Soft sensors for control of nitrogen and phosphorus removal from wastewaters by neural networks

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Abstract In this paper, we describe the results of research aimed to evaluate the possibility of using a neural network (NN) model for predicting biological nitrogen and phosphorus removal processes in activated sludge, utilising oxidation reduction potential (ORP) and pH as NN inputs. Based on N and P concentrations predictions obtained via the NN, a strategy for controlling sequencing batch reactors (SBRs) phases duration, optimising pollutants removal and saving energy, is proposed. The NN model allowed us to reproduce the concentration trends (change in slope, or process end), with satisfactory accuracy. The NN results were generally in good agreement with the experimental data. These results demonstrated that NN models can be used as “soft on-line sensors” for controlling biological processes in SBRs. By monitoring ORP and pH, it is possible to recognise the N and P concentrations during different SBRs phases and, consequently, to identify the end of the biological nutrient removal processes. This information can then be used to design control systems.

Keywords Activated sludge modelling; neural network; nitrogen and phosphorus removal; ORP; pH; real-time control; sequencing batch reactor; soft-sensor

Introduction

Wastewater characteristics are not constant but show large fluctuations in time, in both concentration and flow rate. In spite of these fluctuations, wastewater treatment plants are designed, and frequently operated, on the basis of steady state conditions. Therefore, engineers tend to design wastewater treatment plants with large reactor volumes to achieve high removal efficiency also with high load peaks. This requires high investments and operational costs. For this reason, wastewater treatment plants often operate at very low load conditions for most of the operational period. Besides the well known effect on sludge settleability, low load conditions have also been related to the biological phosphorus removal process failure (Temmink et al., 1996; Brdjanovic et al., 1998).

Therefore, on-line control strategies that take into account the dynamic behaviour of these systems are necessary to optimise the entire process. Moreover, in recent years, the growing need for environmental pollution management and for reducing waste treatment costs have generated an increased interest in identifying procedures to optimise processes and technologies for wastewater treatment plants.

Real-time control of activated sludge processes is a difficult task due to the lack of cheap and reliable on-line sensors for the key state variables. Among the parameters used for monitoring and control, oxidation reduction potential (ORP) has been reported to be reliable for real-time control of wastewater treatment and sludge digestion (Peddie et al., 1990; Wareham et al., 1993a; 1993b; 1994). For biological nutrient removal from wastewaters, ORP has been related to nitrogen removal, whereas it is not considered a primary factor controlling biological phosphorus removal (Koch and Oldham, 1985). ORP has been used for monitoring wastewater treatment both in continuous and batch systems. The exact...
ORP value that can be utilised as an indicator of the biological process has been found to vary considerably (Koch and Oldham, 1985). For this reason, in continuous feed wastewater plants, ORP is maintained within a relatively narrow range where the processes are optimised (Charpentier et al., 1998). In discontinuous feed wastewater plants, ORP measurements is interpreted on the occurrence of signal profile and/or typical breakpoints (Koch and Oldham, 1985; Jenkins and Mavinic, 1989; Peddie et al., 1990; Wareham et al., 1993a; 1993b; 1994; 1995; Ra et al., 1997; 1998).

The pH has been also proposed as a real-time control parameter for nitrogen removal from wastewaters (Al-Ghusain et al., 1994; Yu et al., 1997; Hao and Huang, 1996). In addition, the pH has been related to phosphorus removal processes (Chang and Hao, 1996; Spagni et al., 2001). In discontinuous feed plants, pH signals are interpreted on the basis of typical change in its profile (as previously described for ORP).

Artificial neural networks (NNs) have been recently applied for activated sludge systems modelling and control (Capodaglio et al., 1991; Cote et al., 1995; Fu and Poch, 1996; Zhao et al., 1997; 1999; Olsson and Newell, 1999). NNs are computing procedures used to model complex systems through a process of “learning” from examples, without a priori knowledge about the systems’ structure or parameters. An interesting characteristic of NNs is that they can approximate any continuous function (Pham and Xing, 1995; Haykin, 1999).

Our laboratories are carrying out a study on using ORP and pH signals to design a real-time control system for activated sludge processes. The aim of the study is to use these signals for controlling sequencing batch reactors (SBRs) phases duration, while optimising pollutants removal and energy costs. This paper presents our results on using a NN for predicting biological nutrient (N and P) removal processes in activated sludge, utilising ORP and pH as NN inputs. On the basis of N and P concentrations prediction obtained by the NN, a control strategy can be developed.

**Materials and methods**

**Laboratory-scale plat description**

A 5 L (working volume) laboratory reactor was operated as an SBR with an operative cycle of 6 hours (5 h reactions and 1 h settling). The cycle consisted of an initial anoxic/anaerobic phase followed by an oxic one (2.5 h each). During the first 20–30 minutes of the cycle, the SBR was fed with 1 L of a synthetic media. The feed composition is reported in Table 1. 400 mL of sludge were manually withdrawn, once per day, at the end of the oxic phase corresponding to a solids retention time (SRT) of 20 days. The effluent was withdrawn in the last 10 minutes of the settling phase to a final volume of 4 L. The lab-scale plant was kept at 20 °C ± 0.5°C in a thermostatic chamber. The sludge inoculum was taken from a municipal treatment plant designed for nitrogen and phosphorus removal.

**Table 1 Synthetic feed composition**

<table>
<thead>
<tr>
<th>Compound</th>
<th>Weight (g)</th>
<th>Nutrient solution (minerals)</th>
<th>Concentration (g/L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH$_3$COONa•3H$_2$O</td>
<td>1.7</td>
<td>FeCl$_3$•6H$_2$O</td>
<td>1.5</td>
</tr>
<tr>
<td>Yeast extract</td>
<td>0.2</td>
<td>H$_2$BO$_3$</td>
<td>0.15</td>
</tr>
<tr>
<td>(NH$_4$)$_2$HPO</td>
<td>0.086</td>
<td>CuSO$_4$•5H$_2$O</td>
<td>0.03</td>
</tr>
<tr>
<td>NH$_4$Cl</td>
<td>0.080</td>
<td>KI</td>
<td>0.18</td>
</tr>
<tr>
<td>CaCl$_2$•2H$_2$O</td>
<td>0.014</td>
<td>MnCl$_2$•4H$_2$O</td>
<td>0.12</td>
</tr>
<tr>
<td>MgSO$_4$•7H$_2$O</td>
<td>0.09</td>
<td>NaMoO$_4$•2H$_2$O</td>
<td>0.06</td>
</tr>
<tr>
<td>Nutrient solution</td>
<td>0.6 mL</td>
<td>ZnSO$_4$•7H$_2$O</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>to 1 L</td>
<td>CoCl$_2$•6H$_2$O</td>
<td>0.15</td>
</tr>
<tr>
<td>Tap water</td>
<td></td>
<td>EDTA</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Analytical methods

NO$_{3}$-N, NH$_{4}$-N and PO$_4$-P were analysed by ionic chromatography (HPIC, Dionex 4000i). All the other analyses were performed according to the Standard Methods (APHA, 1995). ORP (Ag/ACl as reference) and pH were measured using Crison probes. The monitoring system (ORP and pH) was implemented on Labview (National Instrument).

Neural networks

Five different NNs were used to predict NH$_{4}$-N, NO$_3$-N and PO$_4$-P concentration trends in the SBR: two for the anoxic/anaerobic phase and three for the oxic one. Five small different NNs have been preferred to a single large neural model to simplify computing operations. ORP and pH were introduced, with time implicit representations, as inputs of each NN. The concentration (NH$_4$-N, NO$_3$-N and PO$_4$-P) profiles were independently considered for the five NNs (NO$_3$-N and PO$_4$-P during anoxic/anaerobic conditions and NH$_4$-N, NO$_3$-N and PO$_4$-P during oxic conditions). Ammonia was not considered for the anoxic/anaerobic condition because it is not a relevant control parameter during this phase. A scheme of the NN model is reported in Figure 1.

The NNs were trained using data obtained during several SBR cycles. A recurrent network was used because it is suitable for dynamic systems like activated sludge in general and SBRs in particular.

Elman NNs were chosen because, among the (partially) recurrent networks, they can be considered the simplest type of NN (Pham and Xing, 1995). The back-propagation algorithm, with the addition of a momentum term, was adopted as a training algorithm. The algorithm used reduces the error between the nutrient concentrations (NH$_4$-N, NO$_3$-N and PO$_4$-P) simulated by the net model and the same parameters (linearly interpolated) measured in the lab-scale SBR. The logistic (sigmoid) function and the linear function were chosen for the hidden and the output layer, respectively. Figure 2 shows a scheme of the Elman net adopted (with the MATLAB notation). The NNs were developed using the neural network toolbox 3.0 of the MATLAB 5.3 software.
Results and discussion

The SBR showed a very good efficiency of nutrient removal and typical enhanced biological phosphorus removal trends of batch systems. Also ORP and pH signals showed typical trends during the SBR cycles which were related to N and P biological removal processes. More details of the SBR performances and signals interpretation are reported elsewhere (Spagni et al., 2001).

During the experiments, it was observed that the NNs input signals (ORP and pH) showed similar characteristic trends but the initial values and the range of each signal varied in different cycles. Moreover, the pH signal range (less than one unit) during the different SBR phases was much lower than that of ORP (about 400 mV). For these reasons it was decided to mathematically transform the signals to simplify the learning procedure. Since the NNs have to be used as real-time control, it was not possible to use the maximum values for each cycle. In fact, this value is not known a priori and the calculation cannot be performed on-line. Therefore, the equations adopted for signals transformation are:

\[
\text{ORP}^* = \frac{\text{ORP} - \text{ORP}_0}{100}
\]

\[
\text{pH}^* = \frac{(\text{pH} - \text{pH}_0) \times 100}{100}
\]

where ORP* and pH* are the transformed signals and ORP_0 and pH_0 are the initial values.

The trained NNs were able to predict the nutrient concentration trends (change in slope or process end) but were unable to predict the experimental (true) concentrations during the SBR cycles, in particular with high or low SBR loads. For this reason, to decrease their range of variation (between 0 and 1), chemical concentrations were normalised, according to:

\[
S_N = \frac{S}{S_{\text{max}}}
\]

where \(S_N\), \(S\) and \(S_{\text{max}}\) are the normalised, the measured and the maximum concentration measured, respectively, during the SBR cycle.

After chemical concentration normalisation, calibration (training procedure) results were generally in good agreement with the experimental data. In particular, four hidden neurons in every NN (and two and one neuron in the input and output layer, respectively, for each net) gave rather good (normalised) concentration predictions (Figure 3). Four hidden neurons seemed to be a good compromise between process modelling and data “over-fitting” (where the noise is also fitted). During aerobic condition, the NH4-N trend is more relevant than that of NO3-N for nitrogen removal process control. However, it was preferred to predict both chemicals because the second (NO3-N) may be used to confirm the end of the nitrification process.

The NNs were then validated using experimental data not used for training. Also in these cases, the NNs predictions were in rather good agreement with the experimental data (Figure 4).

To use the NN model as a soft sensor for real-time control, it was necessary to evaluate if it was able to simulate the nutrient trends during the SBR cycle. The NN model was implemented in Labview and it was adopted for on-line prediction of the nutrients concentration. For this purpose, the model has to calculate the nutrient concentration for every step of ORP and pH acquisition value. The “on-line” NNs validation was carried out modifying the feed composition to assess the model performances under dynamic conditions of (synthetic) wastewater characteristic fluctuations. The feed was modified increasing the ammonia,
phosphate and acetate concentrations (see Table 1) of 20, 25 and 30% respectively. Also in this case, the NNs prediction was in rather good agreement with the experimental data, demonstrating the relative robustness of the model. Figure 5 shows the “on-line predictions” results.

The experimental results demonstrated that NNs might be used to predict nutrient behaviour in SBRs, by using ORP and pH signals only. Based on this prediction, a control strategy may be designed as follows. During the anoxic/anaerobic condition, the phase may be stopped when the denitrification and P release processes are ended. This situation may be identified when the nitrate and phosphate predicted concentrations have no or little variation and/or the NO$_3$-N concentrations are below a fixed value. Similarly, during the oxic phase, aeration may be switched off when the PO$_4$-P and NH$_4$-N modelled concentrations are below fixed values. NO$_3$-N values might be used to confirm the end of the nitrification process.

**Conclusions**

The results of this study demonstrated that NN models can be used as “soft on-line sensors” for controlling biological processes in SBRs. By measuring ORP and pH, it is possible to...
recognise the N and P concentrations during the different SBR phases, and consequently to identify the end of the biological nutrient removal processes.

It has been observed that the NN model was effective to predict the behaviour of chemical trends but it was insufficient to predict the exact concentrations of these chemicals.

Considering that simple, cheap and reliable specific sensors to measure N and P concentrations in activated sludge are not available at the moment, NNs could represent an effective tool to reconstruct these concentrations just by measuring ORP and pH (for which reliable and cheap sensors are available).

N and P predictions through NNs could be utilised to design control strategies in biological nutrient removal processes.

References


