Biological treatment of slaughterhouse wastewater: kinetic modeling and prediction of effluent

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Abstract

In this study three modeling approaches consisting Modified Stover-Kincannon, multilayer perceptron neural network (MLPANN) and B-Spline quasi interpolation were applied in order to predict effluent of up-flow anaerobic sludge blanket (UASB) reactor and also to find the reaction kinetics. At first run, the average total chemical oxygen demand (TCOD) removal efficiency was 48.3% with hydraulic retention time (HRT) of 26 h and 63.8% with HRT of 37 h, at OLR of 0.77–1.66 kg TCOD/m³ d. At the second run, UASB reactor operated with OLR of 1.94–3.1 kg TCOD/m³ d and achieved the average TCOD removal efficiency of 64.74 and 72.48% with HRT of 26 and 37 h, respectively. The Modified Stover-Kincannon performed well in terms of kinetic determination with a high value of regression coefficient over 0.98. The B-Spline quasi interpolation and MLPANN indicated a great fit for effluent prediction with average R of 0.9984 and 0.9986, and MSE of 157.6050 and 129.7796, respectively; however, they gave no information about reactions occurred in the system.

Keywords Biological treatment · TCOD removal · Modified Stover-Kincannon · Artificial neural network · B-spline quasi interpolation

Introduction

The meat processing sector produces a large amount of slaughterhouse wastewater due to slaughtering and cleaning of

facilities and meat processing plants [1]. Slaughterhouse wastewater includes high organic content and nutrients and is mainly composed of proteins and fats, oil and grease (FOG) [2].

Among the various types of treatments, anaerobic processes are the best selection of biological treatment for slaughterhouse wastewater treatment due to high concentration of organic matter and nutrients [3]. Up-flow anaerobic sludge blanket reactor represents a reliable method for treatment of different industrial wastewater. The popularity of UASB reactor stems from low sludge generation, low capital investment and maintenance cost, less land and energy requirements and biogas production [4–6]. Although other methods such as AOPs and membrane technologies can be used, but they suffer from some disadvantages. The AOPs are less popular due to use of chemicals, high expenses and in some case toxicity. Also, the membrane technology is not suggested due to its capital and operating costs, membrane fouling and clogging. Thus, they are usually preferred in post-treatment [7, 8].

In order to monitor and evaluate the performance of biological treatment process, the process modeling is of utmost importance [9]. The kinetic studies can be used for predicting treatment performance of full-scale reactors operating under the same operational conditions [10]. Thus, the most appropriate model should be selected to find the technical faults and to decrease the operating costs in the planning stage [11]. There are numerous kinetic models (i.e. Monod-type kinetic, Grau second order,

Highlights

- Performance of up-flow anaerobic sludge blanket reactor.
- Effect of HRT on removal efficiency.
- Multi-layer perceptron and B-Spline quasi interpolation were used in order to predict the effluent of UASB reactor.
- Kinetic modeling of UASB reactor by modified Stover-Kincannon.

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Stover-Kincannon, Contois, Chen–Hashimoto, etc.) for anaerobic treatment process to investigate the bio-kinetics and also to investigate the importance of relationships between the design and experimental data [12]. Among them, Modified Stover-Kincannon is the most popular model for wastewater treatment which has been applied successfully to anaerobic treatment processes. Turkdogan-Aydinol et al. applied Modified Stover-Kincannon to evaluate the performance of UASB reactor in order to treat municipal wastewater under different conditions which indicates a very high value of determination coefficient ($R^2 = 0.9721$) [13]. The use of Stover-Kincannon model for anaerobic processes have been proved to treat wide variety of wastewater such as poultry slaughterhouse wastewater, palm oil mill, gelatinaceous wastewater and dyeing wastewater [10, 14–16].

Artificial neural networks have become popular tools to predict the biological and chemical wastewater treatment processes [17–19]. In order to monitor and manage wastewater treatment plants properly, the dynamic models ensure the suitable operation and control of wastewater treatment plants, due to dynamic and complicated behavior of wastewater treatment processes [20]. Artificial neural network (ANN) with minimum mean square error (MSE) of 0.1 indicated a precise prediction of a submerged biofilm reactor effluent, but it gave no information about reactions of the process [21]. ANN model was used to predict the phytoremediation of textile dye and an appropriate predictive performance ($R^2 = 0.974$) was achieved [22].

Although the ANNs are accurate predictors, they suffer from some drawbacks such as empirical nature and time consuming in complex conditions. In this regard, an appropriate numerical analysis suggested. As a method of spline approximation, B-spline quasi interpolation is an essential tool of numerical analysis in order to reach into the best estimation. It is used to reduce the estimation time and also to reach into an accurate estimation of effluent wastewater parameters in treatment plant. This method has some advantages like precision, fastness and easy implementation compared to the others [23].

The main objective of this research is investigating the TCOD removal kinetics of anaerobic process by Modified Stover-Kincannon and also prediction of UASB reactor effluent by artificial neural network and B-spline quasi interpolation, a novel method of approximation, in order to find the most effective model. Furthermore, in this study the performance of UASB reactor with different HRT and OLR was investigated in a combined biological treatment process in order to treat slaughterhouse wastewater.

Materials and methods

Experimental set-up

Figure 1 indicates the schematic diagram of continuous pilot scale of combined biological treatment made of plexi-glass

(UASB-Extended-Clarifier). Only, the USAB reactor was considered in this research in order to obtain kinetic coefficients. Using a pump (soft water TYO-2500), influent of UASB reactor was transferred from feed tank into an up-flow anaerobic sludge blanket (UASB) reactor. A circulation system was applied to provide an efficient up-flow velocity in UASB reactor. The sludge properties were assessed from five sampling ports. The reactor was equipped by gas separation system. The working volume of UASB reactor was 26 L.

Pilot startup

Aerobic sludge, facultative microorganisms, was provided from a local slaughterhouse wastewater treatment plant and then during a 2-month period, it was transformed into anaerobic sludge within anaerobic bioreactor. During the period of transforming into anaerobic sludge, microorganisms were fed constantly to provide an appropriate food/microorganism (F/M) ratio for an efficient growth. Then, UASB reactor was inoculated with the anaerobic sludge of 1 L developed in an anaerobic bioreactor. The OLR was increased gradually during start-up. The variations of COD removal reached below 3% for about one week. Sludge growth process occurred at the end of 4 months of start-up. At this time the OLR was 1.18 kg COD/m³d with HRT of 26 h. After start-up, the UASB reactor operated with COD of 1200–3370 mg/L at HRT of 26 and 36 h.

Slaughterhouse wastewater characteristics

The wastewater samples used in this research were provided from a local slaughterhouse plant in Guilan province in Iran. The wastewater of the company was provided through different operations. The samples were supplied from equalization tank after passing the screen. The slaughterhouse wastewater data were analyzed several times and the average results are suggested in Table 1. Two hydraulic retention times were used for each run by adjusting the influent flow-rate. For the first and second run, the average BOD₅ were 565 mg/L and 1410 mg/L, respectively. The FOG of the wastewater was very low which can be ignored. And the TSS varied in the range of 70–150 mg/L. In order to adjust the COD, blood was added to the wastewater separately.

Analytical method

Measuring total COD, total suspended solid, mixed liquor suspended solid, fat, oil and grease, ammonia and phosphate were determined through the APHA standard methods [24]. Turbidity was determined by a turbidity meter (TU-2016-Lutron). TCOD was measured by thermo-reactor (AL125-AQUALYTIC). Phosphate and ammonia concentrations were revealed using spectrophotometer (Jenway).

Fig. 1 Schematic diagram of the pilot

Model development

Roughly, the models can be classified into white and black box models. The white box model can be fully utilized from prior knowledge and physical insights, that is, mathematical equations, such as differential equations, logical relations and similar equation. The other way to build mathematical models, i.e. black box, for a process is that the process is considered totally unknown and is not necessary to use any model structure that represents the physical structure of the process and also have a good flexibility [25].

According to the classification, the Modified Stover–Kincannon are used as white box models, and artificial neural networks and B-Spline quasi interpolation are considered as black box model.

Table 1 Characteristics of slaughterhouse wastewater

Parameter	Unit	Minimum	Maximum	Average
TCOD	mg/L	1200	3370	2337.43 ±836.8
N – NH ₃	mg/L	205	629.3	346.85±112.75
P – PO ₄ ^{3–}	mg/L	16	35.6	21.42±4.5
TU	NTU	90	300	193.22±54.46

TCOD Total COD, TU Turbidity

Stover–Kincannon model

One of the most popular mathematical models for determining the kinetic constant in immobilized systems is Stover–Kincannon [9]. It has been applied to several methods and different wastewater anaerobic filter treating soybean wastewater, anaerobic up-flow filters treating paper-pulp-liquors and anaerobic migrating blanket reactor [26–28]. The substrate removal rate is determined as follows:

$$\frac{dS}{dt} = \frac{Q}{V} (S_0 - S) \quad (1)$$

Where dS/dt is defined as follows:

$$\frac{dS}{dt} = \frac{U_{\max} (QS_0/V)}{K_B + (QS_0/V)} \quad (2)$$

$$\left(\frac{dS}{dt}\right)^{-1} = \frac{V}{Q(S_0 - S)} = \frac{K_B}{U_{\max}} \frac{V}{QS_0} + \frac{1}{U_{\max}} \quad (3)$$

Where;

dS/dt , is substrate removal rate (mg COD/L day); $U_{\max}$, is the maximum utilization rate constant (mg COD /L day), K_B is the saturation value constant (mg COD /L day) and V is the volume of the reactor (L). Combining the inverses of Equations (1) and (2) gives the Modified Stover–Kincannon model Equation (3). If $(dS/dt)^{-1}$ is taken as $V/[Q(S_0 - S)]$ and plotted against the V/QS_0 , the slope and portion of intercept would be $K_B/U_{\max}$ and $1/U_{\max}$, respectively [9].

Artificial neural networks

The common algorithm in environmental process is back-propagation algorithm where an input and output dataset of the system is introduced into a neural net having initial connection weights [21].

Several algorithms (Levenberg-Marquardt, BFGS Quasi-Newton, Resilient Conjugate gradient, Scaled Conjugate Gradient, Conjugate Gradient With Powell/Beale Restarts, Fletcher-Powell Conjugate Gradient, Polak-Ribie re Conjugate Gradient, One Step Secant and Variable Learning Rate Backpropagation) with optimum number of neurons in the hidden layer were applied in order to find the best algorithm based on average MSE and R. In order to predict the performance of the UASB reactor, MLPANN was used.

Among all data, a set was used to test the provided network for estimating the trained network performance. Also a validation data set was used for evaluation of network quality during the training. In the case mean squared error (MSE) reached into less than $ep=0.1$, or after 1000 iteration step, then the network stopped working. Tangent sigmoid (tansig) and linear (purelin) transfer functions were applied for hidden and output layer, respectively (MATLAB software).

The network included one input layer consisting TCOD and HRT, one hidden layer comprising fifteen neurons and one output layer (i.e. TCOD). The structure of the neural network of the research is depicted in Fig. 2.

Cubic B-spline quasi interpolation

Assume that $X_n = (x_j)_{j=-3}^{n+3}$ subject to $x_{-3} = x_{-2} = x_{-1} = x_0 = a$, $x_n = x_{n+1} = x_{n+2} = x_{n+3} = b$. The j^{th} cubic B-spline of degree d for the knot sequence X_n is indicated by $B_{X_n, j}$ or B_j and specified as follows [29]:

$$B_{X_n, j}(x) = \begin{cases} \frac{(x-x_j)^3}{(x_{j+1}-x_j)(x_{j+2}-x_j)(x_{j+3}-x_j)}, & x \in [x_j, x_{j+1}), \\ \frac{(x-x_j)^2(x_{j+2}-x)}{(x_{j+2}-x_j)(x_{j+2}-x_{j+1})(x_{j+3}-x_j)} \\ + \frac{(x-x_j)(x_{j+3}-x)(x_{j+2}-x_{j+1})}{(x_{j+3}-x_j)(x_{j+3}-x_{j+1})(x_{j+2}-x_{j+1})} \\ + \frac{(x_{j+4}-x)(x-x_{j+1})^2}{(x_{j+2}-x_{j+1})(x_{j+3}-x_{j+1})(x_{j+4}-x_{j+1})}, & x \in [x_{j+1}, x_{j+2}), \\ \frac{(x-x_j)(x_{j+3}-x)^2}{(x_{j+3}-x_j)(x_{j+3}-x_{j+1})(x_{j+3}-x_{j+2})} \\ + \frac{(x-x_{j+1})(x_{j+3}-x)(x_{j+4}-x)}{(x_{j+3}-x_{j+1})(x_{j+3}-x_{j+2})(x_{j+4}-x_{j+1})} \\ + \frac{(x_{j+4}-x)^2(x-x_{j+2})}{(x_{j+4}-x_{j+1})(x_{j+4}-x_{j+2})(x_{j+3}-x_{j+2})}, & x \in [x_{j+2}, x_{j+3}), \\ \frac{(x_{j+4}-x)^3}{(x_{j+4}-x_{j+1})(x_{j+4}-x_{j+2})(x_{j+4}-x_{j+3})}, & x \in [x_{j+3}, x_{j+4}), \\ 0, & \text{else} \end{cases} \quad (4)$$

Fig. 2 Structural neural network of the research

An approximation for a continuous function f is approximated by a linear combination of cubic B-Spline functions which could be defined as operators of the form [30, 31].

$$Q_3 f = \sum_{j=1}^{n+3} \mu_j(f) B_j. \quad (5)$$

The major advantage of quasi-interpolants is that they have a direct structure without solving any linear equation system. Furthermore, they are local, i.e. $Q_d f(x)$ value is merely related to $f(x)$ values in an adjacent x . Eventually, they possess relatively small infinity norm, thus they are nearly optimal approximants [32–34].

Given $f_j = f(x_j)$, $j = 0, 1, 2, \dots, n$, the coefficient functional for cubic quasi-interpolant are as:

$$\begin{cases} \mu_1(f) = f_0, \\ \mu_2(f) = \frac{1}{18}(7f_0 + 18f_1 - 9f_2 + 2f_3), \\ \mu_j(f) = \frac{1}{6}(-f_{j-3} + 8f_{j-2} - f_{j-1}), 3 \leq j \leq n+1, \\ \mu_{n+2}(f) = \frac{1}{18}(2f_{n-3} - 9f_{n-2} + 18f_{n-1} + 7f_n), \\ \mu_{n+3}(f) = f_n. \end{cases} \quad (6)$$

The effluent of UASB reactor was predicted by B-Spline quasi interpolation using Matlab software.

Performance of UASB reactor in different condition

In order to investigate the performance of each reactor for removing TCOD, the effluent of UASB reactor was tested regularly during second operation period. In this section, TCOD removal efficiency of UASB reactor will be discussed under different conditions. In this research, the operation was conducted at two runs with different OLR. The HRT was

Fig. 3 TCOD removal of UASB reactor at first run

increased in each run in order to investigate the effect of HRT on removal efficiency.

TCOD removal efficiency at first run

The UASB reactor operated for 44 days in order to investigate the pattern of TCOD alteration in the reactor. The average mixed liquor suspended solid during first run was 6850 mg/L. Figure 3 suggests the TCOD removal of UASB reactor with average organic loads of 0.77–1.66 kg TCOD/m³ d. The average TCOD removal efficiency was 48.47% with HRT of 26 h and 63.43% with HRT of 37 h. Del Nery et al., proposed that poultry slaughterhouse wastewater with the organic loading rate of 1.6 ± 0.4 kg COD/m³ day which was applied to the UASB reactors resulted in TCOD and SCOD removal efficiencies of 67 and 85%, respectively [35].

The UASB reactor operated to treat slaughterhouse wastewater was done and the results indicate that the soluble COD and insoluble COD removal efficiency were 77 and 82%, respectively; with volumetric load of 1.8 kg COD/m³ d [36]. Treatment of slaughterhouse wastewater by anaerobic baffled reactor shows that TOC, COD and CBOD₅ removal efficiency were reached to 89.9, 97.7 and 96.6%, respectively, for influent TOC of 973.3 mg/L at HRT of 3.8 days [3]. An anaerobic reactor (two third of the bottom was filled with sludge blanket and the upper one-third was filled with submerged cubes of polyurethane foam) was used to treat slaughterhouse wastewater. The obtained results suggest that the reactor could remove COD between 90.2 and 93.4% at organic loading rates of 2.49–20.82 g COD/L d, at an HRT of 0.5 day [37].

Fig. 4 TCOD removal of UASB reactor at second run

Fig. 5 Linear plots of Stover-Kincannon kinetic model for the first run and first HRT

TCOD removal efficiency at the second run

The TCOD removal will be lower if the OLR is low. The average mixed liquor suspended solid during second run was 10,980 mg/L. As the Figure 4 suggests, in this period, the HRT was increased from 26 to 37 h. Increasing HRT caused a little improvement in TCOD removal, because anaerobic treatment was not able to remove non-biodegradable organic matter in high extent. The average TCOD removal efficiency was 63.7% with HRT of 26 h and 72.27% with HRT of 37 h.

The average COD removal efficiency obtained by UASB reactor were 85, 84 and 80% with HRTs of 22, 18 and 14 h, respectively, for treating meat processing wastewater [38].

Anaerobic fluidized-bed reactor is another alternative which could remove COD in the range of 75–98.9%, with OLR of 2.9–54 g COD/L. d; at hydraulic retention time (HRT) of 0.5–8 h and influent COD of 250–4500 mg/L [39]. The anaerobic fixed-bed reactor is a viable method for treatment of wastewater rich in solid substances such as slaughterhouse wastewater. The study of two fixed-bed reactors with OLR of 2–18.5 g/L day and HRT of 5 to 0.5 days were operated in parallel. The results indicated that the average COD removal of the reactor with bamboo was 30–85% and the other one with bones was 27–80% [40]. The comparison of UASB reactor and anaerobic filter to treat slaughterhouse wastewater revealed that the COD removal of UASB reactor was 90% for OLR up to 5 kg COD/m³/day and 60% for an OLR 6.5 kg COD/m³/day. For

Fig. 6 Linear plots of Stover-Kincannon kinetic model for the first run and second HRT

Fig. 7 Linear plots of Stover-Kincannon kinetic model for the second run at first HRT

the same organic loading rates, the AF indicated lower removal efficiency [41].

Kinetic modeling of UASB reactor

Modified Stover-Kincannon kinetics

Figure 5 indicates the plot of Stover-Kincannon model in the first run with HRT of 26 h which shows the linear relationship between TCOD loading and TCOD removal rates of the reactor. The saturation constant value (K_B) and maximum TCOD removal rate (U_{max}) were calculated as 6.844 g TCOD/L-day and 15.48 g TCOD/L-day with regression coefficient of 0.9849, for UASB reactor at first run with HRT of 26 h. The saturation constant value (K_B) and maximum TCOD removal

rate (U_{max}) of second HRT were 5.78 g TCOD/L-day and 10.13 g TCOD/L-day with regression coefficient of 0.9958, respectively (Figure 6). The Stover-Kincannon model was applied to anaerobic migrating blanket reactor where the calculated kinetic constants are as follow: the saturation value constant (K_B) and maximum utilization rate constants (R_{max}) were found as 31.55 g COD/L-day and 29.49 g COD/L-day for COD removal [27].

The saturation constant value (K_B) and maximum TCOD removal rate (U_{max}) were calculated as 12.48 g TCOD/L-day and 22.47 g TCOD/L-day with regression coefficient of 0.9958 for UASB reactor at second run with HRT of 26 h, and 87.72 g TCOD/L-day and 123.43 g TCOD/L-day with regression coefficient of 0.9964 for second run with HRT of 37 h (Figures 7 and 8). The maximum COD removal rate

Fig. 8 Linear plots of Stover-Kincannon kinetic model for the second run at second HRT

Table 2 Comparison of kinetic constants in Modified Stover-Kincannon model

Waste water	Reactor	Reactor volume (L)	Removal efficiency	HRT (day)	COD (gCOD/L)	OLR (kg COD/m ³ d)	KB (gCOD/L/day)	Rmax (gCOD/L/day)	Reference
Poultry manure wastewater	UASB	15.7	82–94%	12–15.7	11.78–19.62	0.752–1.635	13.02	11.83	[42]
Textile wastewater	UASB	2.5	29.5–80%	0.25–4.17	4.214	1–15.8	8.2	7.5	[43]
2,4 dichlorophenol	UASB	2.5	65–83%	0.083–0.83	3	6–34	0.034	0.0075	[44]
Poultry slaughterhouse wastewater	SASBR	4	>94%	1.5–2.5	4.2–9.1	2.53–4.97	130.28	121.71	[10]
Poultry slaughterhouse wastewater	SGBR	4	>94%	1.5–2.5	4.2–9.1	2.53–4.97	177.21	164.48	[10]
Synthetic wastewater	anaerobic hybrid reactor ^a	29.4	77–90%	0.5–2	2–15	1–10	186.23	83.3	[45]
Textile wastewater	hybrid reactor	13	82–94%	2.3–9.1	1.15–1.9	1.038–8.21	22.89	212	[46]

^a Fixed bed region**Table 3** Comparison of training algorithms

Description	Algorithm	Abbreviation	TCOD		MSE
			R		
Levenberg-Marquardt	trainlm	LM	0.9984		157.6050
Resilient Conjugate gradient	trainrp	RP	0.9972		249.7595
Fletcher-Powell Conjugate Gradient	traincgf	CGF	0.9964		326.8288
Scaled Conjugate Gradient	trainscg	SCG	0.9960		359.1073
Conjugate Gradient With Powell/Beale Restarts	traincgb	CGB	0.9957		389.6973
BFGS Quasi-Newton	trainbfg	BFG	0.9955		403.4437
Polak-Ribie re Conjugate Gradient	traincgp	CGP	0.9940		554.6056
One Step Secant	trainoss	OSS	0.9933		606.6965
Variable Learning Rate Backpropagation	trainidx	GDX	0.9919		730.8664

Table 4 Error of models with respect to different neurons

Number of neurons	Average MSE	Average R
7	504.3083	0.9944
8	295.1820	0.9968
9	377.4571	0.9958
10	352.5201	0.9961
11	286.8409	0.9969
12	243.6357	0.9974
13	256.8730	0.9972
14	168.2694	0.9982
15	157.6050	0.9984
16	283.0158	0.9969
17	253.4218	0.9972
18	197.3437	0.9978

($U_{\max}$) and saturation constant (K_B) were calculated as 164.48 g COD/L-day and 177.21 g COD/L-day for the Static granular bed reactor [10].

The regression coefficient of the model indicated that the Stover-Kincannon possesses high correlation coefficients for UASB reactor which can be used in predicting the behavior or design of the reactors. Table 2 indicates the kinetic constants of UASB reactor.

Artificial neural network and B-spline quasi interpolation

Different algorithms were applied to predict the characteristics of UASB reactor effluent (Table 3). Levenberg-Marquardt algorithm was investigated to be the best algorithm with average R and MSE of 0.9984 and 157.6050, respectively; after 1000 iteration step. The purelin (linear) and Tansig (tangent sigmoid) were considered to be the best transfer functions for output and hidden layer, respectively.

The optimum number of neurons was chosen based on average R and MSE. The average R and MSE of the optimum model with varied number of neurons are presented in Table 4. Twelve different architectures were applied and the optimum number of neurons was 15, with an average R and MSE of 0.9984 and 157.6050, respectively.

The predicted effluent of UASB reactor by MLPANN and B-Spline quasi interpolation are shown in Figure 9. The increase of HRT enhanced the TCOD removal efficiency in each run. As it is observed, both models could predict the UASB reactor performance properly.

Figure 9 indicates that the B-Spline quasi interpolation is more accurate and there is high correlation between the experimental values and prediction of effluent of UASB reactor. And also, it could be concluded that the B-Spline quasi interpolation had less oscillations while the ANN model oscillated in some parts. The operation time of B-Spline quasi interpolation is very lower than artificial neural network and it has simple implementation and algorithm.

Figure 10 indicates the correlations of MLPANN model and B-Spline quasi interpolation. Both methods indicated appropriate performance in prediction of UASB reactor effluent. The scatter plots show a great fit for MLPANN and B-Spline quasi interpolation with R of 0.9984 and 0.9986, and MSE of 157.6050 and 129.7796, respectively. The predictive capability of the models was almost the same.

Conclusions

In order to predict the effluent of UASB reactor, MLPANN and B-Spline quasi interpolation were applied under different OLR and HRT. Also, the kinetics of UASB reactor treating slaughterhouse wastewater was investigated using Modified Stover-Kincannon model. The pilot has been operated at two

Fig. 9 Effluent TCOD by MLPANN and B-Spline quasi interpolation

Fig. 10 Regression plots of the experimental data and predicted values: **a** ANN model **b** B-Spline quasi interpolation

runs with HRT of 26 and 37 h. The average OLR at first and second runs were 0.77–1.66 kg TCOD/m³ d and 1.94–3.1 kg TCOD/m³ d, respectively. The results of this study are summarized as follows:

1. The UASB reactor indicates a proper performance in TCOD removal.
2. Applying the Modified Stover-Kincannon for UASB reactor indicates a great regression coefficient of more than 0.98.
3. B-Spline quasi interpolation and MLPANN indicate great performance in predicting the UASB reactor effluent.

They result in correlation coefficient of more than 0.99, but they couldn't provide information about reaction.

4. The simple algorithm and implementation, accuracy and also low time consuming are the main advantages of B-Spline quasi interpolation compared to the MLPANN.

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Compliance with ethical standards

Competing interests The authors declare that they have no competing interests.

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