Artificial intelligence based model for optimization of COD removal efficiency of an up-flow anaerobic sludge blanket reactor in the saline wastewater treatment
Alain R. Picos-Benítez, Juan D. López-Hincapié, Abraham U. Chávez-Ramírez and Adrián Rodríguez-García

ABSTRACT
The complex non-linear behavior presented in the biological treatment of wastewater requires an accurate model to predict the system performance. This study evaluates the effectiveness of an artificial intelligence (AI) model, based on the combination of artificial neural networks (ANNs) and genetic algorithms (GAs), to find the optimum performance of an up-flow anaerobic sludge blanket reactor (UASB) for saline wastewater treatment. Chemical oxygen demand (COD) removal was predicted using conductivity, organic loading rate (OLR) and temperature as input variables. The ANN model was built from experimental data and performance was assessed through the maximum mean absolute percentage error (\(9.226\%\)) computed from the measured and model predicted values of the COD. Accordingly, the ANN model was used as a fitness function in a GA to find the best operational condition. In the worst case scenario (low energy requirements, high OLR usage and high salinity) this model guaranteed COD removal efficiency values above 70\%. This result is consistent and was validated experimentally, confirming that this ANN-GA model can be used as a tool to achieve the best performance of a UASB reactor with the minimum requirement of energy for saline wastewater treatment.

Key words | anaerobic reactor, genetic algorithm, neural networks, optimization, saline wastewater

INTRODUCTION
Saline wastewater is widely generated by industry. The primary uses of salty water for industrial processes are in food processing and the textile, leather tanning and petroleum industries (Lefebvre & Moletta 2006). Some industries are located in coastal zones and discharge their wastewater into the ocean, without proper treatment. This has triggered stricter regulations and brought a new focus to wastewater treatment researchers (Campo et al. 2011).

The composition of a saline wastewater depends mainly on the product, supplies, number of units used in the process and the water source. Thus, saline wastewater may contain high organic loads, oil, grease, suspended solids, phosphorus and nitrogen. Among the existing processes, several studies have focused on the performance that biological treatment processes have with these waters. However, these systems have poor organic load removal, caused by the difference in osmotic pressure between the cell and its surrounding environment, a process called plasmolysis (Lefebvre et al. 2006). In aerobic systems, plasmolysis can reduce bacterial activity and it can increase suspended solids in the effluent by the considerable reduction of protozoan floc population and changes in bacteria metabolism (Abou-Elela et al. 2011). In anaerobic systems, the main effect of salt concentration is methanogenesis inhibition (Chen et al. 2008a). Several methods to improve the performance of biological treatments have been reported: previous exposure to incremental saline concentrations (Kimata-Kino et al. 2011), use of halophilic consortia (Abou-Elela et al. 2010) and antagonistic cations (Chen et al. 2008a).

Anaerobic treatment is an alternative for industrial saline wastewater because it presents some advantages...
compared to other traditional systems such as greater organic matter removal at high organic loading rates (OLRs), lower energy requirements, lower sludge production, and lower operating cost and space requirements (Kanat & Saral 2009). Despite the low quality effluent produced by these systems and higher sensitivity to salinity effects, anaerobic treatment of industrial wastewater is possible at loadings up to 24 kg COD/m³.d (COD: chemical oxygen demand) (Chen et al. 2008a). But, for an effective depuration, the system performance must be monitored continuously. Thus, to accomplish the stricter regulations, effective monitoring and control process strategies have become a matter of special concern (Singh et al. 2010).

Modeling approaches have been globally used to estimate and control the performance of anaerobic systems, as well as their design and evaluation (Singh et al. 2010). Modeling of anaerobic processes is a difficult task because they involve complex physical, chemical and biological processes which exhibit a non-linear behavior that is hard to describe using linear mathematical modeling (Yetilmezsoy & Sapci-Zengin 2009; Singh et al. 2010; Huang et al. 2016). Lately, non-conventional modeling techniques such as principal component analysis, support vector machines, swarm intelligence and artificial neural networks (ANNs) have been employed as an alternative to develop accurate models built from experimental data from complex systems. In particular, ANNs have been successfully applied in the prediction of anaerobic processes’ behavior (Rangasamy et al. 2007; Yetilmezsoy & Sapci-Zengin 2009; Singh et al. 2010; Prakasham et al. 2011).

ANNs can emulate biological processes like neuron synapsis to predict optimum experimental conditions (Chen et al. 2008b). These are comprised of simple processing elements inspired by the biological nervous system that can be trained so that a particular input leads to a specific output. The performance of this ANN is determined by the number of connections between elements (Demuth 2002). The advantages of ANNs are that they can be constructed without a detailed knowledge of the process, calibration is easier than for conventional models (i.e. mechanistic, deterministic), a deviation of predicted values from real ones can be corrected with a re-training of the ANN with new experimental data and they possess excellent generalization ability (Yetilmezsoy & Sapci-Zengin 2009; Prakasham et al. 2011; Huang et al. 2016). An ANN can be trained using historical performance data to show the behavior of a particular process under certain operational conditions without compromising the system (Pendashteh et al. 2011). However, ANNs have several limitations like the possibility of getting trapped in local minimums and the difficulty of calculating the derivatives from an optimization use, with conventional optimization techniques. Genetic algorithms (GAs) can be used to avoid these limitations. A GA is an optimization method that is based on natural selection processes (Prakasham et al. 2011; Huang et al. 2016), similar to the biological evolution, where the best individuals will reproduce to procreate children, which have better characteristics than their parents, so that, after a number of generations, the best individual arises. This best individual represents the global optimum of a possible solutions universe (MathWorks 2005). In this model, the introduced data are used to set an initial population, which will evolve through generations into the best individual.

Reported studies have focused on design, optimization, prediction or estimation of several treatment technologies by ANNs which use the historical data for effectively predicting the behavior of some measurement parameters of several biological processes which treated either synthetic wastewater or a real stream (Rangasamy et al. 2007; Yetilmezsoy & Sapci-Zengin 2009). Also ANNs were used to estimate the biogas rate of an anaerobic system and COD removal from an aerobic process (Kanat & Saral 2009; Pendashteh et al. 2011). ANNs have been used to accurately predict the performance of an entire wastewater treatment plant (both aerobic and anaerobic) (Singh et al. 2010). The effects of variation of several conditions on the performance of a real wastewater treatment plant have also been evaluated using a more complete model like the ANN-GA (Fang et al. 2010). These models have other applications like the prediction of biogas production yield in anaerobic processes (Mu & Yu 2007) or the simulation of a biodegradation process from a fluidized bed bioreactor (Venu Vinod et al. 2009). Biogas yield has been enhanced with an ANN-GA model (Prakasham et al. 2011). The performance of an up-flow anaerobic sludge blanket reactor (UASB reactor) and an aerobic (activated sludge) wastewater treatment process has been simulated and improved with an ANN-GA model (Huang et al. 2016).

These studies have proven the efficacy of anaerobic systems in treating saline wastewater. In addition, ANN-GA models can be used to estimate the performance of biological systems in treating several types of wastewater, including saline effluents. Nevertheless, these models have never been used to improve, estimate or optimize
the effectiveness of a UASB reactor that treats a wastewater with complex organic content and salt concentration. In this study an ANN-AG model is used to estimate the performance of an UASB reactor and to find the best performance under the most difficult operational conditions: low energy requirements, high OLR usage and high salinity.

MATERIALS AND METHODS

An ANN-GA model was used to predict optimum performance conditions in a UASB reactor that treated a synthetic saline wastewater (SSWW) prepared with commercial products: dog food, common sugar, milk powder, ammonium chloride and monobasic potassium phosphate (Arango & López 2011). This solution was enriched with a 50 mL/L micro- and macro-nutrient solution; this concentrate solution had a measured COD of 100 g/L (see Table 1). COD in saline wastewater was determined according to Kayaalp et al. (2010).

UASB reactor

A cylindrical laboratory-scale UASB reactor with a 7 L volume made of acrylic was used. The reactor was fed using a peristaltic pump that provides SSWW from a 19 L plastic container. Treated wastewater was collected in another 19 L plastic container. A granulated anaerobic sludge conditioned to treat brewery effluent and marine sediment were used as seeds. Marine sediment was collected in Mazatlán, Sinaloa, México from an estuary that receives fishmeal wastewater discharge.

Data collection

All the collected data from the experimental phase were generated during a 7-month period. Randomly salt concentrations were used in the data collection phase. Granular salt was used to increase salinity and conductivity in the wastewater. A conditioning period was employed to adapt biomass to high salinity and high OLR. The methodology for sludge adaptation to salt concentration above 20 g/L was with stepwise increase of salinity conditions. COD concentration was increased gradually; a low COD adaptation period was needed; in this stage a domestic wastewater (WWRC) was used (mean COD = 0.603 ± 0.178 g/L). After that, biomass was acclimated to a high COD concentration by exposing it to a mixture of WWRC and SSWW (mean COD = 2.26 ± 0.8 g/L). Finally, sludge was subjected to high COD concentrations ranging from 2.74 to 11.42 g/L. During this period, room temperature was used (22.6 and 29.5 °C). As the organic load was increased, the salt concentration was also increased to reach 23 g/L. After a high COD and salt conditioning period, the experimental data were collected. In this phase, several experiments were conducted. To train the ANN, real operational conditions were simulated by randomly varying salt concentration, OLR and temperature. OLR was varied from 1.02 to 9.9 kg COD/m³·d by changing randomly COD or hydraulic retention time (HRT), salt concentration from 4.9 to 32.8 g/L (conductivity from 7.7 to 39.3 mS/cm) and temperature from 16.6 to 32 °C (temperatures below 20 °C were measured during winter conditions while those above 25 °C were reached with an aquarium heater). Removal efficiency and biogas were measured. A total of 51 random scenarios of OLR, salinity and temperature were obtained with their respective removal efficiency value. pH values were measured in all the experiments only for monitoring purposes, and since it is a parameter that cannot be controlled, it was not used for the ANN-GA model.

ANN-GA model

The general methodology for an ANN-GA application model for wastewater treatment system optimization consists of five main stages: data collection, artificial intelligence (AI) model design, ANN training, validation and application. For a proper design, it is necessary to select the right input and output variables that influence the removal efficiency and biogas production. These variables were selected by observing the performance of the UASB reactor during the conditioning period. According
to the results obtained in this phase, the main effects on removal efficiency and biogas variations were observed when OLR and salt concentration were increased. In addition, temperature effects were studied by increasing the range between minimum and maximum temperature.

AI model design and training

After data collection, several ANN architectures were tested. The input variables considered were OLR, temperature and salt concentration (conductivity); removal efficiency was considered as the only output. The ANN’s training process was carried out by testing several architectures and activation functions in order to reach a minimum error goal settled as 0.003. Defining the correct ANN topology is a difficult task; since no theory enables the amount of hidden layers and neurons to be determined for the correct modeling process, it demands the constant monitoring of the error convergence to the settled value. However, employing an adequate programming technique and taking advantage of the available capabilities in processing and data storage of the latest computational systems, this task can be automated, accelerating the training and evaluation process of the ANN, reducing considerably time spent in analysis compared with previous works (Velásco-Mejía et al. 2016). The Levenberg–Marquardt back propagation algorithm was used to determine the non-linear relationships between input and output variables. Sigmoid transfer functions were used in the hidden layers due to their flexibility in combining nearly linear, curvilinear and nearly constant behavior. This transfer functions takes values that range from plus to minus in finite and restrict the output from 0 to 1 (Demuth 2002). The ANN code was programmed in MATLAB®. From the set of 51 experiments, 80% were used for training the ANN and the rest for testing. The ANN performance was evaluated as Velásco-Mejía et al. (2016) mentioned, by calculating the root mean square error (RMSE) and the mean absolute percentage error (MAPE) using Equations (1) and (2):

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (t_i - t_{di})^2}
\]  \hspace{1cm} (1)

\[
\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{t_i - t_{di}}{t_i} \right| \times 100
\]  \hspace{1cm} (2)

where \(t_i\) is the real value, \(t_{di}\) the predicted value by the ANN model and \(N\), the number of testing data.

GA model

As mentioned before, GA emulates the natural selection process to select the best individual. In this work, each possible solution is known as an individual and is codified as a chain of values that correspond to the input vector of the ANN model: [OLR, salt and temperature]; each individual is evaluated by a fitness function (ANN model). An initial population was randomly created. The GA uses three main rules in each step to create the next generation of individuals from the current population: selection rules (selects parents), crossover rules (gives the probability for each parent to procreate new individuals) and, finally, mutation rules (applies randomly changes to individual parents to form children). These parameters and their values are defined in Table 2. The GA was designed using the Optimtool of Matlab. Once the input variable ranges (upper and lower bounds) have been defined, similar to ANNs, there is no theory that enables the definition of the initial parameters of the GA configuration; this task was carried out by defining the initial population, mutation rate, individual selection and crossover type considering the nature of the collected data and adjusting carefully by observing the convergence of the set error (see Table 2).

Finally, an experimental validation of the proposed conditions by the ANN-GA model was carried out in the laboratory-scale UASB reactor. In this part of the study, the same SSWW was used with COD concentrations of \(15.61 \pm 0.395\) g/L, temperature of \(25.23 \pm 1354\) A. R. Picos-Benítez et al. | Optimization of COD removal efficiency in saline wastewater Water Science & Technology | 75.6 | 2017

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of variables</td>
<td>3</td>
</tr>
<tr>
<td>Initial population size</td>
<td>20</td>
</tr>
<tr>
<td>Crossover probability</td>
<td>0.8</td>
</tr>
<tr>
<td>Elite count</td>
<td>2</td>
</tr>
<tr>
<td>Children</td>
<td>2</td>
</tr>
<tr>
<td>Crossover type</td>
<td>Scattered</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.2</td>
</tr>
<tr>
<td>Lower bounds (temperature, OLR, conductivity)</td>
<td>16.6, 1.02, 7.7</td>
</tr>
<tr>
<td>Upper bounds (temperature, OLR, conductivity)</td>
<td>32, 9.9, 39.3</td>
</tr>
</tbody>
</table>
0.27 °C and conductivity of 32.46 ± 0.51 mS/cm. The hydraulic retention time for each experiment was 38.03 ± 0.70 h.

RESULTS AND DISCUSSION

Real collected data

From the experimental phase a total of 51 data were collected, each data consisting of three input variables: OLR, salt concentration and temperature; and one output: removal efficiency. From these data, 80% were used to training the ANN and the other 20% for validation. All the experiments were made randomly to set real experimental conditions. Effects on biological treatment systems were studied, as presented in Figure 1.

According to previous studies on anaerobic treatment of saline wastewater, the main effect on system performance is salinity fluctuations (Boardman et al. 1995; Vidal et al. 1997; Lefebvre et al. 2006; Kimata-Kino et al. 2011; Li et al. 2014); also several OLRs have been used (0.3 to 31 kg COD/m³d) with retention times that go from 3 hours to as long as 12 days (Prasertsan et al. 1994; Guerrero et al. 1997). Finally, it has been ascertained that temperature is a factor that must be controlled in order to achieve maximum removal efficiency (Habets et al. 1997). In this study these three inputs were selected as input variables for the ANN-GA model.

Prediction with ANN

The main objective of the ANN is to predict removal efficiency values from a non-tested operational condition. To achieve reliable predicted values, a solid ANN architecture

Figure 1 | Effects of random variations in conductivity, temperature and OLR on removal efficiency.
is needed. Since there is no established methodology yet, the best ANN configuration is determined by trial and error (Rangasamy et al. 2007; Venu Vinod et al. 2009; Pendashteh et al. 2011; Prakasham et al. 2011).

The ANN was designed to correlate the non-linear relationship of the input variables with the output. After testing many topologies, the minimum error goal was reached as well as an acceptable R value (0.90039). The best ANN architecture was a back propagation network with 3-10-5-1 neurons and a non-linear transfer function (log sigmoid). Several ANN configurations have been already tested for optimization or modeling of anaerobic treatment of non-saline wastewater (Mu & Yu 2007; Rangasamy et al. 2007; Kanat & Saral 2009; Venu Vinod et al. 2009; Yetilmezsoy & Sapci-Zengin 2009; Singh et al. 2010; Prakasham et al. 2011; Huang et al. 2016). The final ANN used in this study is not similar to those used in these studies, mainly due to a non-determinate methodology to select the correct configuration. Linear regressions were calculated for training and testing results of the ANN and to evaluate the correlation of simulated and real removal efficiency (Figure 2). The MAPE (9.226%) and RMSE (6.376%) were calculated to select the final ANN configuration (Figure 3).

Optimization of UASB with GA

GA has been previously used, in combination with ANN, to predict the behavior of anaerobic systems (Mu & Yu 2007; Venu Vinod et al. 2009); also the GA-ANN model was utilized to enhance the performance of an anaerobic reactor (Prakasham et al. 2011; Huang et al. 2016). In this work, the main objective of GA was to find the optimum operational conditions where the UASB reaches maximum efficiency, treating a wastewater with high salinity, high OLR and minimal energy consumption.

According to Chen et al. (2008b) GA provides a population of solutions and these multiple possible solutions reduce the possibility of reaching a local minimum. The GA of the present study supplied three groups of solutions (Table 3); each group was classified into ranges of operational conditions. These values were submitted to confidence interval analysis to avoid the inclusion of isolated data and simplify the selection of the best combination. The selected data are shown in Figure 4 and the distribution of data is shown in Figure 5. The 3D graphs show the spatial distribution in the solutions space. There are three data groups;
each one of them represents a possible combination of operational conditions that gives the best removal efficiency.

As Huang et al. (2010) mentioned, GA-ANN is a tool that helps engineers select the best operational conditions for a certain biological process, either aerobic or anaerobic. Having said this, the selection of a combination of operational conditions to evaluate experimentally the GA model was necessary.

It can be seen that the most feasible solution to test is the one which allows the maximum OLR, requires the least energy and permits a high salinity. The second group of operational conditions shown in Figure 4 and Table 3 was chosen to be evaluated experimentally. The selection criteria of this combination is based on the particular capabilities of anaerobic systems to treat high organic loaded saline wastewater under mesophilic and thermophilic conditions (Kimata-Kino et al. 2011).

From proving experimentally these selected conditions, Table 4 was constructed. It can be observed that removal efficiencies reached 72% and have low variations as long as conditions persist. After evaluating several COD concentrations and HRT, removal efficiency did not change, supporting the consistency of the AG-ANN model.

### Table 3 | Simulated combinations and predicted COD removals

<table>
<thead>
<tr>
<th>Group</th>
<th>Values</th>
<th>Temperature (°C)</th>
<th>OLR (kg COD/m³.d)</th>
<th>Conductivity (mS/cm)</th>
<th>Predicted COD removal (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Minimum</td>
<td>16.601</td>
<td>9.898</td>
<td>38.975</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>16.605</td>
<td>9.899</td>
<td>39.299</td>
<td>58.91</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>16.614</td>
<td>9.900</td>
<td>39.245</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Minimum</td>
<td>24.642</td>
<td>9.898</td>
<td>30.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>25.053</td>
<td>9.899</td>
<td>31.368</td>
<td>74.63</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>25.478</td>
<td>9.900</td>
<td>32.674</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Minimum</td>
<td>30.001</td>
<td>6.492</td>
<td>39.299</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>30.030</td>
<td>6.503</td>
<td>39.300</td>
<td>97.8</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>30.045</td>
<td>6.529</td>
<td>39.300</td>
<td></td>
</tr>
</tbody>
</table>
The selected conditions shown in Table 4 have never been tested before in anaerobic treatment of saline wastewater. Several differences can be observed between previous studies and the present one: the experimental temperature (above 30°C), the substrate (some authors used real industrial wastewater and others a synthetic wastewater based on simple substrates) and several ranges of salinities. Regardless of this, in this work the mean removal efficiency reached 70%, which is comparable with the studies presented in Table 5, proving the consistency of the model.

GA-ANN was helpful in the optimization of the anaerobic treatment of this saline wastewater. As mentioned before, these models have been used to improve the performance of anaerobic systems. However, in this work, instead of selecting one scenario where maximum COD removal efficiency can be achieved, the model gives conditions in which the energy requirements are reduced, allowing the use of high OLR and high salinity and, despite this, it still achieves acceptable performance. These proposed conditions can reduce operational costs to a minimum.

The model generates three groups of combinations that could achieve the highest removal efficiency; however, in real treatment systems it is known that the three variables are hard to control (Lefebvre & Moletta 2006); so the selection of the best combination is based on the maximum value of OLR, a variable that can be manipulated to a certain point, and at a temperature that requires minimal or no energy addition. This provides us with a useful tool to define an operation curve that guarantees at least 70% efficiency at maximum demand (high salinity and high OLR).

**CONCLUSIONS**

An ANN-GA model was used to predict COD removal efficiency and to find the best operational conditions. The
effectiveness of the model was evaluated experimentally. Acceptable removal efficiency values above 70% were obtained with the solution given by the AI model under high conductivity and high OLR without adding energy to the process. Using these kinds of AI models would help to improve wastewater treatment performance of complex saline industrial wastewaters. Finally, the constructed model can be applied to estimate the best operational conditions of similar systems where historical data already exist, since AG-ANN can be easily adapted to a new biological process (Prakasham et al. 2011). Thus AI models can help to drastically reduce experimental time. Also AG-ANN can be used to successfully predict the performance of similar systems, avoiding operating problems. Thus these models can be helpful in reducing operational, construction and experimental costs.

Figure 5 | Distribution of data for selected combinations.

Table 4 | Experimental evaluation of GA-ANN model

<table>
<thead>
<tr>
<th>Experiment</th>
<th>HRT (h)</th>
<th>COD (mg/L)</th>
<th>Temperature (°C)</th>
<th>OLR (kg COD/m³.d)</th>
<th>Conductivity (mS/cm)</th>
<th>Removal efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37.6</td>
<td>15,430</td>
<td>25.13</td>
<td>9.85</td>
<td>32.77</td>
<td>72.0</td>
</tr>
<tr>
<td>2</td>
<td>37.6</td>
<td>15,340</td>
<td>25.54</td>
<td>9.84</td>
<td>32.73</td>
<td>71.6</td>
</tr>
<tr>
<td>3</td>
<td>38.9</td>
<td>16,065</td>
<td>25.03</td>
<td>9.91</td>
<td>31.87</td>
<td>67.6</td>
</tr>
</tbody>
</table>
Table 5 | Operational conditions and results in previous studies

<table>
<thead>
<tr>
<th>Author</th>
<th>Substrate</th>
<th>Process</th>
<th>Temperature °C</th>
<th>OLR (kg COD/m³.d)</th>
<th>Salinity (g/L)</th>
<th>COD removal (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prasertsan et al. (1994)</td>
<td>Real effluent</td>
<td>AF</td>
<td>30–35</td>
<td>0.3–1.8</td>
<td>0.4–4.0</td>
<td>65–75</td>
</tr>
<tr>
<td>Boardman et al. (1993)</td>
<td>Real effluent</td>
<td>UASB</td>
<td>32</td>
<td>13.8</td>
<td>7.7–26.3</td>
<td>77</td>
</tr>
<tr>
<td>Omil et al. (1995)</td>
<td>Real effluent</td>
<td>ACS</td>
<td>37</td>
<td>1–8</td>
<td>13.6–33.7</td>
<td>70–90</td>
</tr>
<tr>
<td>Vidal et al. (1997)</td>
<td>Real effluent</td>
<td>AF</td>
<td>37</td>
<td>14.3</td>
<td>30</td>
<td>80</td>
</tr>
<tr>
<td>Guerrero et al. (1997)</td>
<td>Real effluent</td>
<td>UAF</td>
<td>37</td>
<td>5</td>
<td>7.5</td>
<td>80–90</td>
</tr>
<tr>
<td>Mosquera-Corral et al. (2001)</td>
<td>Real effluent</td>
<td>USBF</td>
<td>37</td>
<td>1–1.25</td>
<td>–</td>
<td>70–90</td>
</tr>
<tr>
<td>Lefebvre et al. (2006)</td>
<td>Real effluent</td>
<td>UASB</td>
<td>≈ 30</td>
<td>0.5</td>
<td>72</td>
<td>78</td>
</tr>
<tr>
<td>Lefebvre et al. (2007)</td>
<td>Synthetic</td>
<td>AR</td>
<td>37</td>
<td>8.08</td>
<td>20</td>
<td>99.9</td>
</tr>
<tr>
<td>Kimata-Kino et al. (2011)</td>
<td>Synthetic</td>
<td>UASB</td>
<td>35</td>
<td>18.3</td>
<td>20</td>
<td>&gt; 90</td>
</tr>
<tr>
<td>Li et al. (2014)</td>
<td>Synthetic</td>
<td>UASB</td>
<td>35</td>
<td>0.25</td>
<td>12–28</td>
<td>52</td>
</tr>
<tr>
<td>This work</td>
<td>Synthetic</td>
<td>UASB</td>
<td>25</td>
<td>9.9</td>
<td>20</td>
<td>70.4</td>
</tr>
</tbody>
</table>

AF: anaerobic filter; UASB: up-flow anaerobic sludge blanket; ACS: anaerobic contact system; UAF: up-flow anaerobic filter; USBF: hybrid up-flow sludge blanket filter; AR: anaerobic reactor.

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