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

S. Marsili-Libelli, A. Spagni and R. Susini

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.

Key words | energy-efficient monitoring, fault monitoring, fuzzy control, long term monitoring, on-line process control, SBR, sensors, wavelets

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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 (Artan *et al.* 2001; Wilderer *et al.* 2001; Artan & 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 reliable and economical 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 by 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 COD/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 the ENEA

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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

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).

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 remotely monitored via 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 system is shown in Figure 1. The monitoring and control software was developed in the LabView™ software platform (National Instruments, Austin, TX, USA), which provided all the necessary data acquisition and processing capabilities and allowed remote operation through its web publishing capabilities.

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. They included on/off switching of aeration and mixing;
- *Cycle-end operations:* 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,

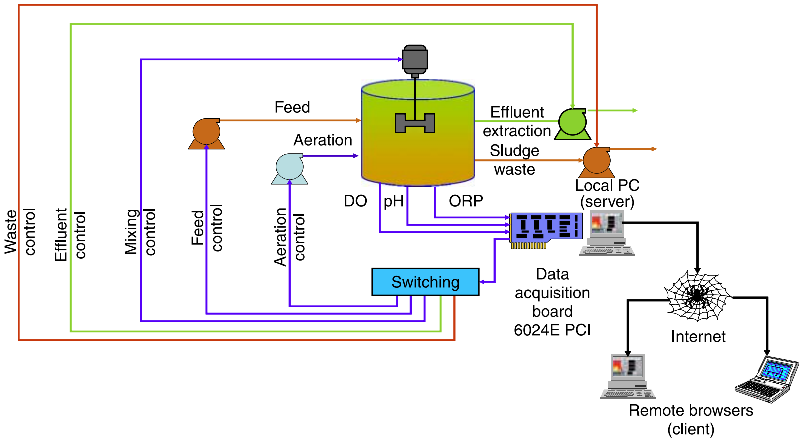


Figure 1 | Monitoring and control system designed around the SBR pilot plant, providing the relevant feedback loops and internet capability.

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 $dpH/dt \to 0+$ $dDO/dt \to 0+$

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.

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 transitions are highlighted in Figure 2, showing an operational record from the pilot SBR process considered in this study.

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 application in the control SBRs is described in Bae *et al.* (2006).

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. $Z = |u_i - u_{i-1}^{\mathrm{Val}}|$. The data validation depends on the value of Z, according to which one of the following actions is taken:

- *Action A:* the sample u_i is accepted without modifications, i.e. $u_i^{\mathrm{Val}} = u_i$

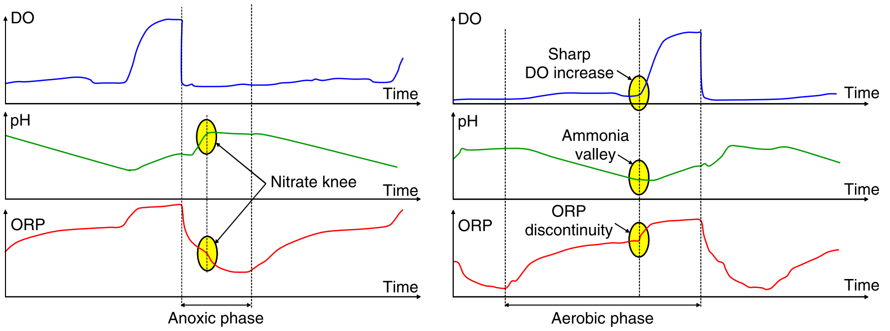


Figure 2 | Relevant patterns indicating the termination of the anoxic/anaerobic phase (left) and the aerobic phase (right).

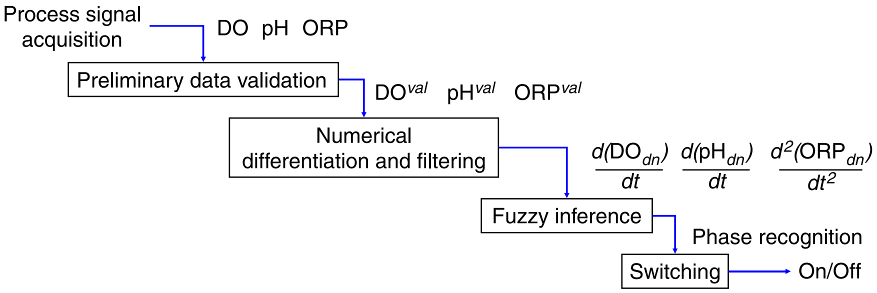


Figure 3 | Structure of the monitoring system. The suffix *val* stands for "validated" and the *dn* for "denoised".

- *Action B:* the validated sample is obtained as the weighted average between u_{i-1}^{Val} and u_i, i.e. $u_i^{\mathrm{Val}} = \gamma_1 u_i + \gamma_2 u_{i-1}^{\mathrm{Val}}$
- *Action C:* The sample is rejected and substituted with the previous validated one, i.e. $u_i^{\mathrm{Val}} = u_{i-1}^{\mathrm{Val}}$

The values of the weights γ_1 and γ_2 are shown in Figure 4 as a function of 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 relation $t_1 = |\sigma| + |\alpha \Delta u_i|$ 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 $t_2 = t_1 + |\beta \Delta^2 u_i|$, where $\Delta^2 u_i$ is the second data variation. The adaptation algorithm requires the estimation of three parameters: noise, first variation, second variation. An example of PDV on the pH signal is shown in Figure 5.

Numerical derivation and wavelet denoising

Data filtering is normally based on the concept of transform and is a way of extracting the information contained in the data. Wavelets are finite-duration signals which can be used to replace sinusoids as basis functions through which the data are represented. In this way time and frequency analysis can be combined through a variable windowing technique and filtering adapts to the time-varying nature of the signal. Wavelets have been widely applied in communications, speech and image processing and are commonly used to process biomedical signal, but their use in the environmental area is virtually unknown. A given signal *s(t)* can be expanded in terms of the (discrete) wavelet $\psi(a,b,t)$ as

$$s(t) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} c_{jk} 2^{j/2} \psi(2^j t - k) \tag{1}$$

where the wavelet functions $\psi(2^j t - k)$ are scaled (by 2^j) and shifted (by k) versions of the original wavelet $\psi(t)$. The coefficients c_{jk} contain the information about the signal behaviour around the scale 2^{-j} around time $k \times 2^{-j}$. The summation limits in (1) in theory are infinite, but in practice extend just up to the limits of the wavelet functions. The signal decomposition at the k level is fully

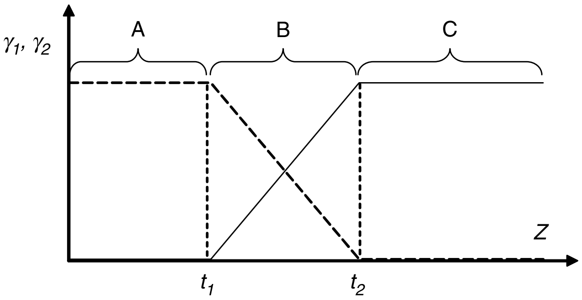


Figure 4 | Weights γ_1 and γ_2 as a function of the auxiliary variable *Z* in the validation actions.

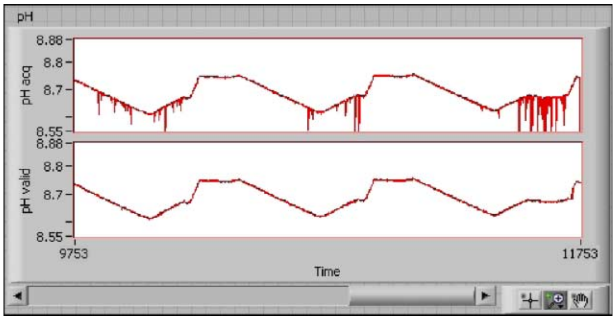


Figure 5 | A sample of pH data before (above) and after (below) the PDV processing. The many artefacts, appearing as large spikes in the original signal, have been entirely eliminated in the validated data.

represented by the coefficients of the *Approximation* cA_k and of the *Detail* cD_k. The latter contains most of the noise component which *adapt* to the signal behaviour. Therefore, the noise component can be limited by thresholding, i.e. compressing the coefficients with magnitude below the threshold towards zero. Then the signal is denoised by combining the original *Approximation* coefficients cA_k and the *modified Details* cD_k. The resulting signal is smooth enough to produce a sufficiently stable numerical derivative. In this application this is applied twice: first to the acquired signals and then to their numerical derivatives, using a Daubechies (**db8**) basis wavelet in a 2-level decomposition.

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).

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, complemented with overriding "hard-limit" controls for safety reasons.

Two fuzzy inferential systems have been defined for detecting the end of 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, as shown in Table 3, where N, Z, P stand for the negative, zero and positive qualifier for each input (antecedents) and Low (L), Negative minus (N −), Negative plus (N +), High (H) are the qualifiers for the consequent. The weights w denote the importance of each rule and the centre-of-gravity defuzzification method was adopted. 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.

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

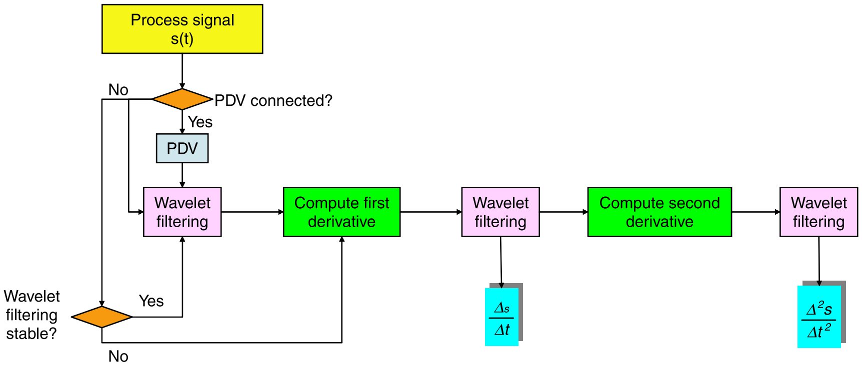


Figure 6 | Extracting the information from the process signals involves repeated application of the wavelet filtering after the Preliminary Data Validation algorithm (PDV).

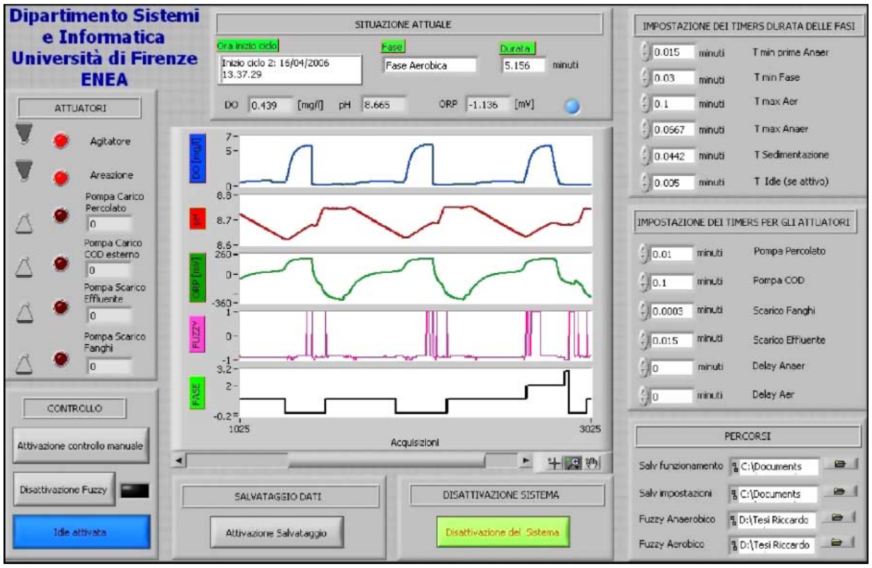
Table 3 | Fuzzy inference rules for the end-of-phase detection

End of aerobic phase					**End of anaerobic phase**				
Antecedents			**Cons.**	**w**	**Antecedents**			**Cons.**	**w**
Ndo	Nph	Norp	L	0.1	Ndo	Nph	Norp	L	0.1
Ndo	Nph	Zorp	N−	0.3	Ndo	Nph	Zorp	N−	0.3
Ndo	Nph	Porp	L	0.1	Ndo	Nph	Porp	L	0.1
Ndo	Zph	Norp	N−	0.3	Ndo	Zph	Norp	N−	0.3
Ndo	Zph	Zorp	N+	0.5	Ndo	Zph	Zorp	N+	0.5
Ndo	Zph	Porp	N−	0.3	Ndo	Zph	Porp	N−	0.3
Ndo	Pph	Norp	L	0.1	Ndo	Pph	Norp	L	0.1
Ndo	Pph	Zorp	N−	0.3	Ndo	Pph	Zorp	N−	0.3
Ndo	Pph	Porp	L	0.1	Ndo	Pph	Porp	L	0.1
Zdo	Nph	Norp	L	0.1	Zdo	Nph	Norp	N−	0.1
Zdo	Nph	Zorp	N−	0.3	Zdo	Nph	Zorp	N+	0.3
Zdo	Nph	Porp	L	0.1	Zdo	Nph	Porp	N−	0.1
Zdo	Zph	Norp	N−	0.3	Zdo	Zph	Norp	N+	0.3
Zdo	Zph	Zorp	N+	0.5	Zdo	Zph	Zorp	H	0.5
Zdo	Zph	Porp	N−	0.3	Zdo	Zph	Porp	N+	0.3
Zdo	Pph	Norp	L	0.1	Zdo	Pph	Norp	N−	0.1
Zdo	Pph	Zorp	N−	0.3	Zdo	Pph	Zorp	N+	0.3
Zdo	Pph	Porp	L	0.1	Zdo	Pph	Porp	N−	0.1
Pdo	Nph	Norp	N−	0.3	Pdo	Nph	Norp	L	0.3
Pdo	Nph	Zorp	N+	0.5	Pdo	Nph	Zorp	N−	0.5
Pdo	Nph	Porp	N−	0.3	Pdo	Nph	Porp	L	0.3
Pdo	Zph	Norp	N+	0.5	Pdo	Zph	Norp	N−	0.5
Pdo	Zph	Zorp	H	1.0	Pdo	Zph	Zorp	N+	1.0
Pdo	Zph	Porp	N+	0.5	Pdo	Zph	Porp	N−	0.5
Pdo	Pph	Norp	N−	0.3	Pdo	Pph	Norp	L	0.3
Pdo	Pph	Zorp	N+	0.5	Pdo	Pph	Zorp	N−	0.5
Pdo	Pph	Porp	N−	0.3	Pdo	Pph	Porp	L	0.3

the VI and a password. Any authorised PC equipped with the LabView runtime module can access 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



Ora inizio ciclo: Inizio ciclo 2: 16/04/2006 13.37.29

Fase: Fase Aerobica

Durata: 5.156 minuti

DO 0.439 [mg/l] pH 8.665 ORP -1.136 [mV]

Pompa Carico Percolato: 0

Pompa Carico COD esterno: 0

Pompa Scarico Effluente: 0

Pompa Scarico Fanghi: 0

0.015 minuti T min prime Anaer

0.03 minuti T min Fase

0.1 minuti T max Aer

0.0567 minuti T max Anaer

0.0442 minuti T Sedimentazione

0.005 minuti T Idle (se attivo)

0.01 minuti Pompa Percolato

0.1 minuti Pompa COD

0.0003 minuti Scarico Fanghi

0.015 minuti Scarico Effluente

0 minuti Delay Anaer

0 minuti Delay Aer

Salv funzionamento: C:\Documents

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

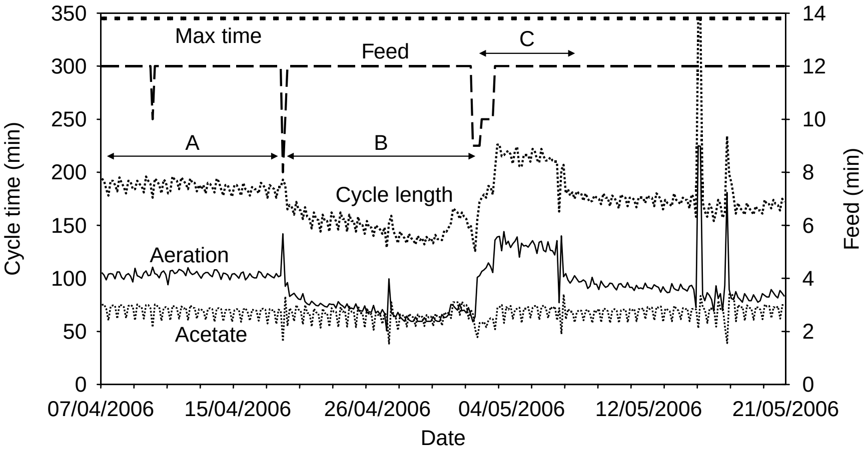

Figure 8 | Initial application of the fuzzy monitoring system. Three operational periods (A, B, C) are analyzed.

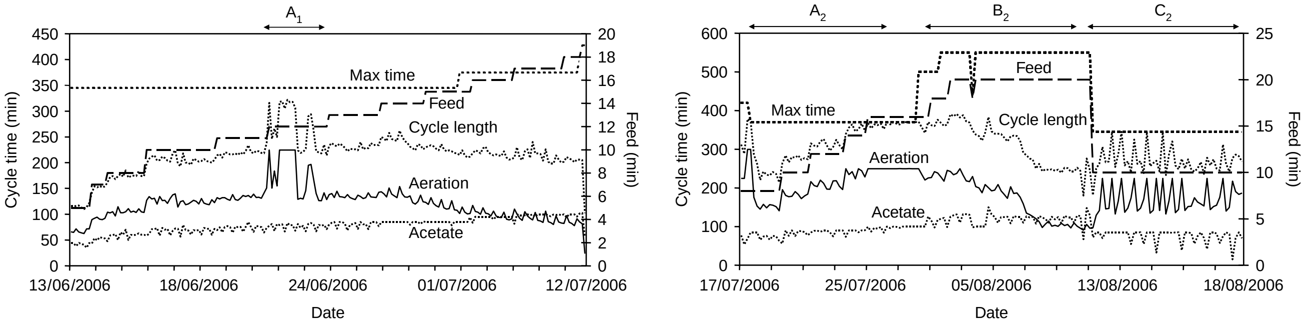

Figure 9 | Other examples of automated operation: monotonic load increase (left) and load increase followed by an abrupt load decrease (right). In both cases the fuzzy monitoring system automatically adjusted to the changing operating conditions without manual intervention.

capable of adjusting the process operation in terms of aeration and cycle length.

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 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 improved 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.

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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