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Membrane permeate flux and rejection factor prediction using intelligent systems

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Backpropagation artificial neural network (BPNN), radial basis function (RBF) and adaptive neuro-fuzzy inference system (ANFIS) were utilized to predict starch removal performance from starchy wastewater using a hydrophilic polyethersulfone membrane with 0.65 μm pore size in a plate and frame homemade membrane module. Our study focuses on evaluation of membrane performance by optimum condition determination of operative parameters which affect the COD removal percentage and permeate flux. In this experiment, a four input vector was surveyed, including flow and temperature of feed, pH and concentration of permeate. In BPNN the number of neurons in the hidden layers needs to be chosen carefully to obtain a reliable network while choosing this structure is very time consuming. The best BPNN performance was obtained with 4 hidden layers for permeation and rejection factor prediction for BPNN. ANFIS and RBF simulations have also been used for comparison with BPNN. The results show a good agreement however the ANFIS prediction was better than two other simulation methods. In the basis of comparison between obtained results in this research, it may be an appropriate interpretation that for those chemical processes with performance which relied upon different variables, good performance prediction will be achieved by ANFIS systems.

1. Introduction

Prediction of filtration performance by mathematical models with different variables is a procedure that requires a good detailed knowledge of filtration process [1]. Efficient alternatives are required to predict the process performance by simulating available data and extending it to unavailable data. An artificial neural network (ANN) model is relatively simple because it can be treated as a nonparametric technique, which can capture the nonlinear characteristics of the system. ANNs have very useful properties concerning process identification. They can handle non-linear processes by means of the information of the given data [2–4]. Accurate ANN predictions were possible without using an industrial or laboratory plant as inputs and that by ANNs it was possible to overcome the difficulties associated with traditional transport models [5]. A number of authors have investigated the applicability of ANN to describe membrane processes (see, for instance, [6–11]). Neural networks have also been used in predicting of backwashing in ultrafiltration process [12].

Fuzzy systems have certain advantages over classical methods, especially when vague data or prior knowledge is involved. Over the last few decades, fuzzy systems have established their reputation as alternative approaches to information processing. These techniques can alleviate the matter of fuzzy modeling by learning ability of neural networks and have been reported since around the beginning of 1990s [13,14]. Since the architecture and behavior of ANFIS are very applicable [4], it has been adopted as a basic component for interpretation researches [15,16].

In general, the main practical advantage of the intelligent systems like ANFIS, RBF and BPNN is that predictions can be performed in an easy, fast and accurate way which is valuable for practical purposes in the design of membranes. The number of experiments, and in turn the associated problems like costs, designs, manufacturing and etc. can be reduced by this way by unavailable data performance prediction and then better understanding of the unknown membrane reactions.

2. Materials and method

2.1. Experimental methodology

Membrane filtration experiments were carried out in a laboratory scale filtration cell.

Retention was measured using [17]:

$$R = 1 - \frac{C_p}{C_b} \quad (1)$$

where R is retention, C_p is the permeate concentration and C_b is the bulk concentration. In this study, a polyethersulfone (PES) was used

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to wastewater treatment. The principle of the process is the starch separation from starch industry wastewater in according to the size of starch molecule by selecting a membrane with pore size smaller than starch molecule diameter. The plate and frame membrane module was made of steel. The properties of flat sheet membranes of hydrophilic polyethersulfone are described in Table 1. A centrifugal pump (Victory KM100) with maximum head of 50 m and maximum flow rate of 50 l/min, and a flow-meter with a maximum capacity of 20 l/min were also used. The process flow diagram of the setup is shown in Fig. 1.

The unit E-1 represents the tank used to store the feed. To prevent starch settling in the tank a mixer is also installed in it. Using the pipeline P-1, the feed (wastewater) leaves the tank and passes through a valve (V-1) and enters the centrifugal pump with maximum head of 50 m and maximum flow rate of 50 l/min (E-2). In this study, a range of flow rates needs to be investigated, so the feed is divided into two streams. One is bypassed to the storage tank (P-4), and the other stream enters the heat exchanger (E-3), after passing from a valve (V-2). The effect of temperature on separation of starch by affecting coagulation could be important, so the temperature variations should be studied. By using the heat exchanger mentioned earlier (E-3), the appropriate temperature interval is achieved. The adjusted temperature feed passes through a flow meter with a maximum capacity of 20 l/min (I-1) and valve (V-4) to enter the plate and frame module, as illustrated. During the main run, all the back wash related valves (including valve V-9) must be closed. To measure and adjust the operative pressures, two barometers are installed on the feed (I-5) and retentate (I-6) stream. The operative pressure is adjusted by using valves V-4 (inlet pressure) and V-5 (outlet pressure). The permeate flow leaves the membrane module, passes through the appropriate valve (V-7) and enters the digital flow meter before being stored in the permeate tank for further analysis. The retentate stream recycles to the feed tank, controlled by valve V-5.

2.2. Experimental analyses

The performance of the filtration process was evaluated by calculating the COD removal percentage (rejection factor) and permeates flux. Variables which potentially can alter microfiltration process are limited. In this case, the driving force is pressure so pressure has a potent symbol on process performances, especially permeate flux. The other parameter that affects the process performances severely is flow feed because this parameter is in direct relation with surface velocity, which determines the shear tension on membrane surface. Shear tension variations on membrane surface will result in rejection factor and permeate variation by affecting the concentration polarization. In all types of membrane processes, viscosity is an important factor and may affect the entire process, so it must be studied. Viscosity is a function of feed concentration, feed temperature and pH. According to the mentioned reasons, filtration performance seems to be dependent on transmembrane pressure, feed flow, feed temperature, pH and starch concentration. Determining the COD removal percentage and permeate flux in different conditions to obtain their functionality upon the parameters mentioned above is a very time consuming and costly procedure.

Table 1
Properties of flat sheet membranes of hydrophilic polyethersulfone.

Description	Polyethersulfone (PES)
Pore size	0.65 μm
Filter size	20 × 20 cm
Minimum bubble point psi (kg/cm^2)	19 (1.33)
Typical flow rate (ml/min·cm^2 @ 10 psi (0.7 kg/cm^2)	100.875
Maximum operating temperature	130 °C (266 °F)
pH resistant	1–14

3. Simulation modeling

3.1. BPNN structure

A successful BPNN requires internal parameters determination such as network architecture and initial weights to meet the required performance [1]. An ineffective design of the network will result in unreliable consequences. Finding a suitable architecture and the corresponding weights of the network is a complex task due to the lack of theoretical parameters or optimal values and need the trial and error approach using different initializations and architecture [18]. For instance the architecture of a typical BPNN is presented in Fig. 2. Matlab 2008 (7.6.0.324) was used to construct and simulate the membrane performance.

The BPNN used in this study is based on the following equation:

$$O_k = S\left(\sum_{j=1}^{m} W_{jk} x S\left(\sum_{i=1}^{n} W_{ij} X_i\right)\right) \quad (2)$$

where O_k is the output value, X_i is the input value of the network, W_{ij} is the connection weight between the input layer and the hidden layer, W_{jk} is the connection weight between the hidden layer and the output layer and S is transfer function.

3.2. RBF structure

Radial basis function (RBF) is a nonlinear layered feed forward network where each layer of neurons receives inputs just from previous layers. The input units feed input values to the hidden layers and then these hidden layers with output layer process the inputs through a nonlinear activation function [19]. RBFs are embedded in a two layer neural network, where each hidden layer implements a radial activated function. The output units implement a weighted sum of hidden unit outputs [20]. Various functions have been used as activation functions for RBF networks [21]. In time series modeling the thin-plate spline is the most used activation function and in pattern classification the Gaussian function is preferred [22–24]. The Gaussian activation function for RBF networks is indicated by:

$$\Phi_j(X) = \exp\left[-\left(X-\mu_j\right)^T \sum\nolimits_j^{-1} \left(X-\mu_j\right)\right] \quad (3)$$

where $j=1$, ..., L and X is the input vector, L is the number of hidden layers, μ_j and $\sum_j$ are the mean and covariance matrix of the jth Gaussian function. The distance between W and X calculated with $||dist||$. The transfer function f is the network function and usually is the Gaussian function. The RBF structure is shown in Fig. 3.

3.3. ANFIS structure

The main purpose of a fuzzy system is to achieve a set of local input–output relationships that describe a process. System modeling requires two main stages: structure identification and parameter optimization. Structure identification deals with the problem of determining the input–output space partition and how many rules must be used by the fuzzy system. Parameter optimization finds the optimum value of all parameters involved in the fuzzy system [25].

A fuzzy system with fuzzy rule base, product inference engine, singleton fuzzifier, and center average defuzzifier and Gaussian membership functions for all fuzzy sets is as follows:

$$f(x) = \frac{\sum_{l=1}^{M} y^{-1}\left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)^2\right)\right]}. \quad (4)$$