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Evaluation of moving bed biofilm reactor (MBBR) by applying adaptive neuro-fuzzy inference systeme (ANFIS), radial basis function (RBF) and Fuzzy Regression Analysis

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Abstract

The purpose of this study is to investigate the accuracy of predictions of aniline removal efficiency in a moving bed biofilm reactor (MBBR) by various methods, namely by RBF, ANFIS, and fuzzy regression analysis. The reactor was operated in an aerobic batch and was filled by light expanded clay aggregate (LECA) as a carrier for the treatment of Aniline synthetic wastewater. Exploratory data analysis was used to detect relationships between the independent and the dependent evaluated data. The models were found to be efficient and robust tools in predicting MBBR performance. Results showed that increasing the neurons in the hidden layer would improve the function of RBF network. The ANFIS model made according to the membership functions of generalized bell, triangular, and Gaussian with R^2 equals to 0.99 and RMS error of 0.027 for the anticipation of the concentration of Aniline and R^2 equals to 0.99 and RMS error of 0.034 for the prediction of removal COD efficiency.

Key words: Aniline, ANFIS, Fuzzy Regression Analysis, Moving Bed Biofilm Reactor, ANN

Highlights

- Application of ANN-based models (RBF network), ANFIS models and Fuzzy regression as a robust tool in predicting MBBR efficiency
- Determination of process efficiency in various operation conditions for the treatment of aniline synthetic wastewater
- ANFIS had more ability than fuzzy regression analysis in simulating and predicting removal efficiency in different experimental conditions.

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Introduction

Aniline is a toxic, organic compound that readily dissolves in water up to 3.5 percent. Due to its high solubility in water, the risk of possible pollution in water resources, especially in cases of chemical spills, is increased. Therefore, any wastewater containing this prototypical aromatic amine (such as dyes, plastic, paint, pigments, herbicides, pharmaceutical preparation and rubber accelerators production) (1-4) is a serious problem and should be treated before being discharged into the environment (5).

Wastewater containing aromatic amines has been shown to be successfully treated by photocatalytic process, electrolysis, adsorption, electro-Fenton, advanced oxidation and biological treatment. This compound is hard biodegradable, making further studies on advanced biological processes necessary (6).

The MBBR was created in Norway at the Norwegian University of Science and Technology in cooperation with a Norwegian company, Kaldnes Miljǿteknologi (now AnoxKaldnes AS) (7, 8). Polyethylene carrier elements in the MBBR process provide sites for biomass attachment in a suspended growth medium. These elements increase the bacteria concentration to be maintained in the reactor, as opposed to the activated sludge process in which biomass volume is suspended in the reactor. The carrier elements can be placed in either an anoxic reactor or an aeration basin. Less space is required in the MBBR process compared to traditional wastewater treatment systems because of biomass attachments on carriers. MBBR was developed to adopt the best features of activated sludge and bio filter processes in one reactor (8). During the past decade it has been successfully used for the treatment of many industrial effluents, and as well municipal wastewater (7). Ayati et al applied two cylindrical MBBRs in upflow stream conditions for the degradation of aromatic compounds at low concentration of synthetic wastewsater (from 700 to 1000 mg/L) maximum removal efficiency (over 80 %) was obtained (9).

In biological wastewater treatment systems such as MBBR, influent characteristic variability might have an influence on operational control. As a result, the modeling of biological process has been a difficult task as most of the available models are just approximations based on probabilities and assumptions. Recently, simulation methods such as ANNs, ANFIS, and Fuzzy Regression Analysis have been increasingly applied in environmental and water resource engineering areas.

The main advantage of these methods over physically based models is that they do not require the complex nature of the underlying process under consideration to be explicitly described in a mathematical form (10). Consequently, unlike traditional parametric models, in an artificial intelligence model it is not required to assume a predefined form for the relationship between input and output variables. Compared to the conventional method, it is possible in this model to construct a complex relationship between input and output variables with a high level of accuracy (11). Biological process prediction without the limitations of conventional mathematical models is an important advantage of ANNs for MBBR operation control.

Delnavaz et al (12) proposed a feed-forward back-propagation neural network to predict the performance of MBBR. The results showed that the optimum ANN model has obtained the correlation for the training and testing sets 0.99 and 0.96 and the RMS errors were 0.02 and 0.042, respectively.

Cristea et al. (13) have studied the capacity of neural networks for the assessment of plant behavior in integrated urban wastewater system simulations. They have proposed that ANN based simulators reveal high accuracy for predicting important process variables and a reduction of the simulation time, compared to the first principle wastewater treatment plant (WWTP) simulator.

Sadrzadeh et al (14) have used neural networks to predict the separation of lead ions from wastewater using electro-dialysis. They have examined a number of different network structures and architectures to compute the amount of lead ions separation. Exceptional alignment between the predicted values and experimental data has been revealed by ANN modeling.

ANN modeling for treatment of zinc-containing wastewater in a sulfidogenic CSTR by a biological process was studied by Sahinkaya (15). Effluent concentrations of sulfate, COD, acetate and zinc were estimated successfully by the developed model.

The simulation of copper (II) bio-sorption efficiency by ANN was done by Prakash et.al (16). The performance of the network for estimating the sorption efficiency was found to be very effective.

While other researchers applied ANN for the prediction of various methods of wastewater treatment, the MBBR modeling was done solely by mathematical models. Modeling techniques could be an excellent way of reducing the frequency at which testing is needed and may have other advantages. Therefore, the novelty of this paper is that it presents predictive models based on the concept of ANN, ANFIS and Fuzzy Regression Analysis in predicting aniline treatment efficiency using MBBR in various conditions.

Material and Method

Reactor setup: All experiments were done in environmental engineering laboratory of civil and environmental engineering faculty of Tarbiat Modares University. The cylindrical MBBR reactor was used in this study (Fig. 1), with each reactor having an internal diameter, height, and wall thickness of 10, 70 and 0.4 centimeters respectively (6). The basis of the process relies on elements of biofilm carrier that are made from different materials such as polyethylene, PVC, and porous aggregates. DO and pH were fixed in the range of aerated biological processes, and indispensable nutrients (COD/N/P = 100/5/1) were added to the reactor. The effective depth of wastewater in the reactor was 60 cm, filled with up to 50% floating biofilm carrier elements made of LECA (Light Expanded Clay Aggregate) with a density of 0.55 gr/cm^3. LECA is an industrial lightweight aggregate that has been used in many building projects. The high surface area of this material makes it more suitable as a carrier in the biofilm reactor. In order to keep the biofilm carrier in the reactor, a sieve (mesh size=5mm) was placed at the inlet. The aeration system was supplied by an aeration pump to produce fine bubbles and provide adequate mixing to keep the carriers moving in the reactor.

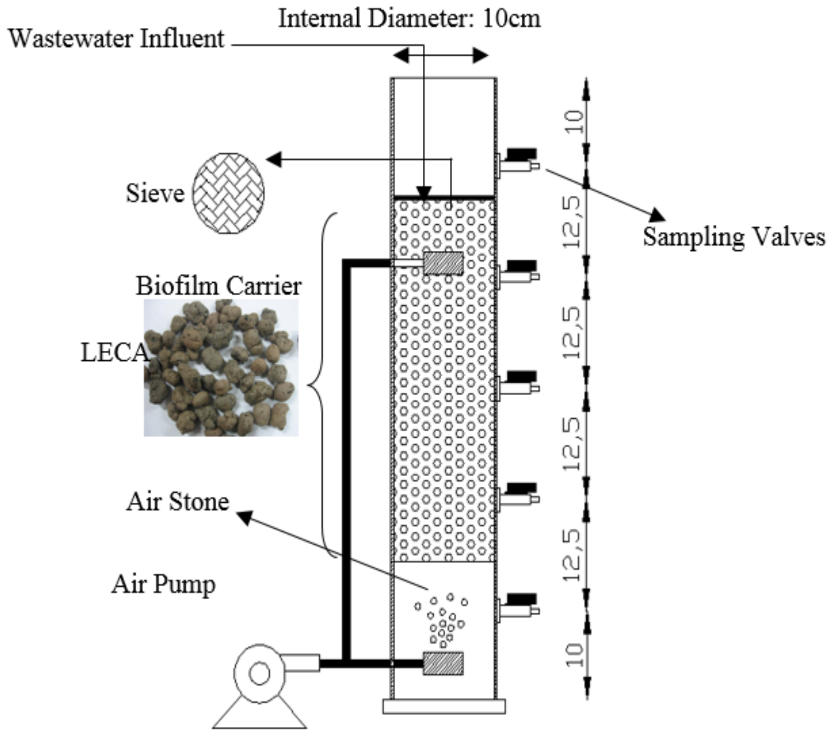

Fig.1- Schematic picture of MBBR Pilot (6)

Synthetic feed wastewater was prepared using aniline, which was supplied by Merck Company. Aniline served as the sole carbon and energy substrate for the biomass in the MBBR. In order to have COD/N/P = 100/5/1 and adequate alkalinity for aerobic conditions (6.5-8), necessary nutrients (urea, KH_2PO_4, K_2HPO_4) were added as a supplemental feed to the reactors for all experimental trials.

The parameters of pH, soluble Chemical Oxygen Demand (COD) filtered through Vattman paper No.42, and Dissolved Oxygen (DO) were measured daily.) DO concentration was always controlled above 3 mg/L during the filling and reacting cycles by adjusting the aeration rate. Coarse bubble air produced by the air pump caused suspension of carriers in the reactor. Mixed Liquor Suspended Solids (MLSS) and Mixed Liquor Volatile Suspended Solids (MLVSS) were examined on acclimation stage. All laboratory experiments were done at room temperature (25–28°C). All analytical tests were done according to the Standard Method Handbook (17). The aniline concentrations were measured by an ultraviolet absorption procedure, as given in the Standard Methods, using a Lambda EZ 150 UV/Vis Spectrophotometer.

During the start up, the reactors (30 days) with the sludge seed were acquired from Ekbatan Wastewater Treatment Plant, located in the west of the capital city of Tehran, and microbial adaptation were conducted with a solution of synthetic wastewater and glucose. At this stage, the removal efficiency reached 80% for $COD_{aniline}/COD_{glucose}= 0.5$. Subsequently, the amount of Organic Loading Rate (OLR) was increased stepwise within 90 days. The reactor’s operation during the adaptation and loading stage is shown in Fig. 2.

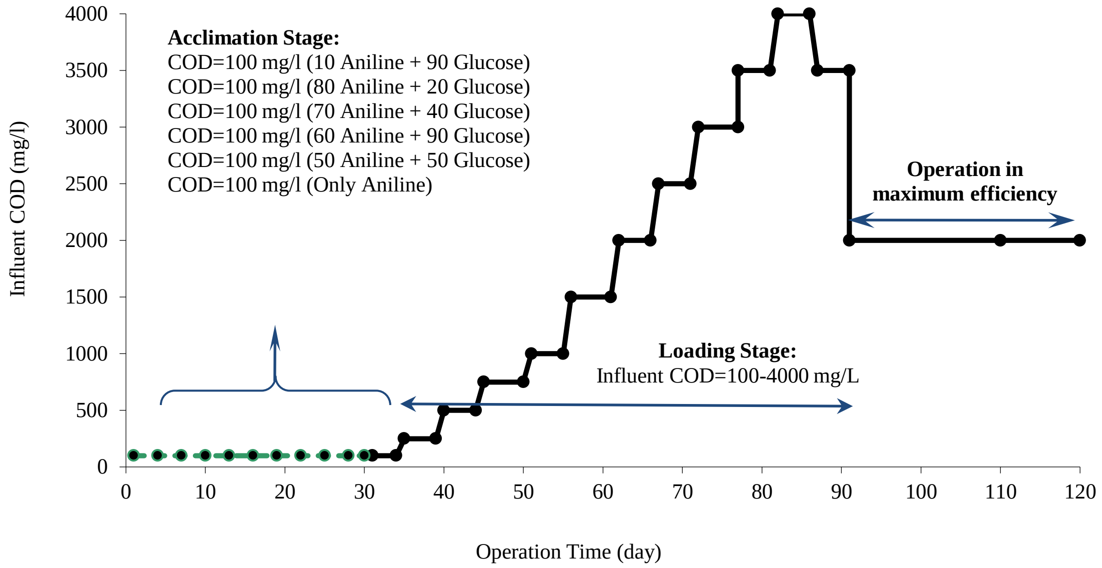

Fig. 2- Duration of reactor operation in acclimation and loading stage

ANN approach: Due to the complexity and non-linearity of environmental phenomena, including water and wastewater treatment processes, ANN acts like a human brain and can be used as a suitable method (18). Equations 1 and 2 show the general trend of the function of ANNs (19).

$$y_i^m = f(v_i^m) \quad (1)$$

$$v_i^m = \sum_{j=1}^{L} w_{ji}^{m\ \ 1} y_j^{m\ \ 1} + b_i^m \quad (2)$$

Where y_i^m represents the inputs of the model, v_i^m represents the *number m* output layer, f represents the transfer function, L represents the number of interfaces with the previous layer, $w_{ji}^{m\ \ 1}$ is equivalent to the weight of each interface and b_i^m represents the Bias, the constant part of the transfer function.

The neural network-based modeling process contains five main aspects: (1) data acquisition, analysis, and problem representation; (2) architecture determination; (3) learning process determination; (4) training of the networks; and (5) testing of the trained network to evaluate the model.

The RBF neural network compared to a multilayer perceptron (MLP) network needs a shorter design time, but on the other hand requires more neurons. This network has the best performance when there are many training vectors (20). RBF networks are defined by the function "*newrb*". This function has the ability to create a trained network with zero errors. The procedure for these networks is to increase the number of Neurons in the hidden layer through the training process to get the performance function to target levels or to achieve the maximum specified number of neurons. Performance functions used in this study were error parameters MSE. One of the remarkable things about RBF networks is that they do not need any assumptions about the model's shape in the modeling process. These networks are generally model-based (21). Fig. 3 displays the view of different RBF network layers. In this research RBF networks were developed by coding in MATLAB.

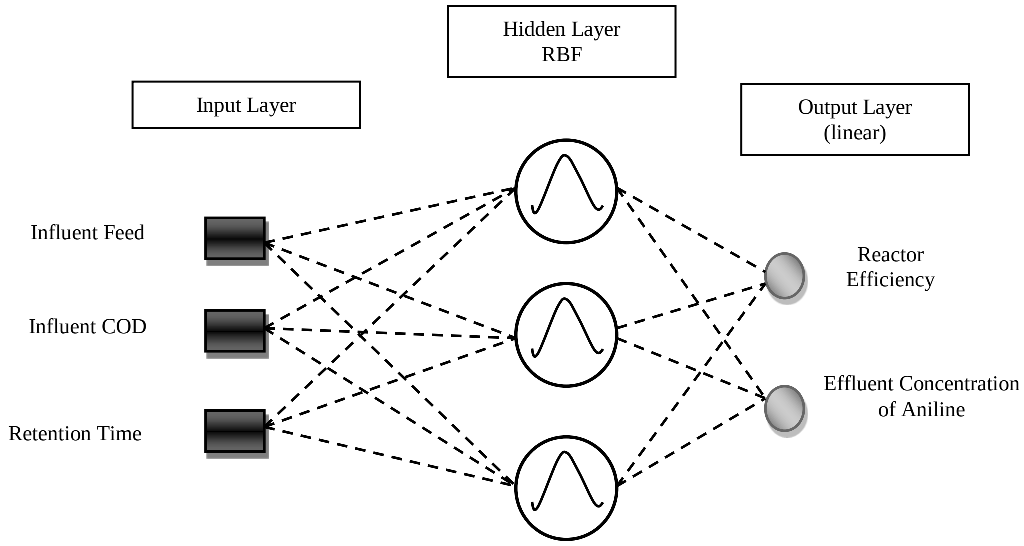

Fig.3- Architecture of RBF model (22)

Fuzzy regression analysis: Regression analysis is a statistical tool used to develop the model, which uses a set of measured data, including the uncertainty of a population, to provide an equation to predict the whole population. Accordingly, one of the variables could be predicted from the other. The overall objective of regression analysis is to find an appropriate and efficient mathematical equation to determine coefficients of the model with the best fitness of the observed data.

The fuzzy theory set was provided in 1965 by Zadeh (22). According to that rheory, if the data is not conclusive in a system examined by regression analysis becuase the random variables are affected by human error or available as dialogic form, fuzzy regression analysis can be a more appropriate tool for simple regression analysis. The basic concept of this method was proposed by Tanaka et al. in 1982 (23).

The fuzzy regression model can be classified into two types based on the functional relationship between dependent and independent variables. If the functional relationship is known, the model is called a parametric fuzzy regression model; otherwise, it is called a nonparametric fuzzy regression model. Many methods have been developed to construct parametric and nonparametric fuzzy regression models (24). These methods are classified into numerical and statistical methods. Numerical methods identify the fuzzy regression model by minimizing the sum of the spreads of the estimated dependent variable. Choi and Buckley (25) and Taheri and Kelkinnama (26) suggested the least absolute deviation method, which is an alternative to the method of least squares. Generally, the fuzzy regression analysis has been criticized, because it is sensitive to outliers; also the spreads of the estimated value become wider as more data is included in the model (26, 27).

In this study, using the software FuReA, fuzzy regression was performed. The software allows users to simulate the dependent parameters using independent parameters of the linear and non-linear functions. Equations 3 and 4 shows the sample functions used in this method considering two independent variables. Equations 3 and 4 indicate linear and quadratic functions respectively (28, 29).

$$Y = a_0 + a_1 X_1 + a_2 X_2 \quad (3)$$

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_3 {X_1}^2 + a_4 X_1 X_2 + a_5 {X_2}^2 \quad (4)$$

Where X_n is independent variable and a_n is constant factor.

ANFIS Model: Fuzzy systems are rule-based expert systems based on fuzzy rules and fuzzy inference. A fuzzy inference system (FIS) can be viewed as a real-time expert system used to model and utilize a human operator's experience or process engineer's knowledge (30). Fuzzy logic can model nonlinear functions of arbitrary complexity. It provides an alternative solution to nonlinear modeling because it is closer to the real world. Nonlinearity and complexity are handled by rules, membership functions, and the inference process, which in turn results in improved performance, simpler implementation, and reduced design costs (31). Neuro-fuzzy consists of fuzzy nodes instead of simple input and output nodes. It uses neural network learning functions to refine each part of the fuzzy knowledge separately. Learning in a distinguished network is faster than learning in the whole network (32).

One approach for the derivation of a fuzzy rule base is to use self-learning features of ANNs, aimed at defining the membership function based on input–output data. The ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a composite learning procedure, ANFIS can construct an input–output data pair for neural network training. ANFIS is more effective than the simple fuzzy logic algorithm and neural networks, since it provides a procedure for fuzzy modeling to get relationshibps between the data, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data (30).

In this research, data sets were divided into training and testing data sets. Four membership functions used in this study were Gaussian (Guassmf), triangular (Trimf), trapezoidal (Trapmf) and generalized bell (Gbellmf) functions and the training's epochs are 300 times. All ANFIS models were done by MATLAB toolbox. Table 1 shows the characters of all models composed in this study.

Table. 1- The characters of ANFIS models

Models	Membership Function			Learning Algorithm
	Influent Feed	Influent COD	Retention Time	
ANFIS1	Trimf	Trimf	Trimf	BP*
ANFIS2	Trapmf	Trapmf	Trapmf	BP
ANFIS3	Guassmf	Guassmf	Guassmf	BP
ANFIS4	Gbellmf	Gbellmf	Gbellmf	BP
ANFIS5	Trimf	Guassmf	Trapmf	BP
ANFIS6	Guassmf	Trapmf	Gbellmf	BP
ANFIS7	Guassmf	Trimf	Gbellmf	BP
ANFIS8	Gbellmf	Trimf	Guassmf	BP

**BP: Backpropagation*

Selection of Database: In this study, the database was collected throughout a six-month continuous period. The reactor was fed with aniline synthetic wastewater. Evaluation efficiency was done at different retention times of 8, 24, 48 and 72 hours and different influent COD from 100 to 4000 mg/L. A total of 300 data pairs have been selected from the experimental database, as mentioned earlier. About 70 percent of data were used for training and about 20 percent for testing and 10 percent for validation of the ANFIS and RBF neural network.

Model training: The training procedure involved presenting the network with the set of experimental data in a patterned format. Each training pattern included the input set of three parameters representing influent feed, influent COD, and retention time and the corresponding output set representing reactor efficiency and aniline effluent concentration. The errors between the target value and predicted output were calculated and stored. The network was then presented with the second training pattern and so on until the network had gone through all the data available for training the network.

Model validation: The testing subset data was used to measure the network distribution (i.e. how accurately the network predicts targets for inputs that were not in the training set). This is sometimes referred to as holdout validation. The correlation and RMS error values were used as the performance criteria and monitored during training.

Results

Experimental results: The effect of different retention times (8, 24, 48 and 72 hours) on the COD removal rate was studied after every step increase in COD. As shown in Fig. 4, at low influent COD (from 500 to 2000 mg/L) the maximum efficiencies was 90% in COD=2000 mg/L after 3 days. A decrease in the removal efficiencies was observed for influent COD from 2000 to 4000 mg/L. It is important to mention that all experiments were done at room temperature and under steady-state conditions.

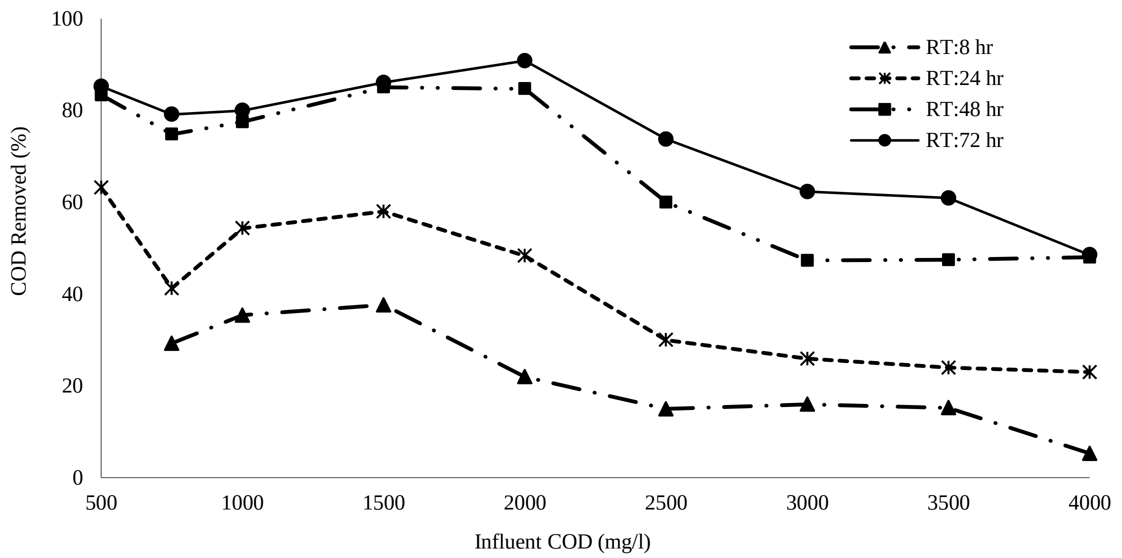

Fig.4- Variation of influent COD in different retention time

Evaluation of MBBR performance by RBF model: The network was trained to predict MBBR performance for treatment of aniline synthetic wastewater using a total of 300 pair data sets. The number of neurons in a hidden layer of RBF network was increased from zero to the possible maximum value (the number of data) by network and fixed RMS error was equal to zero. Fig. 5 shows the trend of changing RMS error based on increasing the number of neurons in the hidden layer.

RBF models automatically increased the number of neurons in the hidden layer to achieve a minimum performance function error. Results showed by increasing number of neurons in the hidden layer RMS error limited to zero.

Evaluation of MBBR performance by ANFIS model: The model composed of generalized bell, triangular, and Gaussian membership functions for applying input variables (influent feed, influent COD, and retention time) has the best performance to predict the removal COD efficiency and the effluent aniline concentration (Fig. 6). The predicted removal COD efficiency and effluent aniline concentration values for different retention times using this model has been depicted in Fig. 7.

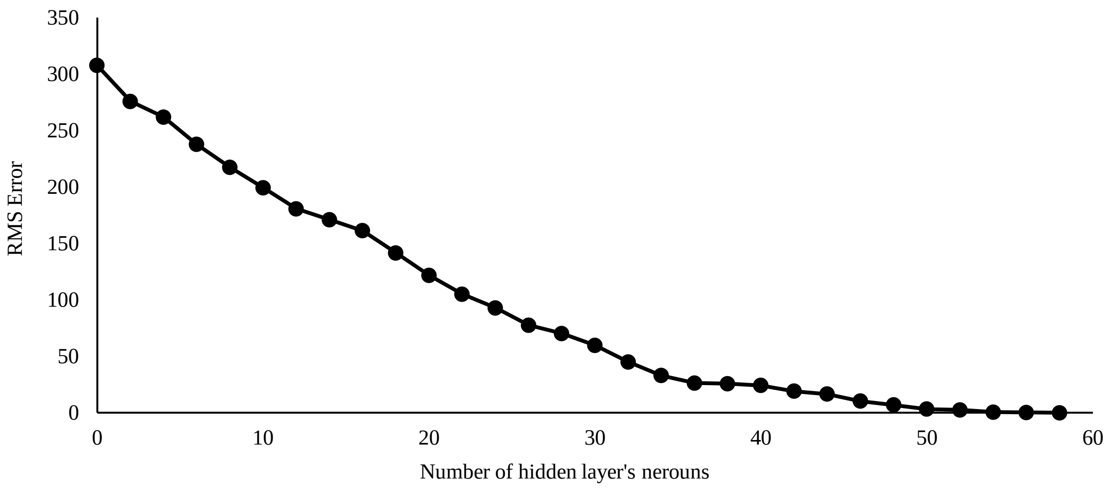

Fig. 5- The trend of changing RMS error based on increasing the number of neurons in hidden layer

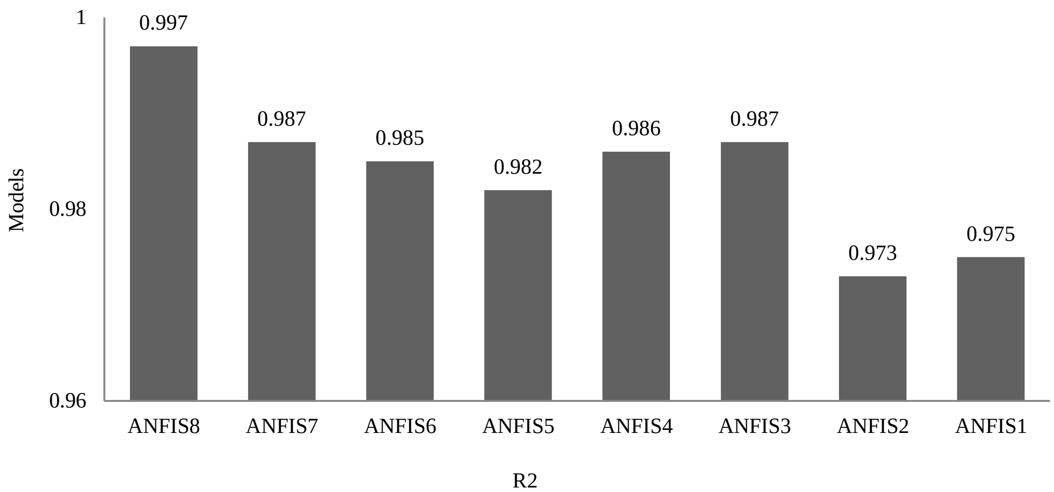

Fig. 6- The performance of ANFIS models

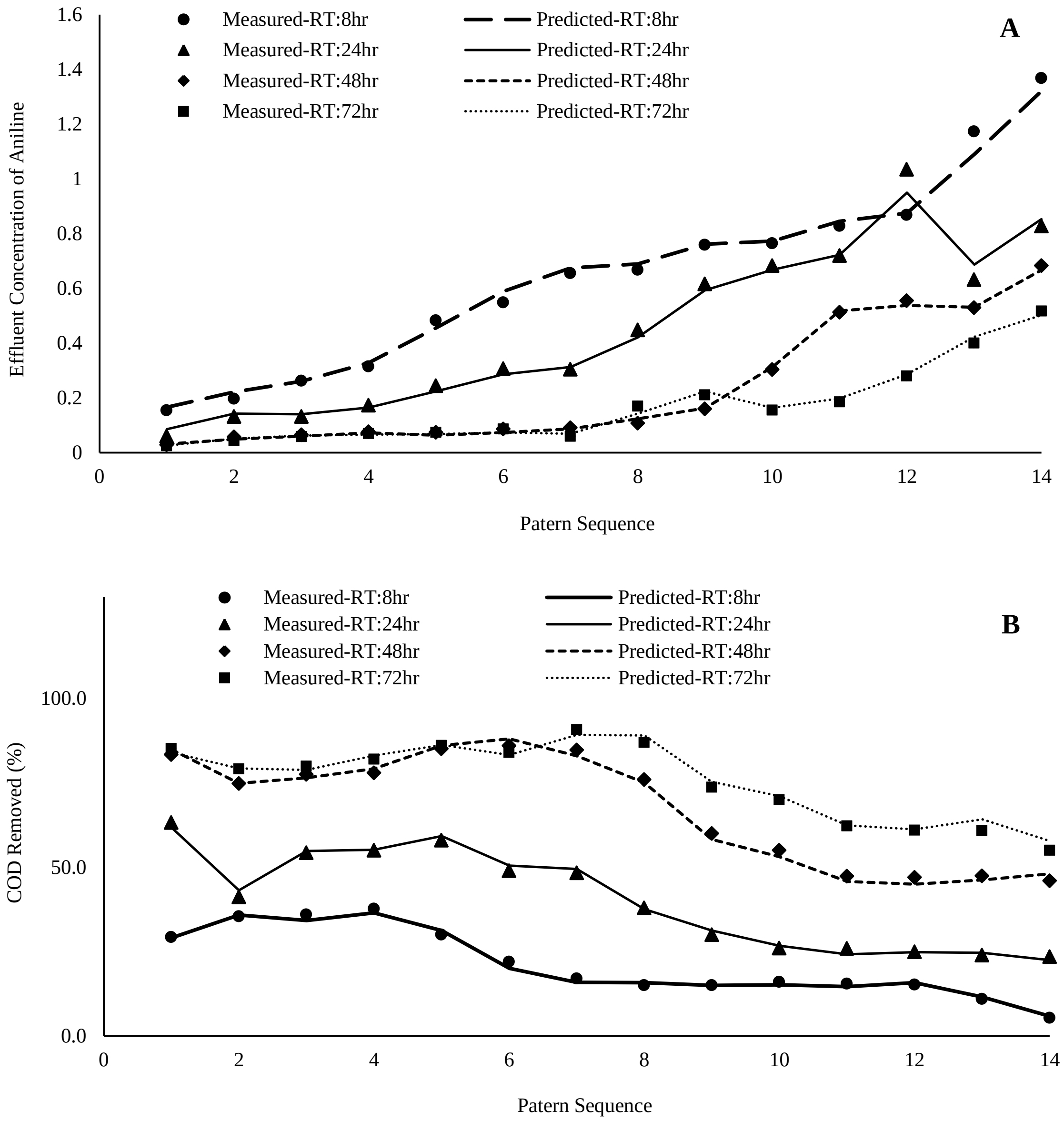

Fig. 7- The predicted effluent aniline concentration (a) and removal COD efficiency (b) values with using the best ANFIS model

Results showed that ANFIS8 model had the maximum R^2 by Gbellmf, Trimf and Guassmf Membership Functions in Influent Feed, Influent COD and Retention Time, respectively. In the similar research, the best results obtained for R^2 and RMS equal to 0.96 and 0.042 respectively, when ANN by hyperbolic tangent, Gaussian and sigmoid transfer functions in hidden and output layers (6).

Evaluation of MBBR performance by Fuzzy Regression Analysis model: Fuzzy regression analysis, using linear and nonlinear functions, showed that the quadratic function had the best performance in predicting the efficiency and effluent aniline concentration (Table 2). Fig. 8 depicts the comparison of the predicted values using fuzzy regression obtained by this function with the measured values.

Table 2- Fuzzy regression analysis using linear and Quadratic functions

Function	Obtained equation	R^2	RMSE
Linear	$Effluent\ Concentration\ of\ Aniline = -0.0003 + 1.58E-07 \times (Influent\ Feed) + 0.000336 \times (Influent\ COD) - 2.39E-05 \times (Retention\ Time)$	0.99	0.013
	$Removed\ COD = 47.05 - 5.91E-04 \times (Influent\ Feed) - 0.01377 \times (Influent\ COD) + 0.551 \times (Retention\ Time)$	0.95	0.749
Quadratic	$Effluent\ Concentration\ of\ Aniline = 9.385 + 0.03499 \times (Influent\ Feed) - 1.058 \times (Influent\ COD) + 0.9477 \times (Retention\ Time) - 0.00003573 \times (Influent\ Feed)^2 - 0.0003441 \times (Influent\ Feed) \times (Influent\ COD) - 0.0026 \times (Influent\ Feed) \times (Retention\ Time) + 0.02172 \times (Influent\ COD)^2 + 0.03785 \times (Influent\ COD) \times (Retention\ Time) - 0.2149 \times (Retention\ Time)^2$	0.99	0.018
	$Effluent\ Concentration\ of\ Aniline = 35.79 + 0.199 \times (Influent\ Feed) - 0.0425 \times (Influent\ COD) + 0.983 \times (Retention\ Time) - 6.68E-06 \times (Influent\ Feed)^2 - 9.62E-06 \times (Influent\ Feed) \times (Influent\ COD) - 2.57E-05 \times (Influent\ Feed) \times (Retention\ Time) + 4.24E-07 \times (Influent\ COD)^2 + 7.28E-05 \times (Influent\ COD) \times (Retention\ Time) - 5.22E-03 \times (Retention\ Time)^2$	0.98	0.481

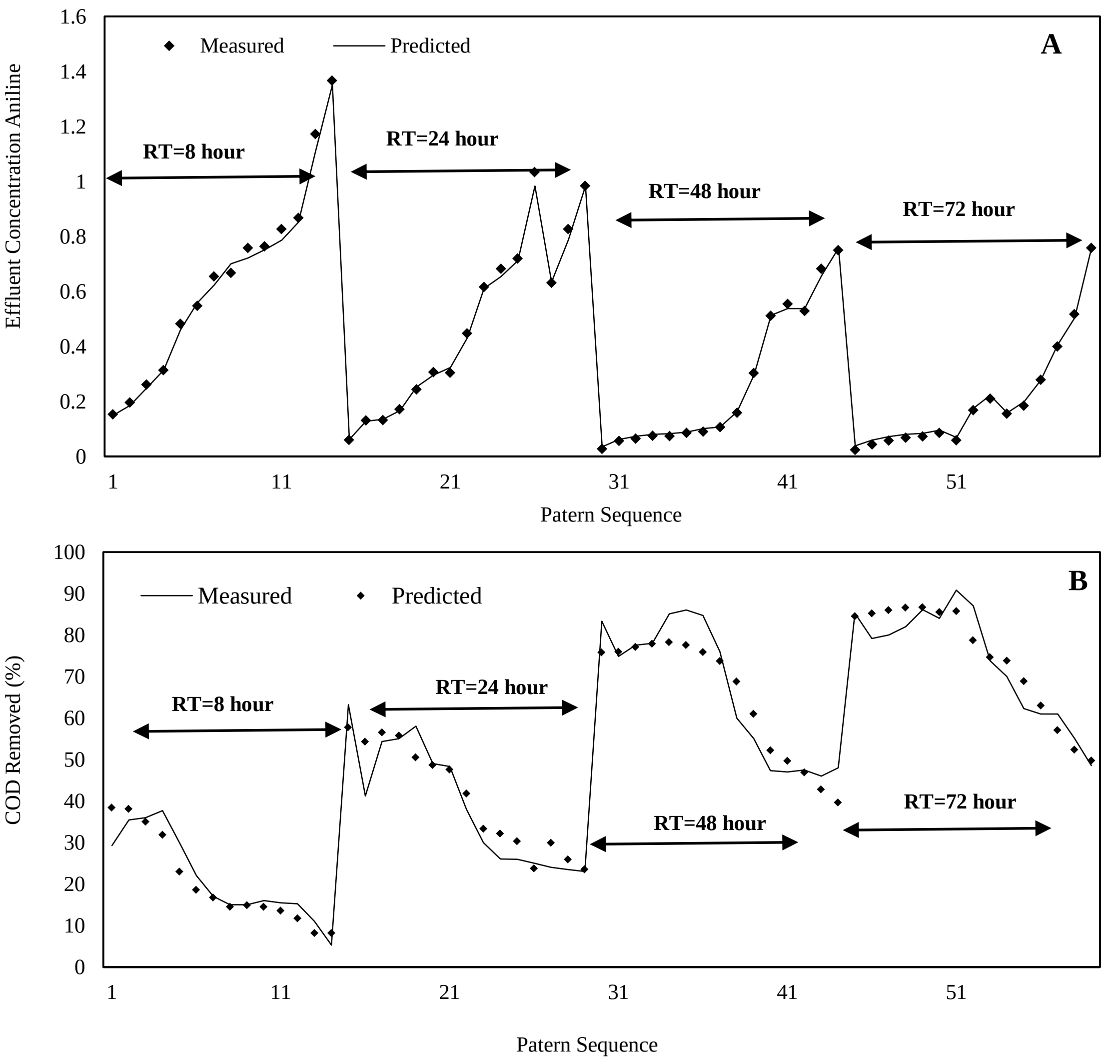

Fig. 8- The predicted effluent aniline concentration (a) and removal COD efficiency (b) values with using fuzzy regression analysis

Table 3- The performance of different modeling methods

Modeling method		R^2	RMSE
RBF network	effluent aniline	0.99	0.003
	removal COD efficiency		
ANFIS	effluent aniline	0.99	0.027
	removal COD efficiency	0.99	0.034
Fuzzy regression analysis	effluent aniline	0.99	0.018
	removal COD efficiency	0.98	0.481

Table 3 illustrates the best performance of RBF network, ANFIS, and fuzzy regression analysis used in this study. The results show that this modeling method has appropriate performance to predict the effluent concentrations of aniline and MBBR efficiency.

Results showed that ANFIS and RBF had more ability than fuzzy regression analysis in simulating the Aniline and COD removal efficiency in different experimental conditions.

Discussion and Conclusion

In this paper, prediction of MBBR in the treatment of aniline synthetic wastewater as a hard biodegradable compound was evaluated. Results showd MBBR as an advanced biological process had a proper COD removal efficiency for the treatment of aromatic amine wastewater. The removal efficiency was affected by concentration and detention time as an operating parameter. The best removal efficiency of 91% in COD of 2000 mg/L after 72 hour was obtained. The ANN, ANFIS, and fuzzy regression modeling were trained and tested on 8, 24, 48, and 72 hour sets of COD and aniline concentration measurements were taken over a period of 6 months. The results showed that the modeling methods used in this study have the ability to predict the effluent concentrations of aniline and removal of COD efficiency. Increasing the neurons in the hidden layer would improve the function of the RBF network, therefore the gain of R^2 was set to 1 and the RMS error was set to zero. The ANFIS model made according to the membership functions of generalized bell, triangular, and Gaussian with R^2 equals to 0.99 and RMS error of 0.027 for the anticipation of the concentration of Aniline and coefficient of determination 0.99 and RMS error of 0.034 for the prediction of removal COD efficiency, had positive results in the process of MBBR modeling. RBF models automatically increased the number of neurons in the hidden layer to achieve a minimum performance function error. Results demonstrate that ANFIS unlike RBF neural networks require a smaller number of neurons, and also have the ability to change various design parameters to achieve optimal results.

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