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Artificial neural network prediction of chemical oxygen demand in dairy industry effluent treated by electrocoagulation

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ABSTRACT

We used electrocoagulation to reduce the chemical oxygen demand of dairy industry effluent. The effects of operating parameters were evaluated, including the electric current density, initial effluent pH, electrolysis time and distance between electrodes. The characteristics of the effluent, namely, the solids content and its fractions, turbidity and chemical oxygen demand, were also considered. An artificial neural network was constructed to model chemical oxygen demand after electrocoagulation; it was trained and validated, yielding a correlation coefficient of 0.96 between predicted and experimental values. Input variables were ranked by their relative importance for the prediction of chemical oxygen demand after treatment by electrocoagulation. Among effluent the Total Dissolved Solids concentration had the greatest relative importance, followed by the chemical oxygen demand. It can be concluded that an artificial neural network can predict chemical oxygen demand after treatment by electrocoagulation. In practice, operating parameters may be adjusted to obtain a greater reduction of chemical oxygen demand and to allow automation of the handling process.

1. Introduction

Electrocoagulation (EC) is an electrochemical method that has been developed in an attempt to improve upon traditional technologies for water and wastewater treatment [1,2]. This alternative treatment has the potential not only to expand the treatment capacity of traditional chemical–physical systems using the same basic fundamentals of coagulation–flocculation but also to provide elements that enhance the method, such as hydrogen generation in the electrolysis step, yielding an upward flow of microbubbles that interact with the bulk effluent [3].

Because of the complexity of the reactions involved in EC, it is difficult to determine the kinetic parameters, leading to uncertainties in the design and scale-up of reactors. A reliable model for any wastewater treatment facility must provide a tool to predict its performance and to control the operation of the process. Such a tool can minimize operating costs and ensure the stability of the operation of the station. This process is complex and achieves a high degree of non-linearity due to the presence of biological constituents that have high variability, making mechanistic modeling difficult. Predicting the operating parameters of plants using conventional experimental techniques are also time-consuming and pose an obstacle to their implementation [4].

The artificial neural networks (ANNs) approach has several advantages over traditional phenomenological or semi-empirical models, since they require known input data set without any assumptions. The ANN develops a mapping of the input and output variables, which can subsequently be used to predict desired output as a function of suitable inputs [5,6].

ANNs seek to develop computational models based on the capacity of the human brain. Their main characteristics are related to the ability to learn by example, to interpolate or extrapolate based on standards provided and to select specific features within the sample universe [5–8]. The basic unit for information processing is the artificial neuron, which can receive one or more inputs, transforming them into outputs. Each entry has an associated weight that determines the intensity of its influence on the output data [6–8]. The Multilayer Perceptron (MLP) ANN is the most commonly used type because it is very versatile and able to solve problems ranging from simple to complex. Hidden layers are inserted between input and output layers depending on the complexity of the problem and the desired accuracy. In formulating the architecture of an ANN, the number of layers and the number of neurons and connections between neurons must be considered [5–7,9].

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The aim of this study was to evaluate the possibility of predicting the final COD of effluent from a dairy industry, according to effluent characteristics and the initial variables of EC treatment, using ANN modeling. In addition, the relative importance of each input variable on effluent COD after EC treatment was assessed.

2. Material and methods

2.1. Characterization of wastewater: Sampling and analysis

We used raw sewage from a dairy industry (15,000 L of milk per day). The wastewater from different sections was gathered at a junction box, which was selected as the sampling site.

The samples were collected using sampling methodology proportional to flow (SMPF) and by simple sampling (SS). Of a total of 275 samples collected, 143 were taken by SMPF, and 132 were taken by SS. Composite samples were collected in 1-h intervals for 8–17 h. Single samples were collected randomly throughout the sampling period.

COD analyses were performed according to the colorimetric method published by the American Public Health Association (APHA) [10]. Samples were digested in a block digester (MARCONI, Dry Block MA 4004). Absorbance readings of samples were performed using a GBC spectrophotometer, model UV/VIS 911A, at a wavelength of 600 nm.

The analysis of solids and their fractions was conducted in accordance with gravimetric method 2540 APHA [10]. For pH measurement, the potentiometric method was followed using a portable digital meter (DMPH DIGIMED, model 2), according to the APHA [10]. Turbidity was measured following the method of the APHA [10] using a TECNOPON-Model TB 1000 turbidimeter.

2.2. Assay of electrocoagulation

Following tests performed according to Valente et al. [11], EC was conducted in batch reactions using a glass reactor ($300 \times 200 \times 135$ mm) and aluminum electrodes. The effluent temperature was maintained at 20 °C ± 2 °C during electrocoagulation tests, close to the annual average temperature (19 °C) at the dairy location. After each test, the polarity of the electrodes was reversed to prevent electrode passivation.

EC tests, which were required to generate the information necessary for the software to define the network topology, were performed according to an experimental type fractional factorial with a central point. Table 1 shows the EC trials using the liquid effluent. Each test was repeated three times. This experiment aimed to generate information about the behavior of EC treatment with different levels of operating variables.

From data analysis of the tests, a 6 mm distance between electrodes was selected; there was no difference in COD removal among the distances tested, but larger distances required a higher consumption of electricity. A rotatable central composite design with three blocks was used to obtain the effects of the operating variables (j, t and pH) in the region that showed the best results in previous tests. This experimental design (Table 2) was conducted in duplicate. The blocks corresponded to samples collected on two different processing days.

Data analysis of tests revealed the need to expand the range of electrolysis time and pH used. Therefore, another experimental design was performed according to Table 3.

To improve generalization of the network, additional tests were performed by setting the current density at 55.4 A m^{-2}, the initial pH at 5.0 and the distance between electrodes at 6 mm. The electrolysis time was varied (10–50 min), and effluent samples were collected by simple sampling, with the aim of promoting greater variability in the input data relating to the characteristics of the effluent. To increase variability in the data input, some samples were treated by EC without pH adjustment. Thus, 275 assays were completed for training, validation and testing of the artificial neural network.

The pH was adjusted, where necessary, with NaOH (1 mol L^{-1}) or H_2SO_4 (0.05 mol L^{-1}) for the effluent to conduct different experimental designs.

2.3. Modeling ANN

An ANN was constructed. A sigmoid transfer function (tansig) with a Levenberg–Maquardt training algorithm was used to adjust the network. To develop the architecture of the ANN, 275 trials of dairy effluent treatment by EC were used and randomized into subgroups: training (165 trials), validation (55 trials) and testing (55 trials).

The number of input neurons was defined by input variables, including effluent Total Solids (TS), Total Suspends Solids (TSS), Total Dissolved Solids (TDS), turbidity and initial COD, as well as operational variables, including initial pH, electrolysis time, distance between electrodes and current density. The output variable was the COD obtained after treatment of the effluent by EC.

The number of hidden layers and the number of neurons in these layers were defined by trial and error, and the best network showed the best prediction of final COD values. In most cases, one hidden layer is sufficient to resolve problems [7]. According to Fletcher and Goss [12], an appropriate number of neurons in the hidden layer can be found using ($2\sqrt{n}+m$ to $2n+1$), where n is the number of neurons in the input layer and m is the number of neurons in the output layer.

2.4. Ordering of relative importance of input variables of ANN

To order the variables studied in terms of their relative importance to the value of the output variable COD after treatment by EC, we used Garson's equation [13]:

$$I_j = \frac{\sum_{m=1}^{m=Nh}\left(\left(\frac{|W_{jm}^{ih}|}{\sum_{k=1}^{Ni}|W_{km}^{ih}|}\right)|W_{mn}^{ho}|\right)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\frac{|W_{km}^{ih}|}{\sum_{k=1}^{Ni}|W_{km}^{ih}|}\right)|W_{mn}^{ho}|\right\}}, \quad (1)$$

Table 1
Design experiments for dairy wastewater treatment by EC.

Assay	Initial pH	Time (min)	Current density (j) (A m^{-2})	Distance (mm)
1	5.0	5.0	37.0	6
2	9.0	5.0	37.0	14
3	5.0	25.0	37.0	14
4	9.0	25.0	37.0	6
5	5.0	5.0	61.6	14
6	9.0	5.0	61.6	6
7	5.0	25.0	61.6	6
8	9.0	25.0	61.6	14
9	7.0	15.0	49.3	10
10	7.0	15.0	49.3	10
11	7.0	15.0	49.3	10

Table 2
Operating variables and their levels in the treatment of liquid effluent from the dairy industry by EC.

Variable	Level				
	−1.633	−1	0	1	+1.633
Electrolysis time (min)	5.0	10.0	16.5	23.0	27.1
pH	4.2	4.5	5.0	5.5	5.8
Current density (A m^{-2})	46.5	49.2	53.5	57.8	60.5