EBPN) is performing well and could predict the removal efficiencies effectively and accurately.

Index Terms— Error back propagation Network (EBPN), Radial basis Function Network (RBFN), upward flow hybrid anaerobic sludge blanket (UHASB).

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1 Introduction

Sewage is the main point-source pollutant on a global scale. Between 90 to 95% of sewage produced in the world is released into the environment without any treatment [Seghezzo, 2004]. On the other hand, virtually 100% of waste water produced in households from most of the cities and towns in some developing countries is commonly discharged in water bodies like rivers and lakes, with immediate and sometimes disastrous effect on public health and quality of environment [Seghezzo, 2004]. In India, about 70% of domestic wastewater is being discharged without/proper treatment into the water bodies [CPCB, 1997].Up flow anaerobic sludge blanket (UASB) reactor is being used with increasing regularity all over the world and especially in India for a variety of wastewater treatment operations. Its use is not only limited to the traditional application of anaerobic systems, viz. sludge digestion and treatment of high strength industrial wastes, but also for the treatment of low strength domestic wastewater. In spite of the widespread application of the UASB technology in India, design of such reactors is mired in empiricism. There are several reasons for this state of affairs. The microbial ecology in an anaerobic reactor is extremely complex with several strains of micro organisms existing in symbiotic relation inside the reactor. Though the interactions between these organisms is well understood in qualitative terms, quantitative description of these inter relationships as applicable to reactor performance is not possible. Similarly, the hydraulics, substrate and biomass transport mechanisms and other process parameters responsible for reactor performance, through understood in qualitative terms, cannot be represented in quantitative terms. Through the efforts of the researchers, a large volume of data on UASB/UHASB reactor performance under various working condition has been obtained. This has undoubtedly increased the understanding of the process. However, prediction of UASB/UHASB reactor performance given specific input conditions is still not possible due to extreme complexity of the process. To implement detailed study or validate mechanism models, much attention has been devoted to the investigation of water quality indices. The effluent quality trend cannot be predicted appropriately using some mechanism models because few data are available. Some soft computation model using neural network implements training to continually adjust the weight factor and bios to make the model output approach as objective out put through a black-box-type operation by taking only the relationship between the system input and output.

2 Experimental Set-Up

The schematic representation of UHASB is shown in Fig. 1. The experimental investigation was carried out utilizing a pilot-scale UHASB reactor with a working volume of 56.52L, a height of 0.9m and internal diameter of 0.30m fed with prescreened domestic sewage from Nehru Nagar area, Bhilai, C.G., India mixed with pulverized vegetable waste. The reactor was equipped with an egg tray filter through which the sewage passed before discharge. It had a modified gas-solidliquid separator and 4 sludge collection points. Methane production was monitored using a plastic bottle with 30L of volume, filled with a NaOH solution (5%w/w). A very slow stirrer (1rpm) was installed in the reactor to avoid channeling and "piston" formation in its sludge bed (rising sludge due to entrapped biogas in the sludge layer) – Goncalves et al. (1994) also used this approach. The input variables analyzed were the pH, alkalinity, Temperature, Total Solids, Turbidity, COD and BOD in the influent samples.

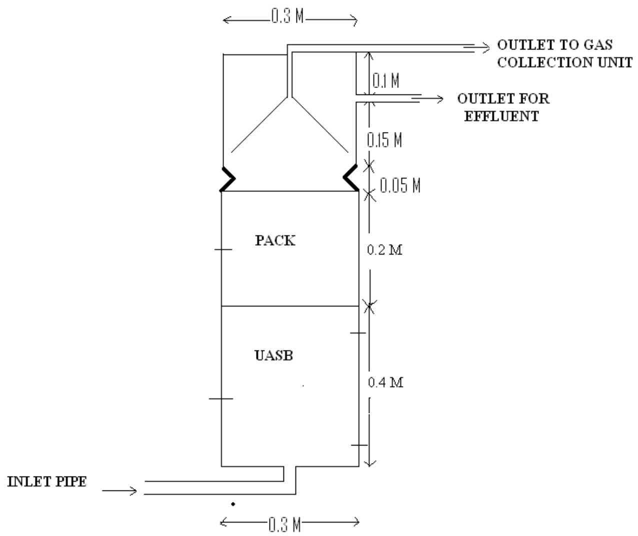


Fig. 1: Schematic diagram of the reactor

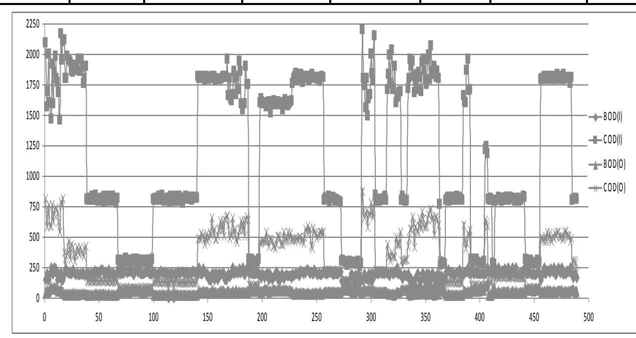
Biological oxygen demand of both influent as well as effluent sewage was determined by dilution method. The BOD in ppm was then calculated using the following equation:

BOD = [(Oxygen Content) Final – (Oxygen Content) Initial] × Dilution Factor

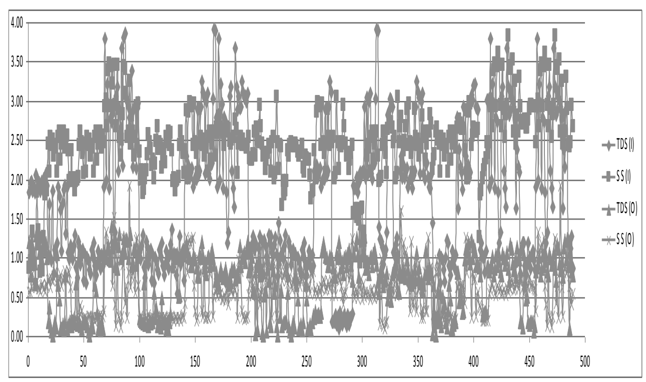
A sample volume of 20 ml or fraction diluted to 20 ml was used for the analysis. Soluble COD was determined after filtering the samples through 0.45 µ membrane filter paper. Total solids, total Dissolved, Total suspended solids, total volatile suspended solids determinations were done. Experimental data were collected and analyzed as per the methods given in standard methods [APHA et al, 1998] in order to evaluate the "steady state" performance and efficiency of UHASB reactor on the basis of (i) COD removal efficiency, (ii) effluent variability, and (iii) operational and pH stability. A sample data collected form the reactor is shown in table 1 in which (I) represents input variables while (O) represents output variables. The distribution of input and output pattern is also shown in Fig. 2. Data are highly non linear, if we will observe there is no mathematical relation between influent and effluent and hence it is a challenging job to develop a model which will produce output with high accuracy .Data used in this piece of research paper are collected from the reactor in between Jan 2009 and Dec 2010, in all there are 489 data out of which 291 data are considered for training while 198 data are considered for testing the ANN model.

TABLE 1
SAMPLE DATA COLLECTED FROM THE REACTOR

TDS (I)	SS (I)	BOD (I)	COD (I)	TDS (O)	SS (O)	BOD (O)	COD (O)
1.92	2.47	150	2200	1.01	0.52	52	875
1.89	2.08	150	1800	0.91	0.29	65	720
1.89	1.91	200	1740	0.97	0.24	72	660
2.02	1.96	160	1560	1.09	0.23	62	685
1.83	1.96	165	1800	0.93	0.26	58	715
1.95	2.08	150	1490	1.02	0.28	56	585
2.1	2.06	200	1630	1.07	0.28	77	695
2.04	2.23	150	1670	1.08	0.28	55	680
2.09	2.56	200	2000	0.92	0.34	72	787



(a)



(b)

Fig. 2: Distribution of the data set (a) influent and effluent of COD and BOD (b) influent and effluent of TDS and SS

3 METHODOLOGY

This study is confined on Artificial Neural Network ANN inspired by biological neural network. Artificial neural network (ANN) is one of the very useful soft computing tools used for prediction. In this piece of research work two very well known neural network EBPN and RBF network are used for prediction these model is shown in Fig. 3 (a) and (b) respectively.

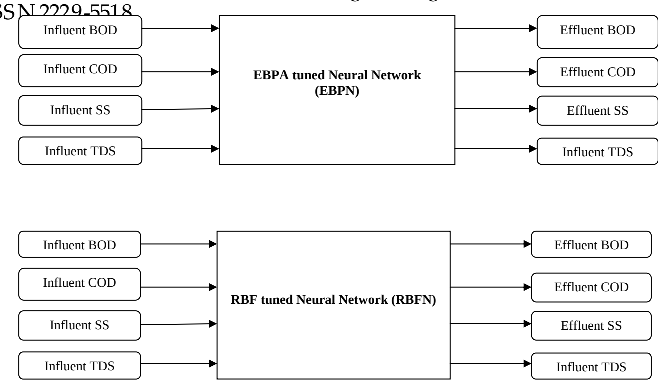


Fig. 3: Architecture of (a) EBPA tuned neural network (EBPN) (b) RBF tuned neural network (RBFN).

The details of each of these two algorithms are explained below:

1. Error Back-Propagation Network (EBPN): The back-propagation learning algorithm is one of the most important developments in neural networks. This network has re-awakened the scientific and engineering community to the modeling and processing of numerous quantitative phenomena using neural networks. This learning algorithm is applied to multilayer feed-forward networks consisting of processing element with continuous differentiable activation functions. For a given set of training input-output pair, this algorithm provides a procedure for changing the weights in a BPN to predict the given input pattern correctly. The basic concept for this weight update algorithm is simply the gradient-descent method as used in the case of simple perception network with differentiable units. This is a method where the error is propagated back to the hidden unit.

The back-propagation algorithm is different from other networks in respect to the process by which the weight are calculated during the learning period of the network. The general difficulty with the multilayer perceptions is calculating the weights of the hidden layers in an efficient way that would result in a very small or zero output error. When the hidden layers are increased the network training becomes more complex. To update weights, the error must be calculated. The error, which is the difference between the actual (calculated) and the desired (target) output is easily measured at the output layer. It should be noted that at the hidden layers, there is no direct information of the error. Therefore other techniques should be used to calculate an error at the hidden layer, which will cause minimization of the output error, and this is the ultimate goal.

The training of the BPN is done in three stages-the feed-forward of the input training pattern, the calculation and the back-propagation of the error, and updating of weights. The testing of the BPN involves the computation of feed-forward phase only. There can be more than one hidden layer (more beneficial) but one hidden layer is sufficient. Even though the training is very slow, once the network is trained it can produce its outputs very rapidly. In this study, the EBPNN was composed of three independent layers; input, hidden and output layers the influent BOD, COD, SS and TDS were taken as the input and effluent of the same is considered as output variables .The complete architecture of EBPN is shown in Fig. 4 in which there are 10 neurons in hidden layers, activation function used in hidden and output layers is log sigmoidal function.

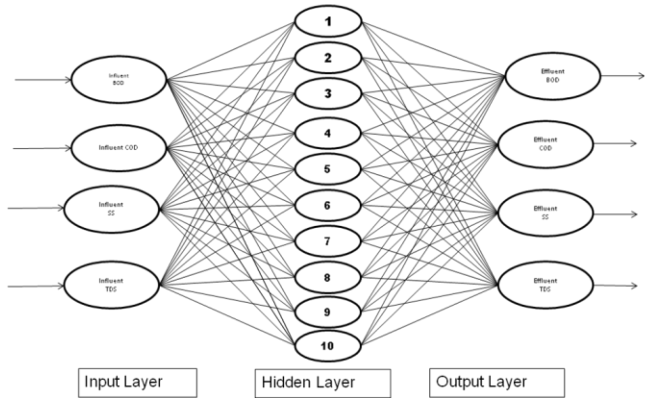


Fig. 4: Architecture of EBPN for prediction

2. Radial Basis Function Network (RBFN): The radial basis function (RBF) is a classification and functional approximation neural network developed by M.J.D. Powell. The network uses the most common nonlinearities such as sigmoidal and Gaussian kernel functions. The Gaussian functions are also used in regularization networks. The response of such a function is positive for all values of y; the response decreases to 0 as $|y| \to 0$ The Gaussian function is generally defined as:

$$f(y) = e^{-y^2}$$

The derivative of this function is given by

$$f'(y) = -2ye^{-y^2} = -2yf(y)$$

When the Gaussian potential function are being used, each node is found to produce an identical output for inputs existing within the fixed radial distance from the center of the kernel, they found to be radically symmetric, and hence the name radial basis function network. The entire network forms a linear combination of the nonlinear basis function. The training is started in the hidden layer with an unsupervised learning algorithm. The training is continued in the output layer with a supervised learning algorithm. Simultaneously, we can apply supervised learning algorithm to the hidden and output layers for fine-tuning of the network. The training algorithm is given as follows.

Step 0: Set the weight to small random values.

Step 1: Perform Steps 2-8 when the stopping condition is false.

Step 2: Perform Steps 3-7 for each input.

Step 3: Each input unit (x_i, for all $i = 1$ to n) receives input signals and transmits to next hidden layer unit.

Step 4: Calculate the radial basis function.

Step 5: Select the centers for the radial basis function. The centers are selected from the set of input vectors. It should be noted that a sufficient number of centers have to be selected to ensure adequate sampling of the input vector space.

Step 6: Calculate the output from the hidden layer unit:

$$v_i(x_i) = \frac{\exp\left[-\sum_{j=l}^{r}\left(x_{ji}-\hat{x}_{ji}\right)^2\right]}{\sigma_i^2}$$

Where the centre of the RBF unit for input variables is the width of ith RBF unit the jth variable of input pattern.

Step 7: Calculate the output of the neural network:

$$y_{net} = \sum_{i=1}^{k} w_{im} v_i(x_i) + w_0$$

Where

k = number of hidden layer nodes (RBF function)

y_{net} = output value of mth node in output layer for the nth incoming pattern.

w_{im} = weight between ith RBF unit and mth output node.

w_0 = biasing term at nth output node.

Step 8: Calculating the error and test for the stopping condition. The stopping condition may be number of epochs or to a certain extent weight change.

Thus, a network can be trained using RBFN.

Architecture of RBFN which is designed for prediction of effluent of UHSAB reactor parameters is shown in Fig. 5 with same number of neurons in input and output layer as EBPN but this network consisting 20 neurons in hidden layer.

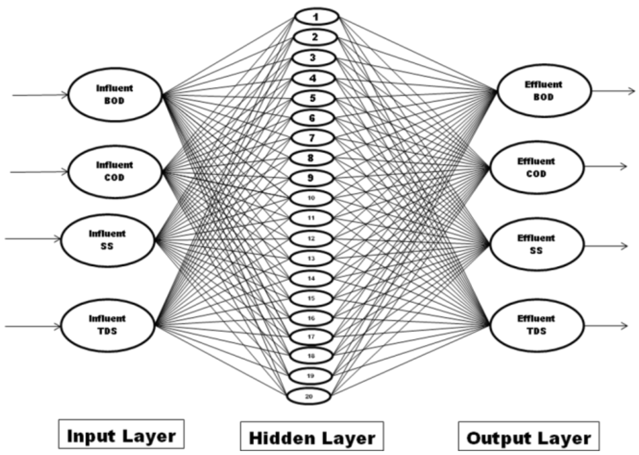


Fig. 5: Architecture of RBF network for prediction

Result and Discussion: Both the model are trained with 291 training data set. Once the network is trained it is tested with 198 testing data set, the result obtained in case of testing are shown in figure 6(a) to (d) and 7 (a) to (d) respectively for EBPN and RBFN model. Simulation result shows that predicted values are closer to the observed values, although in case of solid state (SS) in figure 6(c) predicted value is not close to observed value for some of the data point. However the graph of Fig. 7 is different from Fig. 6 for COD and TDS (Fig. 7(a) and (d)). Although number of neurons in hidden layer of RBFN is more as compare to EBPN then also accuracy is less in case of RBFN.

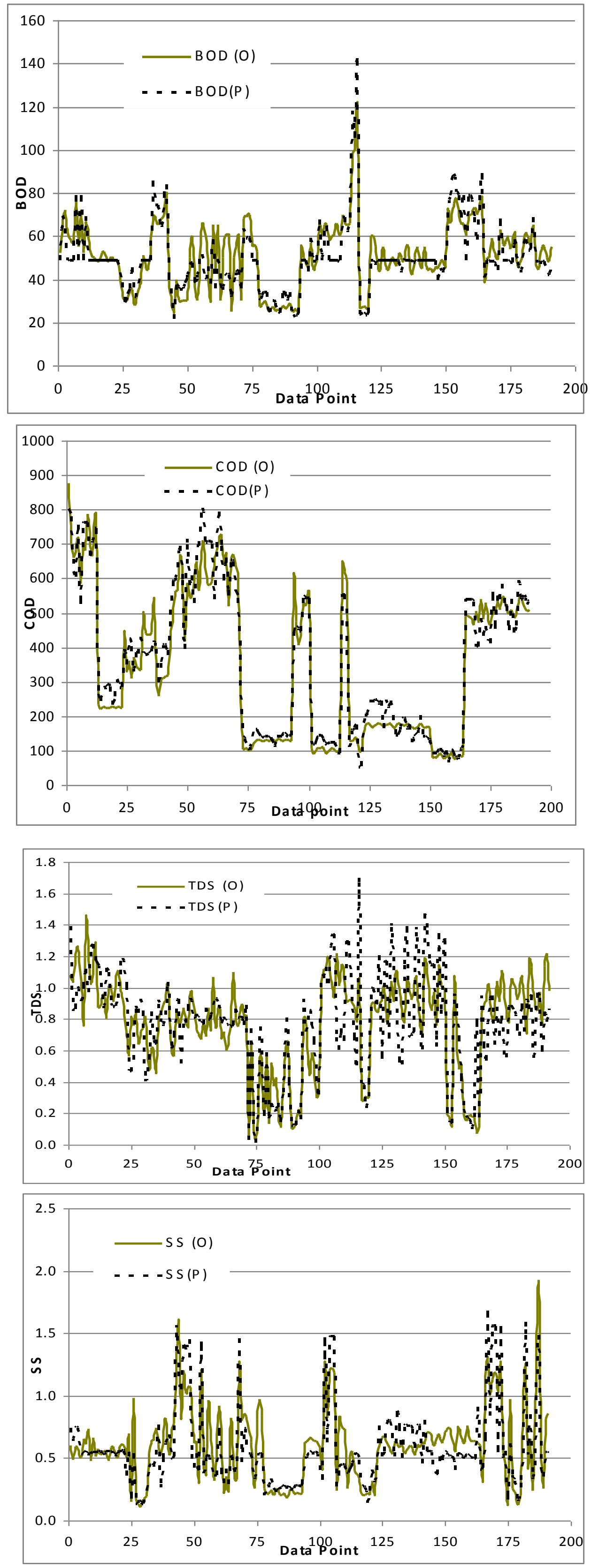


Fig. 6: Comparative graph for prediction of UHSAB reactor using EBPN
(a) BOD(O) Vs BOD(P), (b) COD(O) Vs COD(P),
(c) TDS (O) Vs TDS (P) and (d) SS(O) Vs SS(P)

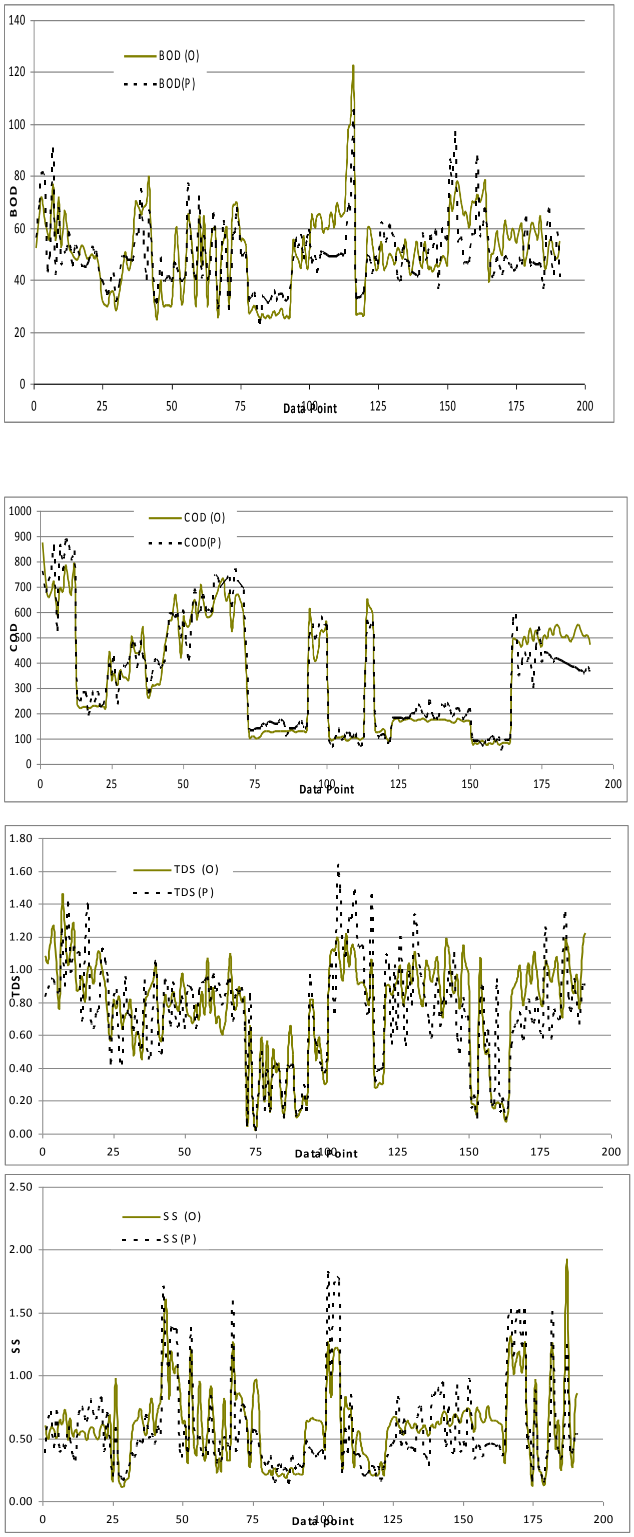


Fig. 7: Comparative graph for prediction of UHSAB reactor using RBFN (a) BOD(O) Vs BOD(P), (b) COD(O) Vs COD(P), (c) TDS (O) Vs TDS (P) and (d) SS(O) Vs SS(P)

In order to compute prediction accuracy of two ANN based model: EBPN and RBFN, mean absolute error (MAPE) is calculated using following equation:

$$\text{MAPE} = \frac{\text{Observed value} - \text{Predicted value}}{\text{Predicted value}} \times 100$$

MAPE for different parameters have been calculated using above formula as shown in table 2, MAPE in case of training is higher than the testing which is obvious which is clearly shown in bar chart in figure 8.

TABLE 2

COMPARISON OF TWO NEURAL NETWORK MODELS: EBPN AND RBFN

ANN based Model	Effluent BOD		Effluent COD		Effluent TDS		Effluent SS	
	Training	Training	Training	Training	Training	Training	Training	Training
EBPN	10.83	11.86	13.33	15.53	21.01	22.258	29.32	26.67
RBFN	12.35	18.73	15.11	16.55	22.43	23.77	29.73	33.19

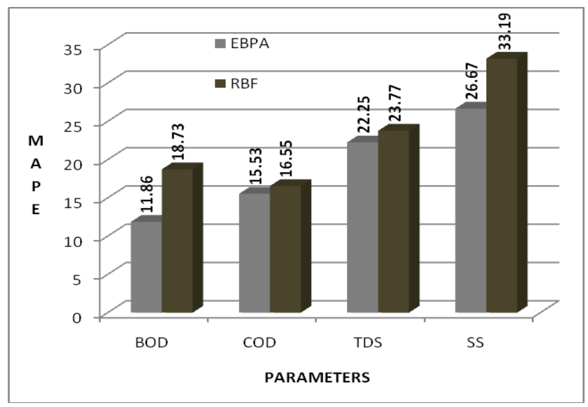


Fig. 8: A comparative chart of testing data using EBPN and RBFN

MAPE in case of testing from EBPN is 11.86, 15.53, 22.26 and 26.67 respectively for BOD, COD, TDS and SS while for RBFN these are 18.73, 16.55, 23.77 and 33.19 respectively for BOD, COD, TDS and SS from table it is clear that for all parameters MAPE in case of EBPN is less as compare to RBFN hence EBPN is more accurate than RBFN. The range of MAPE in case of EBPN is in between 11.86 to 26.67 for testing data while it is in between 18.73 to 33.19 for testing. The range of error in case of EBPN is in acceptable range and can be accepted for the prediction of different parameters of UHSAB reactor. Our results confirm the hypothesis that EBPN are more robust to solve non linear problems where classical mathematical modeling process is unable to predict the effluent from a UHSAB reactor.

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