An intelligent controller for automated operation of sequencing batch reactors

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Abstract In this paper the results are presented of original research into the automatic and "intelligent" detection of breakpoints in Dissolved Oxygen (DO) profiles. The research has been based on a large body of data collected from laboratory SBRs operating on synthetic wastewater. Two different approaches were followed to identify the endpoints. The paper analyses and evaluates the results of automatic breakpoint detection on the basis of geometric features in the DO profiles. This was followed by classification of the detected breakpoints using different soft computing techniques based on Neural Network (NN), Fuzzy Neural Network (FuNN) and Evolving Fuzzy Neural Network (EfuNN) software systems for breakpoint classification. A high rate of successful detection and classification was obtained with up to 96% of the decisions made correctly.

In order to overcome the limitations of this system to adapt to dynamically changing process conditions, an intelligent control model was developed by a combination between an Evolving Fuzzy Neural Net (EfuNN) combined with a logic decision unit. This system has the ability to "learn on-the-fly" and adjust its response pattern in order to maintain a high rate of successful breakpoint detection under varying changing process conditions.

This software system has been successfully embedded on a small programmable controller for integration into larger process control systems for the operation of SBR plants.

Keywords Artificial neural network; biological nutrient removal (BNR); breakpoint detection; dissolved oxygen (DO); nitrogen removal; sequencing batch reactor (SBR)

Introduction

Nitrogen removal by SBR processing

The Sequencing Batch Reactor (SBR) represents a modern approach to the requirement of changing process conditions. 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. SBRs are therefore quickly gaining popularity because of their relatively low capital cost.

One of the other main advantages of the SBR technology is the flexibility, which derives from the possibility to adjust 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 shortly 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 required discharge standards. 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 unnecessary aeration energy.

The purpose of the research presented in this paper is therefore the automatic adjustment of the aerobic step of the SBR cycle to its optimal duration to precisely achieve full nitrification. Once this has been achieved, the outcome can also be implemented for the control of

the anoxic step with relatively little additional effort. An SBR that operates time-optimised steps should get the best possible performance out of the invested plant capital.

Breakpoints

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 other 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. A "profile" in this case is obtained by the monitoring over time of one or more of the measured parameters.

In the past several attempts have been undertaken to control the aerobic and anoxic phases of SBR processes using Dissolved Oxygen (Paul *et al*., 1998), and/or pH as trigger signals for the detection of end-of-nitrification (Al-Ghusain *et al*., 1994) and Oxidation Reduction Potential (Yu *et al*., 1997; Wouters-Wasiak *et al*., 1994; Paul *et al*., 1998) and/or pH for end of denitrification detection (Al-Ghusain *et al*., 1994). The detection of the end points of the biological reactions (or "breakpoints") in the SBR monitoring curves has been accomplished with varying degrees of success as the profiles show a high degree of variability depending on many factors such as raw effluent composition, biomass quality, temperature and other environmental factors.

Hegg (1998) demonstrated mathematically that the endpoint of an aerobic reaction in a SBR could be identified as a bending point in the DO-profile, and as a maximum in the first derivative of the DO-profile (Figure 1).

Automatic on-line detection of this breakpoint allows an efficient control of the aerobic step of the SBR cycle. 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 completion of each individual reaction. This is usu-
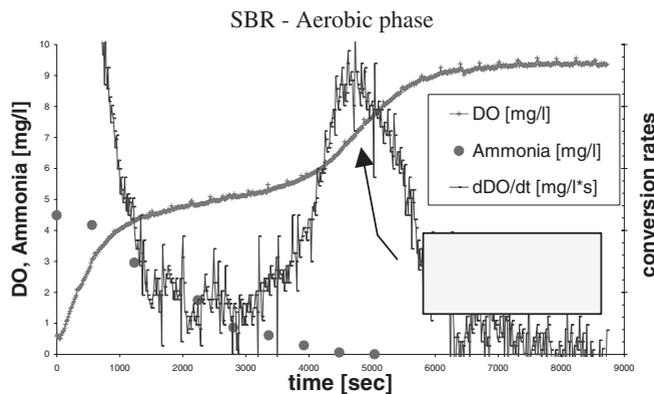

Figure 1 Dissolved oxygen and ammonia concentration measured in a laboratory SBR during the aerobic phase

ally 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, 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 irrespective of how the "shape" and the timing of the DO profile are affected by varying environmental conditions.

Breakpoint detection and classification by artificial neural networks

A number of Artificial Neural Network (ANN) and Fuzzy Neural Net (FuNN) models were tested on their effectiveness to correctly recognise and classify the three types of breakpoints (i.e. End-of-BOD-oxidation, end-of-nitrification, and noise). Neural networks are software systems, which are inspired by the functioning of the brain. To some extent they are able to mimic certain functions such as learning and remembering. Neural net systems are particularly powerful when used for learning complex patterns (this is called *training*) and recognising similar patterns when presented with new data.

The general approach for using neural net systems is "forcing" the networks to "learn" by training with a large amount of data (usually 70–80%) of the available data. The effectiveness of the network is then tested with the remaining 30–20% of the data, which would be new data that the network "hasn't seen before" during the training.

During training, the characteristics of the end-of-BOD-oxidation and end-of-nitrification break points were submitted to inputs of the networks, together with classification data identifying the corresponding breakpoints submitted to the three outputs of the networks. For instance, five geometrical features that were extracted from the profiles (refer to Methods) were used as inputs for a number of neural networks. The networks were configured with 3 outputs: endpoint of BOD removal, endpoint of nitrification, and noise. Each of
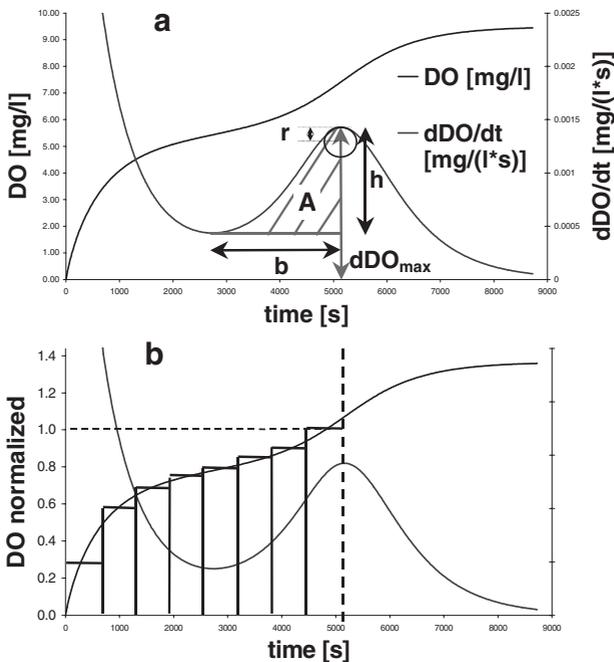
Figure 2 a: Characterisation of a breakpoint in the DO profile through five geometrical features: Area (A), height (h), maximum value (dDOmax), width (b), curvature radius at the top (r). b: Subdivision of the DO profile into N equal intervals

the 3 outputs can have two values: 0 (False) or 1 (True). During the testing phase new data were submitted and successful classification of the breakpoints in the above three categories was recorded by recalling ("reading") the three outputs of the network.

Neural net systems are fairly rigid in the sense that once they are trained to recognise certain patterns they cannot change the recognition features. Should the patterns change, then networks do not have the ability to adapt to modified or new patterns. New developments on Evolving Connectionist Systems (ECOS, Kasabov, 1998; Song *et al.*, 1998) which include Evolving Fuzzy Neural Networks (EfuNN) are focusing on enhanced abilities of neural net systems to *learn* new or changed data and *forget* data that are no longer needed. Some of the work presented in this paper focuses on the adaptive aspect of SBR control systems (De Michele, 2000), which are a prerequisite for effective SBR control under a wide range of varying environmental and climatic conditions.

Methods

Operation of laboratory SBR

A 15 L lab-scale SBR was operated on a 24 hour operating cycle. The reactor was fed with synthetic wastewater under varying conditions of feed concentration and composition. The reactor was fitted with DO, pH and ORP probes. DO profiles were recorded at 15 or 30 second intervals onto a data-logger.

Data processing and analysis

Filtering was applied to the raw data in order to reduce noise. All peaks in the first derivative were detected by calculating the point in time where the second derivative switches from a positive value to a negative value. The breakpoints that were detected by this method include endpoints of BOD removal, endpoints of nitrification and "false breakpoints" due to the noise. In order to be able to correctly classify the breakpoints in one of these three categories, some features were extracted from the geometric characteristics of peaks.

To this end, two different approaches were followed:

1. **Method 1.** Five geometrical features were selected that characterise 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 (Figure 2a). 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.

2. **Method 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 normalised between 0 and 1 by dividing them with the largest of the N DO values (Figure 2b). The absolute values of the dissolved oxygen in this case are irrelevant, but it requires relatively extensive computing resources for further processing by the neural network software that was used for classification of the detected breakpoints.
    Breakpoint classification by artificial neural networks

A dataset of 439 input and output patterns was created after analysing 201 DO profiles. Where applicable, the dataset was divided into a training set of 352 patterns and a testing set of 87 patterns to train and test each neural network system.

The following AI programs have been used:

*   AINET: this is not a neural network, but a neural net-like model. AINET requires no training; and the complete dataset is used for verification, one pattern at a time, using all the other patterns as input.

- Qnet97: a flexible neural net software package which allows to create, train and test Multi Layered Perceptrons (MLP).
- Qwiknet32: a software package that enables the creation, training and testing of MLPs. The trial version was used, with the number of hidden layers limited to one.
- Matlab: a hybrid neuro-fuzzy system was created, trained, and tested using the function "Anfis".
- FuzzyCope3: a hybrid system (Kasabov, 1996, downloadable at *http://kel.otago.ac.nz*).
- An Evolving Fuzzy-Neural Network (EFuNN, Kasabov, 1998; Song *et al*. 1998). Results

Neural net classification

The initial approach was based on the five geometrical features of the first derivative of the DO profile (peak area, peak height, maximum peak value, peak width, curvature radius at top of peak). As neural networks can be used to consider the other extracted features as well one could expect further improvement of these results.

Table 1 shows the results of the neural net classification tests using different detection and neural net classification methods. The results show that generally good recognition rates were obtained, with in some cases more than 95% successful recognition. Methods 1 and 2 for the extraction of geometric features from the DO profiles appear to lead to similar results.

Development of adaptive features

The combination of geometrical features extraction together with the neural net model for classification described in the previous sections would work well and would keep working well in the future if the DO profiles were more or less similar in nature. However, there are many factors influencing the "shape" of the profiles. For instance, the difference between winter and summer temperatures would cause changes in the solubility of oxygen in water. Also temperature differences would affect the physiology of BOD and ammonia oxidising bacteria, and this would also affect the rates of oxygen uptake. As a result, there would be considerable variability in the shape of the profiles.

This means that the previously described control system will most likely fail to automatically determine the correct duration of the nitrification step under all circumstances. For this reason, the research has continued with the development of a more "intelligent system" which has the capability to overcome the limitations associated with the rigidity of neural network systems. There are several requirements for such a control system to be successful:

Table 1 Results of the classification of breakpoints in the DO-profiles using different methods and different neural net based software systems

Method	% Correct recognition of peaks in test set data
Method 1, AINET	87.7
Method 1, QNet 97, MLP	94.4*
Method 2, QNet 97, MLP	95.6*
Method 1 QuickNet32	96.6
Method 1, FuzzyCope3, MLP	96.6
Method 1, ANFIS	93.1
Method 1, FuzzyCope3, FuNN	95.4
Method 2, FuzzyCope3, FuNN	95.4
Method 1, EfuNN	94.3
Method 1 + Method 2, QNet 97, MLP	94.4
Method 1 + Method 2, FuzzyCope3, FuNN	96.6

1. The system must be able to detect when its recognition features are no longer adequate.
2. The system must be able to "learn" and adapt its recognition features as the process characteristics change.
3. The system must be able to make internal adjustments in "real time", which means that there is no loss of control functionality during this process.

The "architecture" of the intelligent control system is schematically shown in Figure 3. The functionality of this system is summarised as follows:

1. **Neural Controller.** This is the neural network system that performs the classification between the end-of-BOD oxidation peak, the end-of-nitrification peak and noise peaks as previously discussed. The classification is based on what the Neural Controller has "learnt" from past experience on correctly classified peaks.
2. **Supervisor.** The Supervisor checks the classification output of the Neural Controller. This unit contains a set of rules, which are designed to test the logic of the classification. One of the most important checks is a test of the DO after the second peak (end-of-nitrification). At that time there would be no BOD or ammonia left so the oxygen demand would be very low. Therefore at that point the DO concentration is an equilibrium between oxygen input by aeration and oxygen consumption by endogenous respiration. As a result, the DO would have reached a maximum value. This DO_{max} is predicted on the basis of an on-line measurement of the temperature in the solution and a reasonable assumption of the atmospheric pressure. If the Supervisor has decided that the recognition of the peaks is correct, then the control of the plant is adjusted according to the end-of-nitrification detection. Should an error be detected then the control system will set a default time value for the duration of the aerobic step.
3. **Neural Estimator.** The Neural Estimator is the "learning part" of the system and is based on an Evolving Fuzzy Neural Network (EfuNN) structure (Kasabov, 1998; Song *et al.*, 1998), which has the ability to "learn on-the-fly". If the score of successful detection and classification deteriorates beyond a certain point because of systematic changes in the conditions of the process then the Supervisor will take a decision to go into a "learning cycle". During the "learning cycle" new knowledge is added to the Neural Net Controller and brings the controller up to date with the modified process conditions. The learning process is reinforced by the Supervisor indicating the incidences of correct recognition. These incidences are "remembered" and so reinforce the learning process.

Although the above procedures have been described for automated control of the aerobic step of the SBR cycle on the basis of DO measurement, the control procedure can be easily extended to include control of the anoxic step using Oxidation Reduction Potential (ORP) measurements.

Towards the development of an on-line intelligent controller
The software system which was developed as a result of this research has limited value for
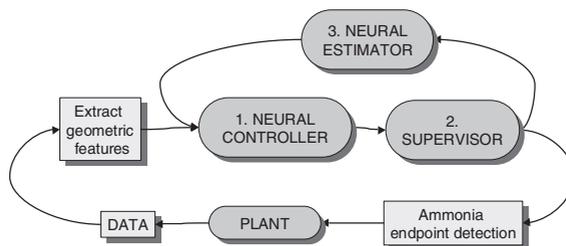

Figure 3 Architecture of the "intelligent" control system for automatic detection of breakpoints

implementation in practice. To this end, efforts have been undertaken to embed the software system on a microprocessor system.

A Z-World Rugged Giant Pk 2100 microprocessor was chosen for this task. The unit is relatively inexpensive and is programmed using a subset of the C programming language. The purpose of the development is future easy integration with existing process control systems such as Programmable Logic Controllers (PLC) or Distributed Control Systems (DCS). "Intelligent" decisions taken by the controller can be signalled to the main process control system by using digital connections or a communications link between the micro controller and the main process control system.

It is expected that the first prototype of this system will be tested on a full-scale plant in the near future.

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Conclusions

Automatic detection of the endpoint of nitrification during the aerobic step as part of the SBR operating cycle was done using a number of geometrical characteristics in the first derivative of the Dissolved Oxygen profile. A combination of geometrical features was classified using neural network software with a very high success rate of up to 96% of all tested cases.

An intelligent control model was developed by a combination of Evolving Fuzzy Neural Net (EfuNN) systems and a logic decision unit. This system has the ability to "learn on-the-fly" and adjust its response pattern in order to maintain a high rate of successful breakpoint detection under varying changing process conditions.

Acknowledgements

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