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Intelligent monitoring system for long-term control of Sequencing Batch Reactors

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Abstract This paper discusses the application of artificial intelligence (AI) concepts to the monitoring of a lab-scale Sequencing Batch Reactor (SBR) treating nitrogen-rich wastewater (sanitary landfill leachate). The paper describes the implementation of a fuzzy inferential system to identify the correct switching sequence of the process and discusses the results obtained with six months of uninterrupted operation, during which the process conditions varied widely. The monitoring system proved capable of adjusting the process operation, in terms of phase length and external COD addition, to the varying environmental and loading conditions, with a percentage of correct phase recognition in excess of 95%. In addition, the monitoring system could be remotely operated through the internet via TCP/IP protocol.
Keywords SBR, Fuzzy Control, Fault Monitoring, Wavelets, On-Line Process Control, Sensors, Energy-Efficient Monitoring, Long Term Monitoring,

INTRODUCTION

Sequencing Batch Reactors (SBRs) are widely used as a flexible and low-cost process for biological wastewater treatment. The SBR process is normally operated on a fixed schedule of a series of phases: fill, react, settle, draw, and idle. (Wilderer et al., 2001; Artan et al., 2001; Artan and Orhon, 2005). In normal design, each phase has a prescribed duration regardless of the process dynamics and wastewater strength; this may result in a highly inefficient operation, hence the need to provide advanced monitoring and control tools to adapt the switching sequence to the actual process requirements.

Since the SBR process is often used in low-cost applications, the key factor is the use of simple and cheap on-line process measurements to infer the concentration of the chemical variables, which are difficult or expensive to measure directly (NH_4^+, NO_x^-, and PO_4^{3-}). There has long been a general consensus that the switching sequence should be adapted to the actual load using pH, Oxido-Reduction Potential (ORP) and Dissolved Oxygen (DO) as indirect process indicators (see e.g. Pavšeli et al., 2001; Spagni et al., 2001).

Leachate generated in old landfills is a high-strength wastewater and is characterized by a low BOD/TKN ratio. Therefore, nitrogen removal can be achieved only if an external biodegradable COD source is provided for the denitrification process.

The aim of this study is to develop a robust and reliable monitoring tool for adjusting the phase length and COD addition in SBRs treating sanitary landfill leachate.

This research is the result of a peer cooperation among ENEA, the University of Florence and National Instruments Italy to test the potentials of monitoring systems applied to biological wastewater treatment processes.

Treatment system (SBR)

A lab-scale SBR (working volume of 20 L) treating leachate generated in an old landfill was operated at ENEA, Water Management Division laboratory in Bologna, Italy, with a full cycle composed of a series of 4 sub-cycles (fill, anoxic and oxic react), followed by one hour of settling. The sequence of sub-cycles used in the present study, is typical when dealing with concentrated wastewaters. On the basis of characteristics of the leachate used in the present study (Table 1), sodium acetate was added during the anoxic phase in order to supply biodegradable COD for denitrification. The SBR was equipped with pH, ORP and DO sensors (WTW, Weilheim, Germany). More details of the treatment system are reported in Spagni et al. (2007).

Table 1 – Main leachate characteristics and variability, with n representing the number of samples.

	unit	Mean	Max	Min	SD	n
pH	-	8.00	8.70	7.55	0.30	19
CODt	mg/L	1615	3060	528	652	19
CODf	mg/L	1493	2980	440	632	19
BOD_5	mg/L	301	1000	30	467	4
TKN	mgN/L	1082	1610	252	372	18
NH_4^+-N	mgN/L	958	1519	167	405	19
Ptot	mgP/L	5.7	9.5	2.1	2.5	16

Structure of the monitoring system

The process signals (DO, pH and ORP) were acquired through a Digital Acquisition (DAQ) Board 6024E (National Instruments, Austin, TX, USA) and monitored by a local PC with TCP/IP internet connection. To close the feed-back loop a bank of solid-state switches, operated by the DAQ digital outputs, controlled the peristaltic pumps (feed, effluent extraction and sludge waste) the stirrer and the aerator. The complete monitoring system is shown in Figure 1. The monitoring and control system was developed in the LabView™ software platform (National Instruments, Austin, TX, USA), which provided all the necessary data acquisition and processing functionalities and also allowed remote operation its web publishing capabilities .

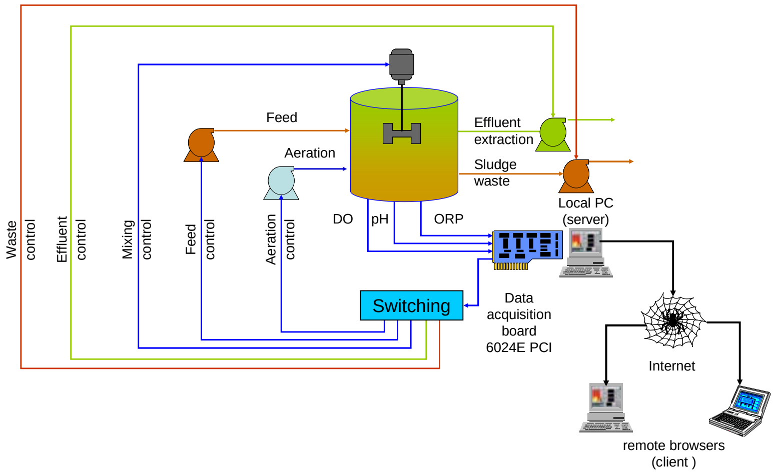

Figure 1 - Monitoring and control system designed around the SBR pilot plant, providing the relevant feedback loops and internet capability.

The basic operations performed by the monitoring system were:

- Phase-end recognition and switching: this resulted in time saving with respect to the fixed-timing switching scheme. Phase-end operations included on/off switching of aeration and mixing;
- Cycle-end involved operation of effluent extraction and sludge waste pumps;
- Organic carbon (acetate) addition for denitrification.

PROCESS CONTROL BY PATTERN RECOGNITION

The existence of significant process patterns in the SBR cycle and its detection by artificial intelligence algorithms have been extensively demonstrated (see e.g. Luccarini et al.,2001; Marsili-Libelli et al., 2001; Spagni et al., 2001; Sin et al., 2004; Bae et al., 2006; Marsili-Libelli, 2006). However, never before these features have been incorporated in a stand-alone monitoring system conceived for long-term unattended operation. After a detailed investigation the most relevant behaviours indicating the end of the anaerobic/anoxic and the aerobic phases in the case of nitrogen removal were defined (Pavšeli et al., 2001; Bae et al., 2006). If phosphorus removal is also required an extended list of indicators can be defined (Spagni et al., 2001; Sin et al., 2004; Marsili-Libelli, 2006). From Table 2 it appears that all the relevant indicators are composed of signal derivatives, hence the need to filter the process data and derive them in a numerically robust way.

Table 2 - Meaningful process indicators used by the pattern recognition algorithm.

Phase	End of process	Indicator
Anaerobic/Anoxic	Denitrification	Nitrate knee
Aerobic	Nitrification	• Sharp DO increase • Ammonia valley • ORP discontinuity $\frac{dpH}{dt} \rightarrow 0+ \quad \frac{dDO}{dt} \rightarrow 0+$

The use of the second ORP derivative is justified by the need of detecting the important "nitrate knee" discontinuity, marking the depletion of nitrate and the transition from anoxic into anaerobic conditions. These conditions are highlighted in Figure 2, showing an operational record from the pilot SBR process considered in this study.

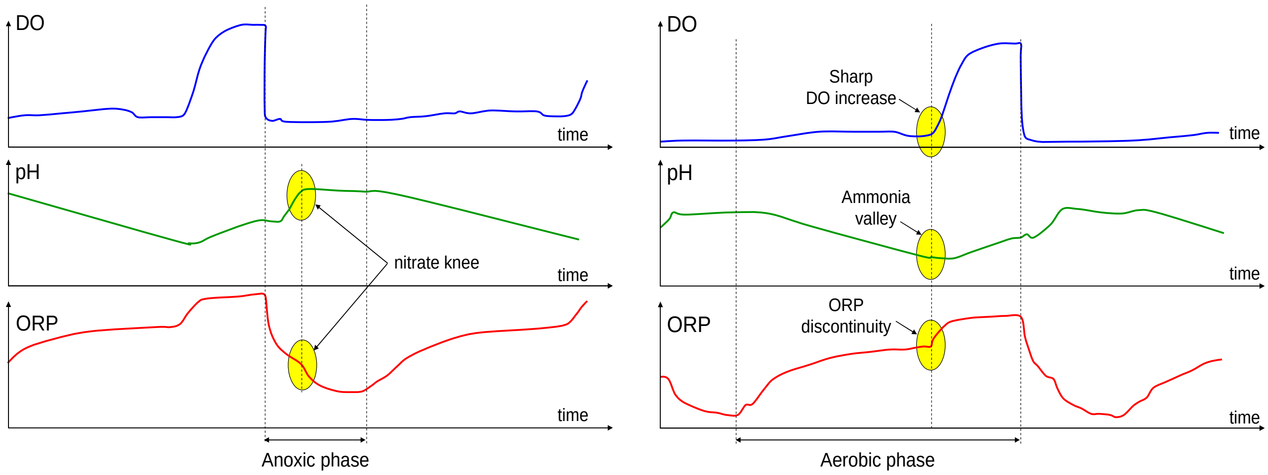

Figure 2 - Relevant patterns indicating the termination of the anoxic/anaerobic phase (left) and the aerobic phase (right).

MONITORING SYSTEM

The monitoring system is composed of a number of successive operations on the data, as shown in Figure 3. Right after acquisition, the data are validated and denoised using a wavelet filter, then numerical derivation is performed and a fuzzy inference algorithm is used to detect the end of the current phase. The ensuing decision to terminate the phase activates the relevant actuators, thus closing the control loop. The sequence of operations in Figure 3 is now briefly reviewed, though for space reasons not all the procedures can be described in details. The interested reader is referred to Marsili-Libelli (2006) for a detailed description of the wavelet filtering and the principles of the fuzzy inferential system, though in this application a linguistic approach was followed, instead of the fuzzy clustering procedure used in that paper. Another fuzzy applications in the control SBRs is described in Bae et al., 2006.

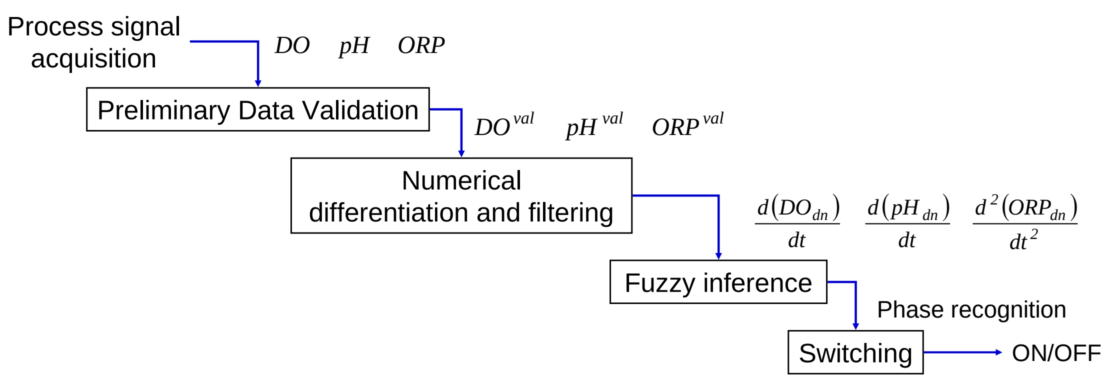

Figure 3 - Structure of the monitoring system. The suffix *val* stands for "validated" and the *dn* for "denoised".

Preliminary data validation (PDV) algorithm

The key to successful monitoring is the ability to decide whether the acquired data are meaningful and possibly correct acquisition or sensor errors, in other words to provide a Preliminary Data Validation (PDV) algorithm. This procedure is the front-end of the monitoring system and is based on an educated comparison between the last acquired sample and the previously validated data. PDV tends to regularize data by removing sudden and unexplained variations between adjacent samples. A decision variable is defined as the absolute difference between the last sample u_i and the already validated previous one u_{i-1}^{Val}, i.e. $Z = \left| u_i - u_{i-1}^{Val} \right|$. The data validation depends on the value of Z, according to which one of the following actions is taken:

- Region A: the sample u_i is accepted without modifications, i.e. $u_i^{Val} = u_i$
- Region B: the validated sample is obtained as the weighted average between u_{i-1}^{Val} and u_i, i.e. $u_i^{Val} = \gamma_1 \cdot u_i + \gamma_2 \cdot u_{i-1}^{Val}$
- Region C: The sample is rejected and substituted with the previous validated on, i.e. $u_i^{Val} = u_{i-1}^{Val}$

The values of the weights γ_1 and γ_2 are shown in Figure 4 as a function of Z.

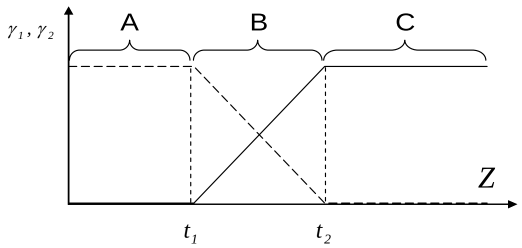

Figure 4 - Validation action as a function of the auxiliary variable Z.

The PDV algorithm must decide whether the variation u_t - u_{t-1} is due to a sensor failure or is coherent with the process evolution. For this reason the breakpoints t_1 and t_2 are adaptive to accommodate the process variations. They are defined by the relations $t_1 = \left| \sigma \right| + \left| \alpha \Delta u_i \right|$ where σ is the noise standard deviation and $\Delta u_i = u_i - u_{i-1}$ is the first variation of the data. Likewise t_2 is defined as $t_2 = t_1 + \left| \beta \Delta^2 u_i \right|$, where $\Delta^2 u_i$ is the second data variation. The adaptation algorithm requires the estimation of three parameters: noise, first variation, second variation. The standard deviation of the measurement noise is directly estimated from the data through a moving window of 1000 samples. The first variation is computed as the linear regression on the last ten samples. As a result, the t_1 value increases with a real variation of the data, widening the acceptance range and avoiding the rejection of u_i whenever its variation is not due to noise but to a real process change. In fact if the variation tends to *0*, t_1 tends to σ and $t_2 \rightarrow t_1$. Incorporating the second variation into the algorithm requires the development of a model to judge if a trend variation is justified by the process features. The second rate of change widens the (t_1, t_2) interval, where the weighted average is used. In this way the algorithm still keeps track of the data and reconciliation occurs when the new sample differs from the previous by less than t_1. The weighting coefficients for the three measured variables are shown in Table 3. If a sudden process variation occurs such that u_t - $u_{t-1} \geq t_2$ the algorithm looses track of the data and substitutes the last data, which are deemed wrong, with constant values equal to the last validated sample. To avoid this hook-up the data noise is considered: if *n* constant values are observed the algorithm is disconnected and the data are simply fed through. The algorithm is connected again as soon as *m* consecutive inputs satisfy the relation $u_t - u_{t-1} < t_1 + 0.5(t_2 - t_1)$. The selection of *m* and *n* is based on the following considerations: if *n* increases, the algorithm can cope with sustained error conditions, but at the same time its disconnection is delayed. On the other hand, increasing *m* delays reconnection with the possibility of loosing valuable data. The best values of the PDV parameters for this monitoring application are shown in Table 3.

Table 3 - Weighting coefficients for the Preliminary Data Validation algorithm.

	Noise σ	First variation α	Second variation β	n	m
DO	0.04	4.5	60.0	3	3
pH	0.0035	3.3	70	14	3
ORP	0.5	5.0	225.0	3	3

The large value of *n* for the pH is due to the fact that this parameter is not subject to sudden variations and a large *n* enables the algorithm to cope with a sustained malfunctioning. In fact the pH signal was found to be the most disturbance-affected one.

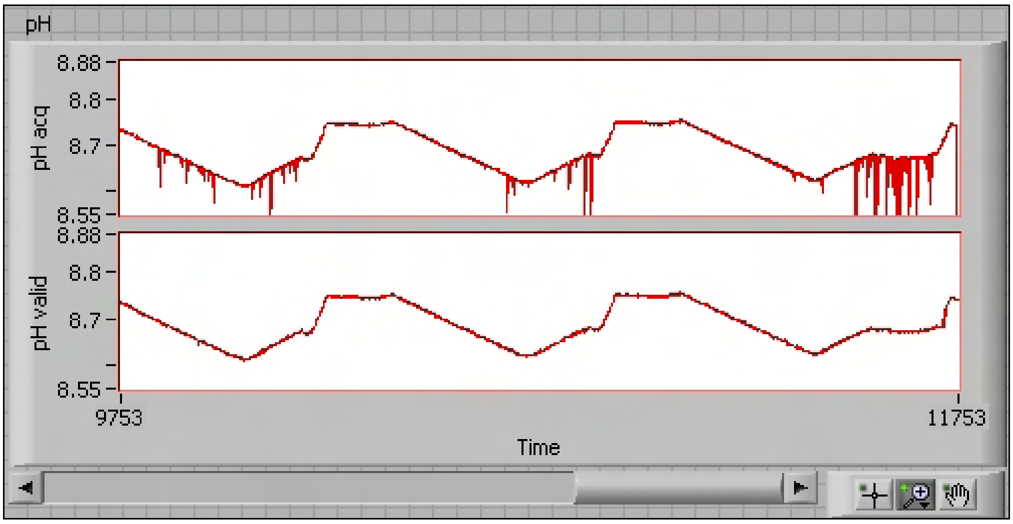

Figure 5 - A sample of pH data before (above) and after (below) the PDV processing. The many artefacts, appearing as large spikes in the original signal, have been entirely eliminated in the validated data.

Numerical derivation and wavelet denoising

This procedure is entwined with the previous PDV algorithm in the sense that in some instance it is preferable to avoid PDV and directly process the data with the wavelet filter in view of their derivation. Further, wavelet filtering is repeatedly applied after each derivation, to smooth out the numerical noise. The relationship among PDV wavelet filtering and numerical derivation, implemented with second-order central differences, is shown in Figure 6. The wavelet filtering was performed with the Daubechies **db8** wavelet. For a thorough description of the wavelet theory the reader is referred to Polikar (1999), whereas its application to the SBR process is described in Marsili-Libelli (2006).

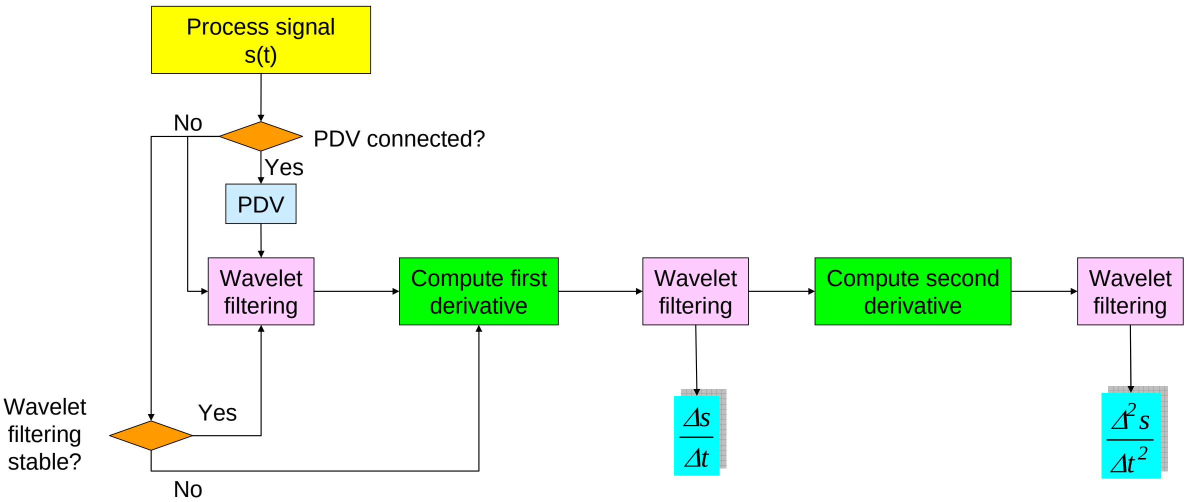

Figure 6 - Extracting the information from the process signals involves repeated application of the wavelet filtering after the Preliminary Data Validation algorithm (PDV).

Fuzzy inferential system

This algorithm is designed to detect whether the conditions occur to terminate the current phase, according to the relevant patterns of Table 2 and Figure 2. The complete monitoring and control system driving the switching logic is composed of the inferential fuzzy module, supplemented with overriding "hard-limit" controls for safety reasons.

Two fuzzy inferential systems have been defined, one for each phase (anoxic/anaerobic and aerobic). The end of the phase, according to the indicators of Table 2, are detected by maximizing the degree of truth of a set of fuzzy implication based on the first derivative of DO and pH and the second derivative of ORP. Defining three membership functions for each phase, a complete set of $3^3 = 27$ fuzzy rules was obtained for each of the two recognition systems. The fuzzy inference system was implemented using the LabView PID Control Toolkit ™.

The user interface of the monitoring system (front panel) is shown in Figure 7. The left panel contains the actuators, the right control are used to set the deterministic timers. The central graphic shows the three main process signals (DO, pH, ORP) together with an indication of the fuzzy recognition and phase status.

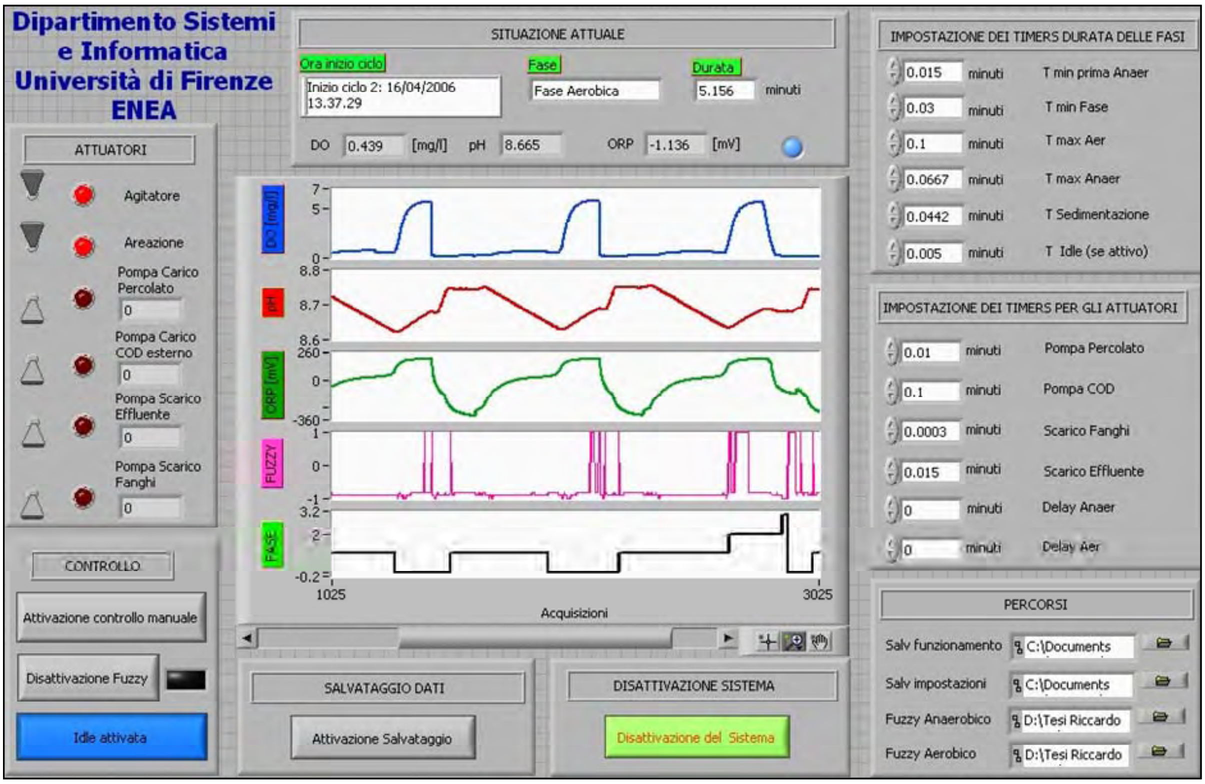

Figure 7 - LabView™ front panel of the monitoring system.

System operation via the internet

The system can be remotely operated through the internet using the web publishing capabilities of LabView™ Virtual Instruments (VI) and the TCP/IP protocol. It suffices to specify the IP address and port of the local PC, the name of the VI and a password. Any authorised PC equipped with the LabView runtime module can access the visualize the VI and take control of the front panel.

ANALYSIS OF LONG-TERM OPERATION

The system was continuously operated from March to August 2006, under the supervision of the fuzzy monitoring system just described, which proved capable of handling the seasonal temperature variations and several feed changes. Some intervals of this uninterrupted operation are now analyzed. The initial application of the fuzzy monitoring system, in the period 7 April - 21 May 2006, is shown in Figure 8, where three interesting operational periods can be singled out. Period A represents a stable operation with constant process parameters, whereas during period B the plant increases its efficiency requiring progressively shorter cycle lengths to process the same amount of feed. Notice the large reaction of the process when the feed is momentarily decreased between A and B periods. The reverse is true during period C, when after a brief feed decrease, the efficiency is lower and longer cycle lengths are required to process the same feed. These variations may be due to the varying biomass response, but the monitoring system is capable of adjusting the process operation, in terms of aeration and cycle length, accordingly.

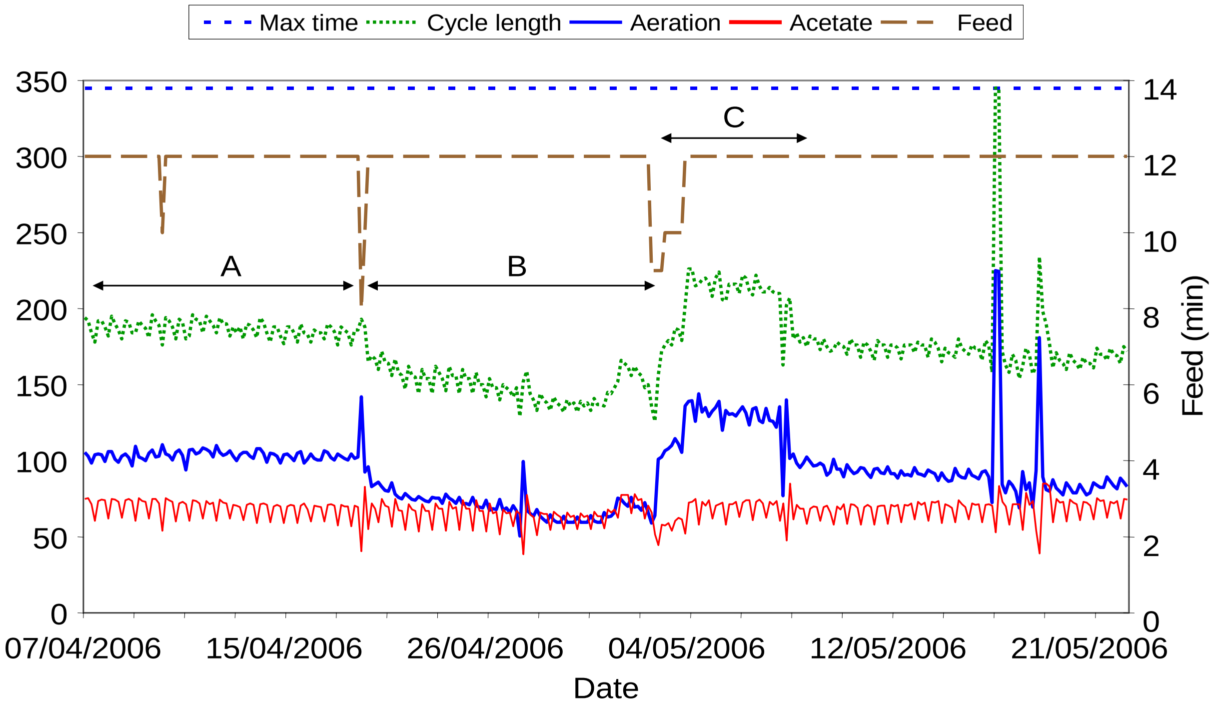

Figure 8 - Initial application of the fuzzy monitoring system. Three operational periods (A, B, C) are analyzed.

Two further operational records are shown in Figure 9. The left plot refers to the period 13 June - 12 July 2006, during which the feed was progressively increased: in the first part (up to 24 June) the process parameters were adjusted accordingly by the monitoring system. Then, in the period 24 - 28 June (A_1) both cycle length and aeration markedly increased, returning to their normal values in spite of a further feed increase, denoting an increased removal efficiency of the biomass. The right plot refers to another period of increased feed, followed by an abrupt load decrease. Three differing behaviours can be selected: in period A_2 the feed was continuously increased and all process parameters varied accordingly, whereas during period B_2, when the load was kept constant at its highest value, again the biomass appears to adjust to this condition and decreases some of its requirements, cycle length and aeration but not acetate addition. Finally, during the ensuing low-feed period (C_2) the operation is less stable, denoting the difficulty of the biomass to adjust to this new condition. In all cases, however, a correct process operation was provided by the monitoring system.

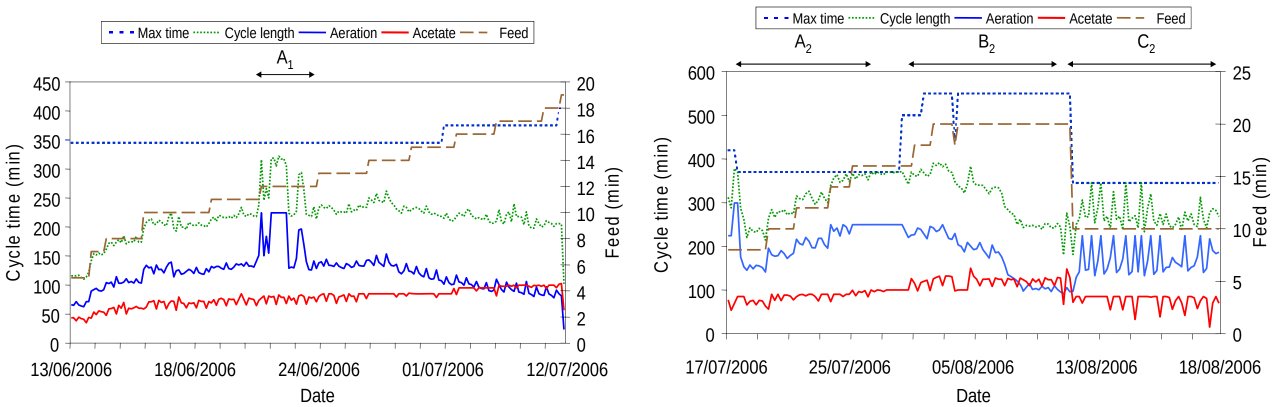

Figure 9 - Other examples of automated operation: monotonic load increase (left) and load increase followed by an abrupt load decrease (right). In both cases the fuzzy monitoring system automatically adjusted to the changing operating conditions without manual intervention.

CONCLUSIONS

A long-term monitoring system for the SBR process, based on artificial intelligence concepts, has been designed and engineered to control a 20L SBR pilot plant both locally and remotely. The inferential controller is based on a preliminary data validation algorithm (PDV) followed by a numerical filtering and differentiation and a fuzzy inferential system to decide the most appropriate control action, consisting of aerobic/anaerobic phase switching, mixing, acetate addition, water and sludge extraction. The system was implemented in the LabView™ software platform and could be operated by a remote station using the platform native web publishing tools. Six months of continuous, unattended operation with a correct phase-end detection in excess of 95% demonstrated the robustness of the monitoring system, which was capable of steering the process through the seasonal temperature variations and several feed changes.

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