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ADAPTING RUNGE - KUTTA LEARNING ALGORITHM IN ANFIS FOR THE PREDICTION OF COD FROM AN UP-FLOW ANAEROBIC FILTER

Vijayabhanu R. and Radha V.
Department of Computer Science, Avinashilingam Institute for Homescience and Higher Education for Women, India
E-Mail: vijayabhanuresearch@gmail.com

ABSTRACT

Water consumes vast area in the earth's surface and safe drinking water is essential for humans and other organisms to survive in the world. Eliminating waste matters from water is the necessary requirement nowadays. The ultimate purpose of wastewater treatment is the protection of good quality water which is the most priceless resource. Use of Artificial Neural Network (ANN) models is gradually increasing to predict wastewater treatment plant variables. This detection helps the operators to take proper action and manage the process accordingly as per the norms. Anaerobic processes are often preferred to aerobic processes for treating waste streams that contain high Chemical Oxygen Demand (COD) concentrations. Up-flow Anaerobic Filter (UAF) is a common process used for various anaerobic wastewater treatments. COD is used to measure the strength (in terms of pollution) of waste water. COD level in the effluents of the UAF determines the pollutants in the wastewater. The proposed method uses cheese whey as an influent. It is tested in the anaerobic reactor using COD test to predict the level of oxygen requirement of the effluent. Predicting the effluent parameters is a time consuming process when using Classical Models as it involves complexity and high non-linearity. Hence the proposed method uses an efficient technique namely Z-Score Normalization technique as a preprocessing step, Particle Swarm Optimization (PSO) for feature selection process and Adaptive Neuro-Fuzzy Inference System (ANFIS) with RungeKutta Learning Method (RKLM) as a learning algorithm is used for prediction of COD. Experiments conducted on a real data indicates that the application of Z-Score normalization schemes followed by a PSO feature selection and ANFIS with RKLM prediction results in better performance compared to other methods.

Keywords: ANFIS, rungekutta learning method, chemical oxygen demand, particle swarm optimization, waste water treatment, Z-score.

INTRODUCTION

Water is the major requirement for all life and also for economic development. Increase in the urbanization, industrialization, and other anthropogenic activities results in degrading the quality of water day by day. This hazardous wastewater can't be discharged directly on the ground or in the water bodies. Necessary treatment is required before discharging this wastewater. Owing to the lack of space, technical manpower, scale of operations, it is difficult for each industrial unit to provide individual Waste Water Treatment Plant (WWTP). However, the quantum of pollutants released by small scale industries may be more than an equivalent large-scale industry (Monika Vyas *et al*., 2011).

Wastewater Treatment Plant is designed to filter water that has been mixed with waste matter. Waste Water treatment is necessary to remove organic and inorganic matter, to remove pathogenic organisms, to protect the environment and human health. Food and dairy processing water, water discharged from homes, papermaking water, industrial processing water, extreme pH water, metalworking and plating water, slaughterhouse water, oil contaminated water, pharmaceutical and pesticide water are some of the various types of Wastewater (www.cep.unep.org). There are various treatment processes used to treat Wastewater depending on the type and severity of the contamination. Wastewater can be treated by various chemical treatment methods, physical treatment methods, and biological treatment methods. The proposed method treats agro food wastewater.

Anaerobic processes are often preferred to aerobic processes for treating waste streams that contain - COD concentrations. Various reactors used in anaerobic wastewater treatment processes are anaerobic contact reactor, anaerobic filter reactor, Up-flow Anaerobic Filter (UAF), fluidized-bed reactor. The Anaerobic Filter can be operated in either up-flow or down-flow mode. The up-flow mode is suggested because there is less risk in handling the fixed biomass. It will be washed out easily.

Anaerobic treatment of wastewater is extremely suited for industries releasing exceedingly concentrated (more than 1,500 mg COD/l) wastewaters, with nitrogen concentrations that are not excessively high (Dixon. M *et al*., 2005).

Most wastewaters of this category comes under the soft drink factories, beer breweries, food and food processing industry, and paper producing or processing factories and certain chemical industries. For this purpose, cheese-dairy wastewater is taken for the treatment. In this work, the performance of the UAF with cheese-dairy wastewater was considered for modeling the ANN to predict the effluent COD level in accordance with the UAF. A schematic diagram of the laboratory scale UAF used in this work is shown in Figure-1.

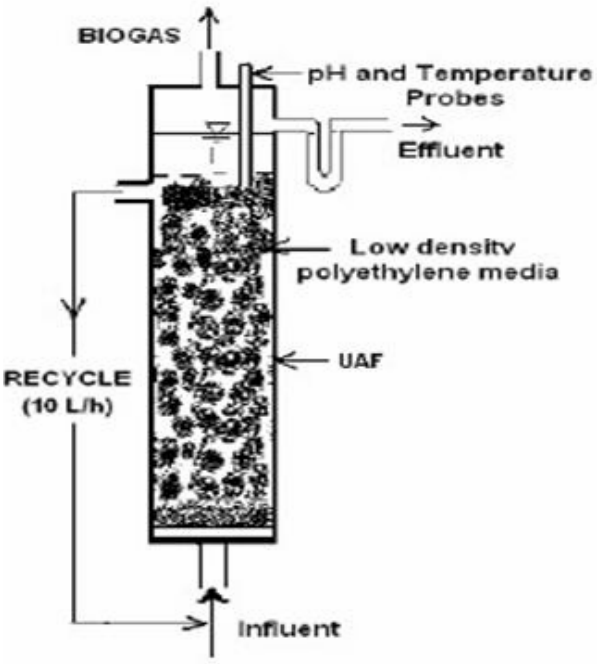

Figure-1. Schematic diagram of a laboratory scale UAF.

In this work, the prediction of COD level using ANN is structured as follows: Data collection and preprocessing followed by normalization using Z-Score, which is preceded by Feature selection algorithm such as Particle Swarm Optimization (PSO) with an effort to conclude the prediction of COD using ANFIS RungeKutta Learning Method by the model when applied to the description of Up-flow Anaerobic Filter (UAF) treating agro-food industrial wastewaters such as cheese-dairy.

The paper is organized as follows: Section II describes related works, Section III describes methodology used in the proposed work, Section IV deals with the experimental results and Section V describes conclusion of the proposed work.

RELATED WORK

Hamed *et al*., 2004 predicted that the ANN-based models provide an efficient and a robust tool to increase WWTP performance. The need to meet stringent effluent standards for COD, Nitrogen and Phosphorous in wastewater treatments has been determined in recent years for nutrients removal. The Biological Nutrients Removal (BNR) processes either for nitrogen or both nitrogen and phosphorous removal can be performed only when the necessary amount of carbon in the treated wastewater is available. As a result the primary settling tanks in these Waste Water Treatment Plants (WWTPs) are generally absent to preserve the particulate fraction of the influent COD (Nielsen. B *et al*., 2000) (Bolzonella. D *et al*., 2002).

Rajinikanth *et al*., 2009 carried out research to determine the suitability and stability of an UAF with small buoying polyethylene supports for the treatment of wastewater discharged from various small-scale agro-food industries to evaluate the maximum treatment capacity according to the various substrates, hydrodynamics inside the reactor and the specific biomass activity. Jayalakshmi *et al*., 2011 proposed various normalization methods used in Back Propagation Neural networks (BPN) to enhance the reliability of the trained network.

Anil Jain *et al*., 2005 studied the performance of different normalization techniques such as min-max, Z-Score, and tanh normalization schemes and fusion rules in the context of a multimodal biometric system. Z-Score normalization is optimal if the scores of all the modalities follow a Gaussian distribution. Therefore, rules must be developed to allow a practitioner to choose a normalization scheme after analyzing the genuine and impostor score distributions of the individual matchers.

Seydi Ghomsheh *et al*., 2007 applied PSO with some modification in it to train the parameters of ANFIS structure. These changes are stimulated by natural evolutions. The proposed method uses ANFIS RKLM with PSO as a feature selection process to get better results of COD level prediction.

METHODOLOGY

Process of anaerobic wastewater treatment system

The steps involved in the prediction of COD level present in wastewater treatment are shown in Figure-2.

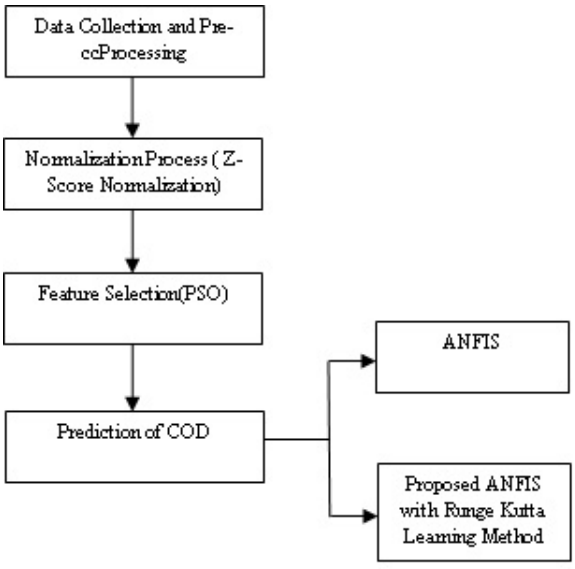

Figure-2. Steps involved in prediction of COD.

Data collection and pre-processing

Daily records from the operation of an UAF treating cheese whey agro-food wastewater during a period of 6 months were obtained.

The data must be processed to establish the validity and quality of data consisting of variable measurements. This is because of the endless sources of disturbances. The sources of disturbances include electromagnetic interference, defective installation, insufficient maintenance or erroneous use and handle

measuring system. Hence, before any study of the measurements, it is necessary to preprocess the data.

The preprocessing is performed using K-NN algorithm which detects and replaces the missing values and outliers.

Normalization

The normalization process for the raw dataset has significant effect on preparing the data to be suitable for the training. Without normalization process, training the real dataset would have been very slow. Normalization can be used to scale the data in the same range of values for each input feature in order to minimize bias within the dataset for one feature to another. It also speeds up training time by starting the training process for each feature within the same scale. Normalization technique is used to improve the prediction accuracy of ANFIS model to calculate the COD level. The proposed method uses Z-Score normalization for improving prediction accuracy.

Z-Score normalization

The Z-Score is the most frequently used score normalization technique which is computed using the arithmetic mean and standard deviation of the particular data. This technique can be estimated to execute well if previous knowledge regarding the average score and the score variations of the matcher is available. If there is no previous information regarding the nature of the matching algorithm, then it is necessary to calculate the mean and standard deviation of the scores approximately. The normalized scores are given by

$$s_k' = \frac{s_k - \mu}{\sigma} \quad (1)$$

Where μ represents the arithmetic mean and σ represents the standard deviation of the given data. Each feature will have the mean value 0 after Z-Score normalization. The unit of each value willbe the number of standard deviations which will be far away from the mean. Z-Score normalization will give exact values to the small values ofσ.

Feature selection algorithm for prediction of COD

Feature selection allows feature space reduction, which helps to reduce the training time and to improve the prediction accuracy. It can be attained by removing redundant, irrelevant, and noisy features (i.e., selecting the subset of features that can achieve the best performance in terms of accuracy and computational time). Feature selection method based on the number of features examined for sample classification is needed in order to speed up the processing rate, to avoid incomprehensibility and to increase the predictive accuracy. In this work, PSO is used to implement a feature selection.

PSO is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 [11] [12]. Initial simulations were changed to develop the original version of PSO. In order to produce the standard PSO, Shi introduced inertia weight into the particle swarm optimizer (Eberhart R.C *et al*., 2001). A population of random solutions is initialized to PSO called 'particles'. Each particle can be treated as a point in an S-dimensional space. The i^{th} particle is represented as $X_i = (x_{i1}, xi2, ….., x_{is})$. The best previous position (pbest, the position giving the best fitness value) of any particle is recorded and represented as $P_i = (p_{i1}, p_{i2}, ….., p_{is})$. The index of the best particle among all the particles in the population is represented by the symbol 'gbest'. The rate of the position change (velocity) for particle i is represented as $V_i = (v_{i1}, v_{i2},….., v_{is})$. According to the following equation the particles are manipulated:

$$v_{id} = w * v_{id} + c_1 * \text{rand}() * (p_{id} - x_{id}) + c_2 * \text{rand}() * (p_{gd} - x_{id}) \quad (2)$$

$$x_{id} = x_{id} + v_{id} \quad (3)$$

where d = 1, 2,..., S, w is the inertia weight which is a positive linear function of time changing according to the generation iteration. Appropriate selection of the inertia weight provides a balance between global and local exploration. This results in less iteration on average to measure the most favorable solution. The acceleration constants c1 and c2 in equation (2) indicates the weighting of the stochastic acceleration terms which pull each particle towards the pbest and gbest regions. High values result in abrupt movement towards target regions while low values allow particles to roam away from the target regions before being pulled back. Rand () and Rand () are two random functions in the range [0, 1].

Particles' velocities on each dimension are limited to a maximum velocity, Vmax (Xiangyang Wang *et al*.,) how large steps through the solution space in each particle are allowed to take. If Vmax is too high, particles might be rushed towards good solutions. On the other hand, If Vmax is too small, particles may not explore beyond locally good regions adequately. It could be trapped in local optima. The first part of equation (2) provides the "flying particles" with a degree of memory capability allowing the exploration of new search space areas. "Cognition" part is the second part, which represents the private thinking of the particle itself. Final part is the "social" part, which indicates the collaboration among the particles. Equation (2) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. According to equation (3), the particle flies toward a new position. The performance of each particle is measured according to a pre-defined fitness function.

PSO algorithm

Inputs

m = the swarm size; c_1, c_2 = positive acceleration constants
w = inertia weight
MaxV = maximum velocity of particles
MaxGen = maximum generation
MaxFit = maximum fitness value

Output
Pgbest = Global best position

Algorithm
Begin
Swarms $\{x_{id}, v_{id}\}$ = Generate (m); /* Initialize a population of particles with random positions and velocities on S dimensions*/
Pbest (i) = 0; i = 1, ..., m, d = 1,...,S
Gbest = 0; Iter = 0;
While (Iter<MaxGen and Gbest<MaxFit)
{For (every particle i)
{Fitness (i) = Evaluate (i);
IF (Fitness (i)>Pbest (i))
{Pbest (i) = Fitness (i); $p_{id} = x_{id}$; d = 1, ..., S }
IF (Fitness (i)>Gbest)
{Gbest = Fitness (i); gbest = i ;}}
For (every particle i)
{For (every d)
{$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * rand() * (p_{gd} - x_{id})$
IF (v_{id}>$MaxV$) {v_{id} =$MaxV$;}
IF (v_{id}<- $MaxV$) {v_{id} = - $MaxV$;}
$x_{id} = x_{id} + v_{id}$}}
Iter = Iter+1 ;} /*rand () and Rand () are two random functions in the range [0, 1]*/
Return P_ {gbest}

End

PSO is easy to implement and there are few parameters to adjust. Noise in the dataset is reduced by using PSO as a feature selection to improve prediction accuracy of COD effluent in wastewater.

ANFIS for prediction of COD

COD test is a common water quality test used to measure the total amount of organic compounds in a water sample indirectly using a strong oxidizing agent such as Potassium Dichromate. A high COD value indicates a high concentration of organic matter in the water sample. It can be predicted with high accuracy using proposed ANFIS RKLM.

ANFIS

ANFIS is a method based on the input-output data of the system under consideration. Success in obtaining a reliable and robust ANFIS network depends heavily on the choice of process variables involved as well as the available data set and the domain used for training purposes (Buragohain M *et al*., 2008). Basically, a fuzzy inference system is composed of five function blocks (Jang J.S.R, 1993):

a) Rule base containing a number of fuzzy if-then rules.
b) A database which defines the membership function of the fuzzy sets is used in the fuzzy rules.
c) The decision-making unit which perform the inference operation on the rules.
d) Fuzzification inference transforms the crisp inputs into degree of match with linguistic values.
e) Defuzzification inference which transforms the fuzzy results of the inference into a crisp output.

For simplicity, a fuzzy inference system with two inputs x and y, and one output is assumed., a common rule set with two fuzzy if - then rules is defined for the first-order Sugeno fuzzy model is as follows:

Rules-1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rules-2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

Here type-3 fuzzy inference system proposed by Takagi and Sugeno (Jang J.S.R, 1993) is used. In this inference system the output of each rule is a linear combination of input variables added by a constant term. Average weight of each rule's output is the final output.

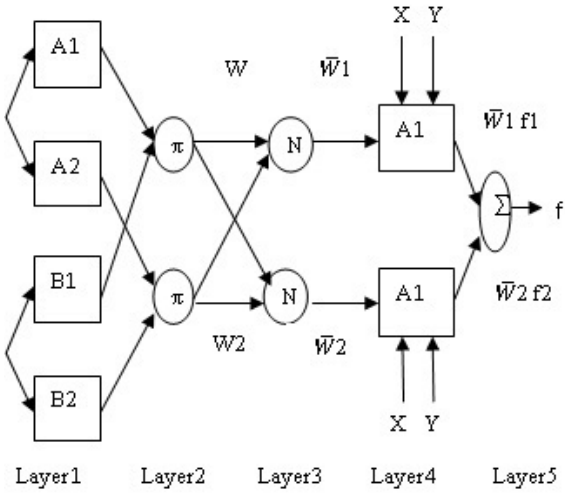

Figure-3. A typical ANFIS architecture.

Figure-3 shows a typical ANFIS architecture. Each node in Layer 1 is an adaptive node with a node function which may be a Gaussian membership function or any membership functions. Each node in Layer 2 is a fixed node labeled Π which indicates the firing strength of each rule. All nodes in Layer 3 are a fixed node which is labeled as N represents the normalized firing strength of each rule. In Layer 4 every node is an adaptive node with a node function. In Layer 5, single node is a fixed node labeled Σ, represents the overall output (Z). It is defined as the summation of all incoming signals (Dastorani M.T *et al*., 2009).

ANFIS with Runge - Kutta Learning Algorithm

The subsequent to the development of ANFIS approach, a number of methods have been proposed for learning rules and for obtaining an optimal set of rules. In this work, an application of RKLM is essential for classifying the behavior of datasets, for learning in ANFIS network. RKLM is a powerful way of solving the behavior

of a dynamic system if the system is characterized by ordinary differential equations. In (Wang *et al*., 1998), the proposed method is applied to several problems. This method is examined for the successful estimation of the system states while long run. It should be emphasized that the neural network architecture realizes the changing rates of the system states instead of the $[\underline{x}(k), \underline{r}(k)] \leftrightarrow [\underline{x}(k+1)]$ mapping. Thus the RKNN approach can be used to alleviate the difficulties caused due to the discretization methods. The first order discretization brings large approximation errors. Here *h* denotes the Runge-Kutta integration step size.

The most often used method of RKLM is fourth order Runge-Kutta approximation. The update mechanism depends upon the error back propagation. The update mechanism depends upon the error back propagation. FNN based identification scheme can be determined by using the following equations.

$$\dot{\underline{x}} = \underline{f}(\underline{x}, \underline{r}) \quad (4)$$

$$\underline{x}(i+1) = \underline{x}(i) + \frac{h}{6}(\underline{k}_0 + 2\underline{k}_1 + 2\underline{k}_2 + \underline{k}_3) \quad (5)$$

$$\underline{k}_0 = N(\underline{x};\ \varphi) \quad = \quad N(\underline{x}_0;\ \varphi) \quad (6)$$

$$\underline{k}_1 = N\left(\underline{x} + \frac{1}{2}h\underline{k}_0 ;\ \varphi\right) \quad = \quad N(\underline{x}_1; \varphi) \quad (7)$$

$$\underline{k}_2 = N\left(\underline{x} + \frac{1}{2}h\underline{k}_1 ; \varphi\right) \quad = \quad N(\underline{x}_2;\ \varphi) \quad (8)$$

$$\underline{k}_3 = N(\underline{x} + h\underline{k}_2;\ \varphi) \quad = \quad N(\underline{x}_3;\ \varphi) \quad (9)$$

where, f is a generic parameter of neural network. Two paths should be considered in this propagation. They are the direct connection to the output summation and the next is through the FNN stages of the architecture. Therefore, each derivation involves two terms except the first one. The fourth order Runge-Kutta approximation rule is summarized below:

$$\frac{\underline{k}_0}{\varphi} = \frac{N(\underline{x}_0;\ \varphi)}{\varphi} \quad (10)$$

$$\frac{\underline{k}_1}{\varphi} = \frac{\underline{k}_1}{\underline{x}_1}\frac{\underline{x}_1}{\underline{k}_0}\frac{\underline{k}_0}{\varphi} + \frac{\underline{k}_1}{\varphi} \quad (11)$$

$$\frac{\underline{k}_2}{\varphi} = \frac{\underline{k}_2}{\underline{x}_2}\frac{\underline{x}_2}{\underline{k}_1}\frac{\underline{k}_1}{\varphi} + \frac{\underline{k}_2}{\varphi} \quad (12)$$

$$\frac{\underline{k}_3}{\varphi} = \frac{\underline{k}_3}{\underline{x}_3}\frac{\underline{x}_3}{\underline{k}_2}\frac{\underline{k}_2}{\varphi} + \frac{\underline{k}_3}{\varphi} \quad (13)$$

$$\Delta(i) = \frac{h}{6}\left(\underline{d}^T(i) - \underline{x}^T(i)\right)\left(\frac{\underline{k}_0}{\varphi} + 2\frac{\underline{k}_1}{\varphi} + 2\frac{\underline{k}_2}{\varphi} + \frac{\underline{k}_3}{\varphi}\right) \quad (14)$$

In (14), *h* represents the learning rate and $\underline{d}^T(i)$ represents the measured state vector of the plant at time index i. This work integrates the RKLM in ANFIS for better prediction accuracy, training time and estimation performance.

EXPERIMENTAL RESULTS

Daily records from the operation of an Up-flow anaerobic filter treating cheese whey agro-food wastewater during a period of 6 months were obtained. Most real-world databases contain missing, unknown, or erroneous data. The missing values and outliers can be eliminated using K-Nearest Neighbor algorithm (K-NN). In the anaerobic data, the total samples based on the effluent Chemical Oxygen Demand (COD) when using COD, Volatile Suspended Solid, Total Suspended Solid as inputs in the crude supply stream from the dataset is found to be treated up to 80%.

The influent COD levels, the controlling parameters of up-flow anaerobic reactor were considered as the input parameters. The model was trained to recognize these input parameters in order to predict the corresponding effluent level of COD as output parameters. The model was trained with the data in the training subset with influent COD levels, flow rate and Organic Loading Rate (OLR) to optimize the network weights so as to minimize the appropriate error function. After preprocessing, n number of features were selected based on PSO algorithm and it is given as input.

In order to evaluate the performance of the proposed model, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) are used in this paper. The following equations define the parameters.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|w_0 - w_p| \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(w_0 - w_p)^2} \quad (16)$$

where w_0 is the actual values of W_{t+1} with {i = 1, 2, …n} observations, n is the total observation number and w_p is the predicted W_{t+1} value.

The regression coefficient (R^2) values for both the models are also determined and compared. The comparison is shown in Table-1. The table values show that ANFIS with RKLM provided better results in performance.

Table-1. Comparison of ANFIS and ANFIS RKLM

Methodology	MAE	RMSE	R^2
ANFIS	0.32	56.75	0.65
ANFIS with RKLM	0.15	48.32	0.78

Figure-4 shows that the proposed method has lower mean square error when compared to ANFIS method. Thus the ANFIS with Runge-Kutta Learning Method gives better performance in reducing the error rate.

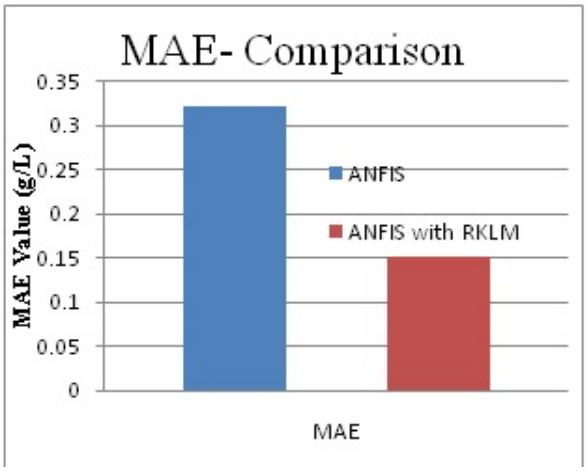

Figure-4. Comparison of MAE values for ANFIS and ANFIS with RKLM.

Figure-5 illustrates that the proposed method has lower root mean square error when compared to ANFIS method. Thus the ANFIS with Runge-Kutta Learning Method gives better performance in reducing the Root Mean Square Error. It achieves relatively higher performance than the ANFIS method.

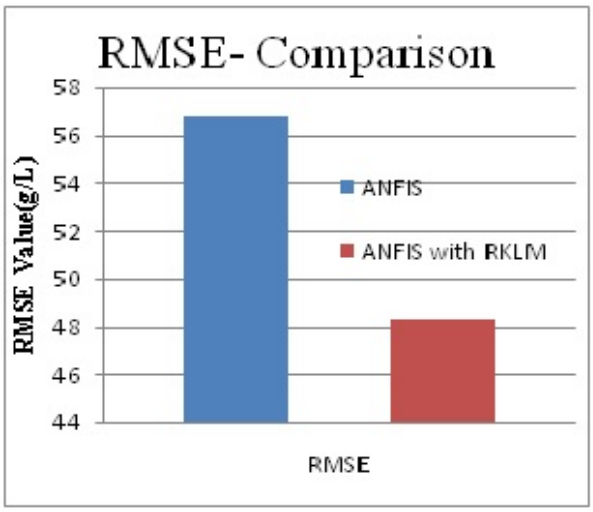

Figure-5. Comparison of RMSE values for ANFIS and ANFIS with RKLM.

Figure-6 represents that the regression coefficient (R^2) is higher in ANFIS with RKLM. Hence the proposed achieves higher Regression coefficient than ANFIS method.

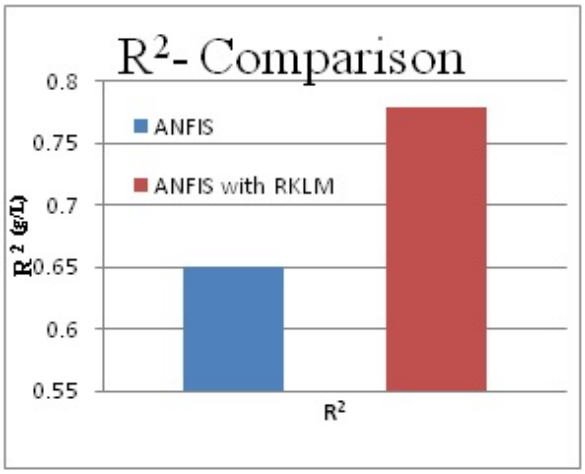

Figure-6. Comparison of R^2 values for ANFIS and ANFIS with RKLM.

Thus ANFIS with RKLM has less MAE and RMSE values, and gives more regression coefficient values in predicting COD level in wastewater. The proposed method achieves better performance in prediction of Effluent COD present in wastewater.

CONCLUSIONS

Modeling a WWTP is difficult to accomplish due to the high non-linearity of the plant and the non-uniformity and variability of the crude supply as well as the nature of the biological treatment. In this paper, raw data from the anaerobic wastewater treatment system, during a period of 6 months has been analyzed to recognize and eliminate the missing values and outliers using the K-Nearest Neighbor algorithm (KNN). The ANN model was trained and tested by Z-Score as normalization process, Particle Swarm optimization (PSO) for feature selection to improve prediction accuracy and finally ANFIS with RKLM to predict the target COD Levels using MATLAB. The ANFIS with RKLM training algorithm provided good estimates of COD levels covering a range of data for training and testing purposes on comparing the results with the ANFIS training algorithms.

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