Intelligent Control of Sequencing Batch Reactors (SBRs) for Biological Nitrogen Removal

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Abstract

This paper shows the application of several kinds of artificial intelligence techniques in the development of a control system for a biochemical process. A wastewater treatment process for nitrogen removal in a sequencing batch reactor (SBR) is presented first; two different approaches to identify the endpoint of the biological reactions are introduced. The paper compares and analyzes the results for this task by using different AI techniques based on several kinds of neural networks and fuzzy neural networks.

Keywords: biological process, Sequencing Batch Reactor (SBR), nitrification, denitrification, control, dissolved oxygen (DO), intelligent system, neural networks.

1. Description of the task

Water is needed for a lot of different human activities; after being used, it is discharged as wastewater of different kinds: municipal, industrial, agricultural… Wastewater has to be treated before it is returned to the environment, removing polluting chemical compounds (e.g. organic carbon, nitrogen and phosphorus) and pathogenic forms of life such as bacteria, viruses, amoebas and larvae of parasites.
Biological processes are usually employed for the removal of organic carbon and nitrogen from wastewater. Bacteria that agglomerate in flocs of activated sludge convert the harmful compounds into harmless matter such as water, carbon dioxide and nitrogen gas.
The flocs of activated sludge are mixed with the wastewater in a biological reactor; as their density is slightly higher than 1 kg/l, stirring is necessary to keep the flocs in suspension.
Biological wastewater treatment involves several different biological reactions: organic carbon (BOD) is oxidised to water and CO_2, with consumption of oxygen; ammonia is oxidised to nitrate (*nitrification*), again with consumption of oxygen, and nitrate is further reduced to nitrogen gas (*denitrification*). The last reaction is inhibited if dissolved oxygen is contained in the water.

BOD oxidation:
Organic Carbon + $O_2 \rightarrow H_2O + CO_2$

Nitrification/Denitrification:
Ammonia+$O_2 \rightarrow$ Nitrates $\rightarrow$ Nitrogen gas (N_2)

Some biological reactions require that oxygen is supplied into the reactor (aerobic reactions), while other reactions are inhibited by oxygen (anoxic reactions).
Biological wastewater treatment therefore requires several different stages. A typical biological process involves the following sequence of phases:

1. Fill stage: the wastewater is fed into the biological reactor
2. Anoxic phase: nitrates are converted into nitrogen gas. No oxygen has to be supplied.
3. Aerobic phase: organic carbon and ammonia are oxidised. Oxygen has to be supplied.
4. Decant: Stirring is turned off, allowing the activated sludge flocs to settle.
5. Discharge: the clean effluent flows out of the biological reactor.

The different phases can be separated in space (continuous flow activated sludge systems) or in time (Sequencing Batch Reactors).
Unlike the traditional continuous flow activated sludge processes, where different reactions are carried out in separated tanks, SBRs allow the use of a single tank for the whole process.

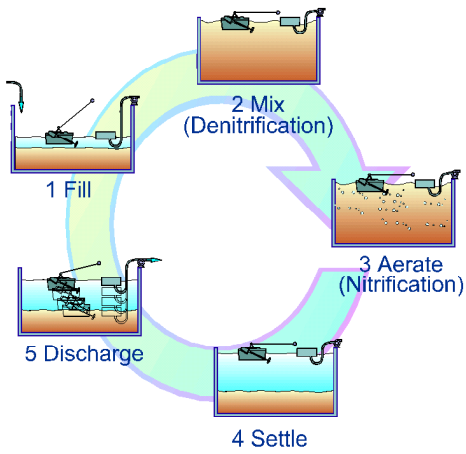

Figure 1. Sequencing Batch Reactor (SBR) Process

The term "Sequencing" means that different reactions are performed in time sequence: one phase starts after the previous one is finished. "Batch" refers to the operation mode of the reactor: during the biological reactions the reactor is closed; there is no influent fed and no effluent discharged. The concentration of a pollutant decreases steadily during the reacting phase; a biological reaction is completed when the concentration of the pollutant drops to zero.

One of the main advantages of the SBR technology is the flexibility, which derives from the possibility of adjusting the duration of the different phases.

Real-time control of the process uses this advantage; a possible control strategy is based on the identification of the endpoint of a biological reaction. Switching to the next phase short after the detection of the reaction endpoint provides an optimum solution for both the process performance and the economics of the plant. In fact, if the duration of a phase is too short, the removal of the pollutants is not complete and the quality of the effluent will not meet the limits imposed by the law. On the other hand, cycles which are longer than necessary decrease the capacity of the plant (volume of wastewater treated per day); an aerobic phase which is too long would also mean wasting energy for aeration.

A cost-effective and reliable way to identify the endpoint of a biological reaction is by on-line monitoring of chemical parameters such as pH (a measure of the acidity of a solution), ORP (Oxidation-Reduction Potential) and DO (Dissolved Oxygen). During a biological reaction a pollutant is converted into harmless compounds, with simultaneous consumption or production of oxygen or acidity. This causes a continuous variation of chemical parameters such as DO, pH and ORP. It can be therefore expected that the endpoint of a biological reaction can be recognised as a discontinuity (a "breakpoint") in the profile of one of these chemical parameters. With the term "profile" we mean a graph where the time is on the x-axes and the measured chemical parameter is on the y-axes.

The reactions in a SBR and their effect on the chemical parameters are shown in Table 1 and Figure 2.

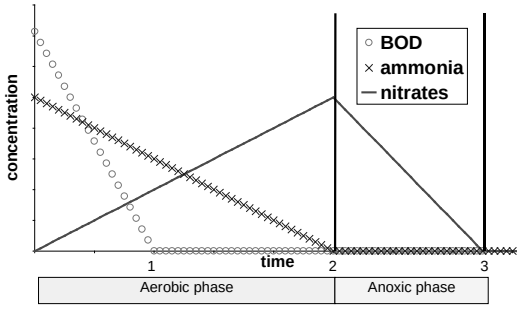

Figure 2. Removal of polluting matter in a SBR.

Table 1. Biological reactions in SBR

Aerobic phase		*Effect on:*
$BOD + O_2 \rightarrow Water + CO_2$	1	DO
Ammonia + O_2 $\rightarrow$ Nitrates + Water + Acidity	2	DO, pH
Anoxic phase		
Nitrates + Acidity + BOD $\rightarrow N_2$ + Water + CO_2	3	ORP, pH

This paper deals with the identification of the reaction endpoints in the DO profile.

Some authors remarked that the endpoint of nitrification in a SBR can be identified as a breakpoint in the DO-profile [1, 2, 3]. Wouters-Wasiak and co-workers [4] remarked that stopping the aeration shortly after its detection would be a good control strategy. A similar procedure was proposed by Koh and co-workers [5] who recognised a breakpoint in the DO-profile at the end of the oxidation of methanol in a pharmaceutical wastewater. Paul and co-workers [6] developed a control-system (INFLEX) for alternated aerobic-anoxic continuous flow activated sludge systems based on ORP- and DO- breakpoint detection.

Ip and co-workers [7] studied an alternating aerobic/anaerobic completely mixed activated sludge system. They recognised the DO-breakpoint at the end of BOD and ammonium removal, and had a further look into its signification. Liao & Lee [8] simulated some DO-profiles in a SBR, but they made no effort to identify the endpoints of the biological reactions.

It was demonstrated mathematically [9] that the endpoint of an aerobic reaction in a SBR can be identified as a bending point in the DO-profile, and as a maximum in the first derivative of the DO-profile (see Fig. 3).

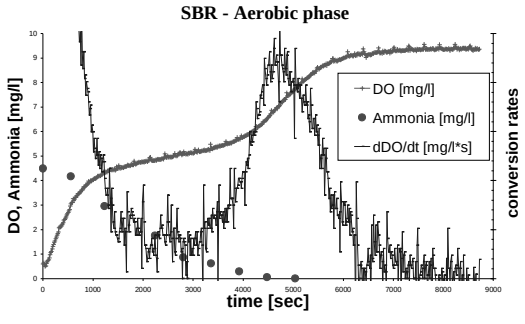

Figure 3. Dissolved Oxygen and ammonia concentration measured in a SBR during the aerobic phase

Automatic on-line detection of this breakpoint allows an efficient control of an SBR-reactor. A control model aiming to achieve this task has to deal with the following problems:

1. Because of the noise in measured DO-data, it is not possible to identify the exact time corresponding to the maximum in the first derivative of the DO-profile, but only a time interval in which this maximum is more likely to be found.
2. Noise in measured DO-data is responsible for false peaks in the first derivative of the DO-profile. These false peaks can be mistaken for breakpoints.
3. When there are two or more aerobic reactions going on at the same time, a breakpoint in the DO-profile will be found at the end of each of them. This is usually the case, as oxygen is used for BOD oxidation and nitrification. The control system has to be able to recognize which breakpoint corresponds to the end of which reaction.
4. The shape of a peak in the first derivative of the DO-profile changes for different conditions in the reactor. It is particularly affected by different values of temperature (Fig. 4), by the intensity of the aeration, and by the activity of the bacteria. The system has to be able to recognize the endpoint of the reaction independently from the values of these parameters.

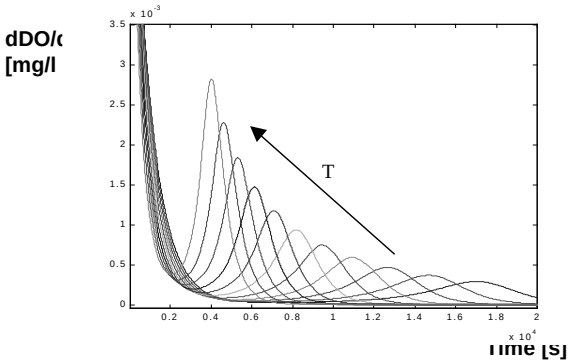

Figure 4. Effect of temperature on the shape of the peak in the first derivative of the dissolved oxygen at the end of nitrification (mathematical model).

This paper presents the partial results of a research project aiming to develop a control system for SBRs based on automatic on-line detection of breakpoints in DO- and ORP-profiles. Traditional mathematical approaches and filters are used to deal with the first two problems. Several breakpoints are identified in every DO-profile, and they have to be assigned to one of the following categories: endpoint of BOD oxidation, endpoint of nitrification, noise. This is a problem of classification, and it can be solved by employing connectionist software techniques such as neural networks and fuzzy neural networks. As it was mentioned above in point 4, the shape of the breakpoints is subject to a high degree of variability. The shape of the DO-profiles can vary depending on biological factors (characteristics of the bacteria), on environmental factors (including the weather), on the hydraulics of the reactor and on the noise. Still, the control system has to be able to classify the breakpoints correctly in a possibly very wide range of different conditions.

2. Methods

The DO data are measured in a 15l lab-scale SBR, which is run in the lab of Waste Solutions Ltd. in Invermay (Mosgiel, Otago). A DO probe is plunged into the reactor; the DO-data are collected at regular intervals (15 or 30 seconds) by a data-logger and are further transmitted to a PC, where they are saved on file.
Two filters in series are applied to remove the noise from the raw data. The first one is a differentiator, giving as an output the first derivative of the dissolved oxygen versus time.
All the peaks in the first derivative are detected by calculating the point in time where the second derivative switches from a positive value to a negative value.
The breakpoints that are detected this way include endpoints of BOD removal, endpoints of nitrification and "false breakpoints" due to the noise. In order to be able to classify them into one of these three categories, some features have to be selected, which allow to characterize and to distinguish them.
Two different approaches have been tried:
1. Five geometrical features were selected that characterize the peak in the first derivative of the dissolved oxygen: the height, the width, the maximum value, the area, and the curvature radius at the top (Fig. 5).
   The main advantage of this approach is that all the information is condensed into a very limited number of features. The main disadvantage is that the absolute values of the DO have to be used; this can cause problems if the DO-probe is not calibrated properly.

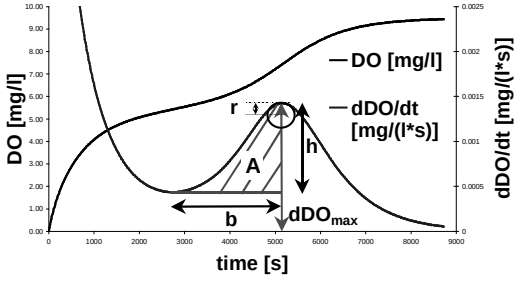

Figure 5. Characterisation of a breakpoint in the DO profile through five geometrical features: Area (A), height (h), maximum value (dDO_{max}), width (b), curvature radius at the top (r).

2. The time between the beginning of the aerated phase and the breakpoint is divided into N equal intervals; different values of N have been tried (N=20, 25, 50). The average value of the dissolved oxygen in each time interval is considered; the values are normalized between 0 and 1 by dividing them with the largest of the N DO values. See Fig. 6.
   The absolute values of the dissolved oxygen in this case are irrelevant, but a neural network with a large number of inputs has to be trained.

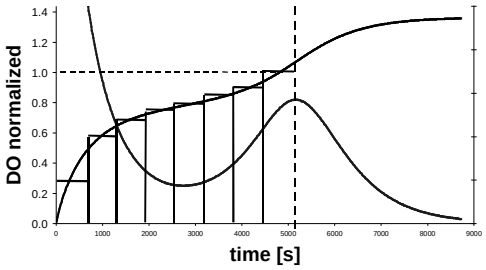

Figure 6. Subdivision of the DO profile into N equal intervals.

The 5 geometrical features or the N normalized DO values can be used as inputs for a neural network with 3 outputs: endpoint of BOD removal, endpoint of nitrification and noise. Each of the 3 outputs can have two values: 0 (False) or 1 (True).

3. Analysis of the results

A dataset of 439 input and output patterns was created after analyzing 201 DO profiles. The dataset was divided into a training set of a 352 patterns and a testing set of 87 patterns to train and test a neural network.
The following AI programs have been used:

- AINET: it is not a neural network, but a NN-like software. It requires no training; the whole dataset is used for verification, one pattern at the time, using all the other patterns as input.
- Qnet97: a very flexible software that allows to create, train and test MLPs with up to 5 hidden layers, and 4 different activation functions. A random subset of data for testing is automatically extracted from the complete dataset. There is therefore no need to split the dataset into different sets for training and testing.
- Qwiknet32: a software that allows to create, train and test MLPs. The trial version was used, with the number of hidden layers limited to one. The training algorithm is extremely fast.
- Matlab: a hybrid neuro-fuzzy system was created, trained and tested using the function "Anfis". As Anfis allows one output only, 3 separated systems had to be created and trained for each output.
- FuzzyCope3: a hybrid system [12] and the software created in the Knowledge Engineering Laboratory (KEL), Information Science Department of the Otago University. FuzzyCope3 has several neural network simulators that include a MLP and a fuzzy-neural network, FuNN [12]. It is available free from: http://kel.otago.ac.nz/.
- EFuNN: an evolving fuzzy-neural network method [10] and the software created in the KEL, Information Science Department of the Otago University. A comprehensive description to the methodology for applying EFuNNs to biological data modeling is presented in [11].

Linear separation of the clusters in a two-dimensional dataset, just by drawing the border lines between the three classes on a graph, gave quite good results, too (See Figure 7). This method though is limited by the number of inputs, not more than two, while AI systems can deal with a larger number of inputs.
The results are reported in Table1.

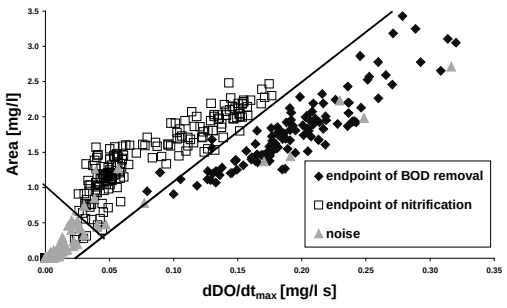

Figure 7. Linear separation of the clusters

Table 1. Results of the classification of breakpoints in the DO-profiles using different methods and different AI programs.

I. Input data: $(dDO/dt)_{max}$, A, b, h, log(rho)

1. Linear separation of the clusters (manually)

	#errors	correct	wrong	
	26	94.08%	5.92%	(dDO/dt)max and Ap

2. AINET

	#errors	correct	wrong	
	54	87.70%	12.30%	(best result, after trying all the possible combinations of the 5 parameters)

3. Multi Layer Perceptron

	#errors	correct	wrong	
train	11	96.85%	3.15%	(QNet97, 1 Hidden Layer: 10 Neurons, sigmoid transfer function)
test	8	91.11%	8.89%	
train	8	97.71%	2.29%	(QNet97, 2 Hidden Layers: 6-6 Neurons, sigmoid transfer function)
test	6	93.33%	6.67%	
train	14	95.99%	4.01%	(QNet97, 3 Hidden Layers: 6-6-5 Neurons, sigmoid transfer function)
test	5	94.44%	5.56%	
train	12	96.59%	3.41%	(QwikNet32, 1 Hidden Layer: 10 Neurons, sigmoid transfer function)
test	3	96.55%	3.45%	
train	10	97.16%	2.84%	(FuzzyCope3, MLP: 1 Layer, 10 Nodes)
test	3	96.55%	3.45%	

4. Fuzzy Neural Networks

	#errors	correct	wrong	
train	11	96.88%	3.13%	(Anfis, Matlab, trained with 24 epochs)
test	6	93.10%	6.90%	
train	4	98.86%	1.14%	(FuzzyCope3, FuNN: 5 Members, 2 Actions, 20 Rules)
test	4	95.40%	4.60%	

5. Evolving Fuzzy Neural Networks

	#errors	correct	wrong	
train	0	100.00%	0.00%	(EfuNN, 2 epochs, 296 nodes)
test	5	94.25%	5.75%	

II. Input data: DO profile divided into N points

6. Multi Layer Perceptron

	#errors	correct	wrong	
train	0	100.00%	0.00%	(Qnet97, N = 50 points, 2 Hidden Layers: 12-12 Neurons, sigmoid transfer function)
test	5	94.44%	5.56%	
train	5	98.57%	1.43%	(Qnet97, N = 25 points, 2 Hidden Layers: 12-12 Neurons, sigmoid transfer function)
test	4	95.56%	4.44%	
train	0	100.00%	0.00%	(Qnet97, N = 20 points, 2 Hidden Layers: 12-12 Neurons, sigmoid transfer function)
test	10	88.89%	11.11%	

7. Fuzzy Neural Networks

	#errors	correct	wrong	
train	3	99.15%	0.85%	(FuzzyCope3, N = 25 Points, FuNN: 5 Members, 2 Actions, 25 Rules)
test	4	95.40%	4.60%	

III. Combination of I and II

8. Multi Layer Perceptron

	#errors	correct	wrong	
train	2	99.43%	0.57%	(Qnet97, N = 25 points+5, 2 Hidden Layers: 10-10 Neurons, sigmoid-gaussian-sigmoid transfer function)
test	5	94.44%	5.56%	

9. Fuzzy Neural Networks

	#errors	correct	wrong	
train	5	98.58%	1.42%	(FuzzyCope3, N = 25 Points+5, FuNN: 5 Members, 2 Actions, 30 Rules)
test	3	96.55%	3.45%	

The two different approaches to characterize the breakpoints seem to lead to similar results. The first approach has the obvious advantage that only 5 inputs are given for a neural network; the training is much faster.
The results obtained using different programs are quite similar, too. With the algorithm of FuNN, FuzzyCope3 is probably the program that gives the best results (in terms of samples that are classified correctly).
AINET did not perform as well as neural networks or fuzzy neural networks; even linear separation of the clusters achieved better results. It is the feeling of the authors that AINET is not the proper tool for this task.
Anfis performed better than AINET and than linear separation of the clusters, but not quite as well as the other programs.
All the other programs perform very well, and the choice of the one rather than the other depends on different aspects.
QNet and QwickNet are MLPs. Their training is very fast, but the trained networks are black box models, with no possibility of extracting rules, and they cannot adapt to new conditions or new training samples. Their use is probably the best option if the second approach is chosen, where training speed is important because of the large number of inputs, and where extracting rules does not make any sense.
FuzzyCope achieves the highest percentage of correctly classified samples in both the training and the test set; it proves therefore to be a good tool. It also allows extracting rules; particularly in the case where the first approach is chosen, this can help to understand how the classification is done.
EFuNN is an evolving fuzzy neural-network: the weights and the number of nodes can be modified automatically during its use, learning from new examples and forgetting old examples. This can be very interesting for an on-line control system, where new data are continuously measured and new samples are created. Unsupervised acquisition of new samples seems to be a major problem though: correctly classified breakpoints could be used for further training and evolving of the network, but how to make sure that their classification is indeed correct?

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