TOWARDS AN INTEGRATED CO-OPERATIVE SUPERVISION SYSTEM FOR ACTIVATED SLUDGE PROCESSES OPTIMISATION

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Abstract: This paper deals with the design of an integrated co-operative supervision system to optimise activated sludge wastewater treatment. For this purpose a biological wastewater treatment pilot plant, suitable for industrial up scaling and composed of a biological reactor, a settler, sludge recirculation and aeration systems, has been carried out. The reactor configuration is adjustable to treat both urban and industrial wastewater. The pilot plant scale allows to reproduce industrial hydrodynamics and is illustrated by RTD (Residence Time Distribution) measurements. The supervisory system includes instrumentation and industrial supervisor. The integrated co-operative supervision approach emphases the importance of process behavior anticipation. Information for the human operator will be extracted from a suitable model and a state estimator, which results are presented.

Keywords: Water pollution – Biotechnology – Process equipment – Supervision – Modelling – Observers

1. INTRODUCTION

Activated Sludge Process is a biological treatment commonly used for urban and industrial wastewater. Nevertheless performances improvement requires an efficient supervisory system which is still a research subject. On one hand, numerous laboratory-scale pilot plants have been developed for many years but their small size weakens hydrodynamics influence on the treatment efficiency. Therefore results can be hardly implemented on real processes. On the other hand, some experiments (such as toxicity, foaming …) cannot be carried out on industrial plant because working conditions must be maintained. Consequently, a medium pilot plant scale seems to be judicious. In addition the pilot plant configuration has to be adjustable so as to reproduce most of full scale encountered configurations: urban/industrial effluent, adjustable reactor configuration, etc.

A modular pilot plant has been realized and is shown on figure 1. It may be used for a wide range of experiments as for example: toxicity tests, fungi treatment tests instead of bacteria use, hydrodynamics influence studies, biological modelling and control strategies validations.

At the same time on real processes, human operator tasks are various and complex: monitoring, data interpretation, local control loops tuning, process behavior prediction, dysfunction detection, fault diagnosis. To perform his duty, the operator faces many difficulties due to imprecise and incomplete information and, for some processes, to numerous alarms. In this context, having at his disposal an efficient on-line tool for decision aid becomes essential (Rosen, *et al.*, 2003).

Fig. 1. The activated sludge pilot plant.

The purpose of the work described in this paper is to develop a co-operative supervision system for operator decision support. This system, which makes use of automatic control methodologies and recent research results such as modelling or estimation of unmeasured variables, will be tested on the pilot plant. One reference plant is an urban reference simulator (Copp *et al.*, 2002). The activated sludge process of an industrial paper mill, partner of the project, is the other reference plant.

In the following part 2, design and realisation of the pilot plant is described and first experimental results are shown. Part 3 details the integrated supervisory approach, including model and observer design and validation.

2. PILOT PLANT REALISATION AND RTD EXPERIMENTS

2.1 Pilot plant design and sizing

All the components of an industrial biological treatment process are included in the pilot plant:

- a bioreactor in which the biomass assimilates pollution. A movable aeration system creates aerobic compartments to treat both urban (aerobic and anoxic phases) and industrial paper mill (aerobic only) effluents. Movable baffles allow to adapt hydrodynamic behavior to different process configurations (channel aerator, carrousel etc.)
- a settler, in which the biomass agglomerates in falling flocks (sludge) that lets the superficial water purified. Real settling conditions are obtained thanks to its industrial shape (a slight slope cone with a scraper surmounted by a cylinder)
- a sludge recirculation system which allows to maintain a constant biomass concentration in the process.

The pilot plant has been sized according to the urban and industrial reference plants, which characteristic data are shown on Table 1. The three first parameters characterize the working conditions, which have to be realizable by the pilot plant. Thus the input flow range and the reactor volume have been dimensioned as a compromise between a realistic size and the previous constraints.

Table 1. Characteristic data of reference and pilot plants

Data	Urban plant	Industrial plant	Pilot plant
Volumic load to be treated C_v ($kg_{BOD}.m^{-3}.d^{-1}$)	1	0.97	0.8 – 1.3
Residence time (h) based on the total input flow	3.6	8.72	2 – 12
Recirculation flow to input flow ratio	1	1.2	1 – 2
Input flow ($m^3.d^{-1}$)	20000	5000	0.25 – 1.5
Reactor Volume (m^3)	6000	4000	0.250

[1]C_V (Volumic load) is the ratio of input biodegradable substrate mass per day to reactor volume.
[2]COD (Chemical Oxygen Demand) is the measurement of the oxygen quantity needed to treat all organic matter.
[3]BOD_5 (Biological Oxygen Demand) is the measurement of the dissolved oxygen needed to treat biodegradable organic matter in 5 days.

2.2 Realization

Additional elements complete the pilot plant (Figure 2). A steered and cooled storage tank allows an effluent supply autonomy of five days whereas a buffer tank allows pH and nutrient adjustments of the effluent. The whole process is secured by an independent electrical device for human and material safety.

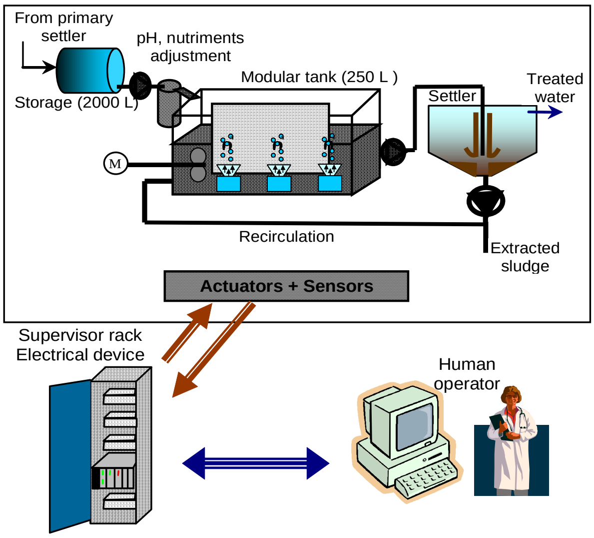

Fig. 2. Schematic representation of the pilot plant.

The pilot plant is provided with many measurements:

- on-line sensors: pH, temperature, oxygen concentration, redox potential and conductimetry;
- off-line measurements with an automatic sampling device: Chemical Oxygen Demand[2], Biological Oxygen Demand[3], nitrogen compounds concentrations for effluent and treated water.

Control loops on the liquid level and on the dissolved oxygen concentration in the bioreactor are implemented through the supervisor.

The industrial tool PC3000 by Eurotherm™ has been chosen for the plant supervision. All the sensors and actuators are linked to the input/output modules of the supervisor rack. The process control files (discret events control, continuous control loops, dysfunctions detection) are implemented on the motherboard. The displayed data on the operator synoptic screen are updated each second. The operating modes proposed to the operator are detailed in the sequel.

2.3 Operating modes

On figure 3, the synoptic screen (which is under construction) presents the global scheme of the pilot plant (reactor, settler, pipes system). Besides each continuous actuator (pumps and valves), both measured value and manual setpoint are displayed. Measurements, set points and on-off actuators are given on the table under the scheme.

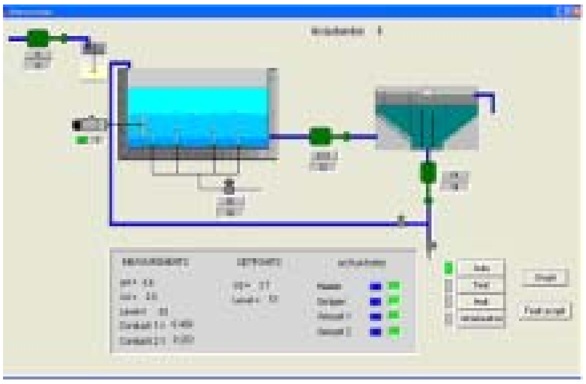
Fig. 3. Pilot plant synoptic

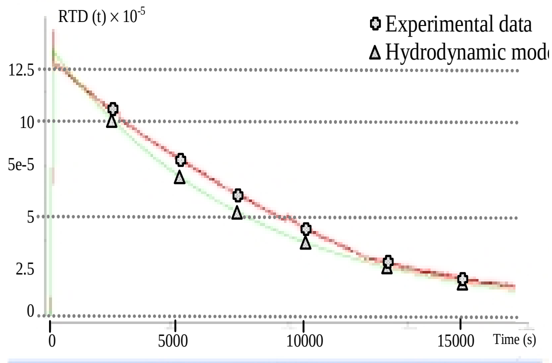

Fig. 4. RTD evolution (adimensionnal form).

The different operating modes are available at the right bottom of the screen and can be activated at any moment by the operator.

- The auto mode assigns the set points to their nominal values and switch-on the required control loops. A dysfunction routine scans continuously in case of dysfunction (sensors measurements going through security thresholds, actuators faults). The auto mode is then interrupted, a color code advises the operator on the screen, and the dysfunction mode automatically runs.
- The test mode is proposed to test manually the PID tuning, to disconnect the control loops and to handle manually dysfunction problems.
- The halt mode allows the pilot plant emptying for cleaning or effluent change.

2.4 RTD experiments

Residence time distribution (RTD) experiments on the bioreactor have been compared with similar experiments on an industrial process to verify the hydrodynamic scaling-up. The pilot bioreactor configuration is a carrousel and the flows are adjusted to fit industrial configuration.

Tracing experiments have been carried out by injecting pulses of a KCL solution. The concentration is collected by a conductimetry sensor at the reactor output. The resulting RTD function corresponds to the ratio of instantaneous tracer concentration to the integral concentration recovered at the output.

Because of the normalisation of RTD data, the very long residence time and the unity area of the curve, RTD scale (figure 4) is very small. The duration of the experiment is more than five hours, which is considerable and consequently the expected final zero value of concentration is not reached and may take a rather longer time. On the first points of the experimental graph, the rough disturbance corresponds to a weak short-circuit due to experimental protocol, which is of course not visible on the model.

The hydrodynamic model (figure 4) is identified by using the software DTSPRO® 4.2. After many tests and though the curve shape is not exactly reproduced, the more accurate model is proposed. It is composed of a plug flow reactor (very small size thus it can be considered as neglected) followed by a well-mixed reactor. The industrial data lead also to a well-mixed reactor, which validates our methodology (experimental results are confidential and cannot be published).

These results are first experiments and need therefore to be improved and extended with many other ones. However, they are sufficiently good to consider that the bioreactor design and technological choices are the right ones to create similar hydrodynamic behaviors between pilot and industrial plants.

In a further work, the effect of hydrodynamics on the treatment efficiency will be studied. Simply by baffles placements, the experimental RTD may be adjusted. The correlation between the RTD and the number of perfectly-mixed reactors, proposed by Potier (Potier, *et al.*, 1998), will be easily verified on the pilot plant, thanks to its modular conception.

3. INTEGRATED SUPERVISION

In part 2.3, the common supervisory tasks have been described. The information that is available for the operator is strictly limited to direct on-line measurements or off-line backward measurements. Finally all the data interpretation, which consists in deducing the biological treatment quality in the reactor and in predicting the treatment efficiency, is entirely in charge of the human operator. Moreover, the simulation of possible different actions in case of dysfunction or disturbances is not possible. The interest of a real co-operative supervisory tool to help the operator in his every day decisions is developed in the following part.

3.1 Interest of a co-operative supervision system

Here is a scenario example of a process dysfunction. The chosen event is the decrease of biomass concentration in the bioreactor, due to a dysfunction on the recirculation system (pump fault and flow sensor fault) or to biomass disease. The process events are described in figure 5 (mid-column): due to the dysfunction, the first consequence is the decrease of biomass concentration in the bioreactor. The

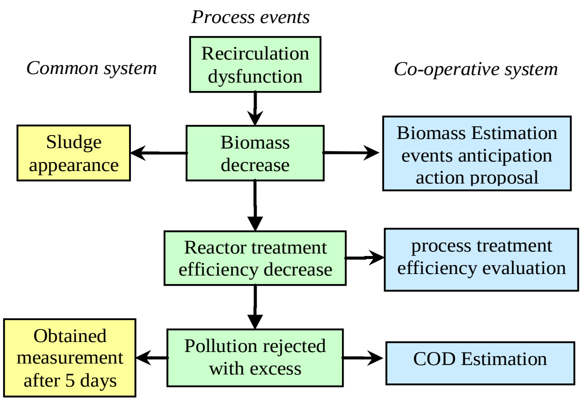

Fig. 5. Dysfunction scenario and comparison of common and co-operative systems

treatment efficiency is then also decreasing, and at the same time the reactor pollution increases. At last, the treated water that is rejected in the river is more and more polluted and if nothing is done, exceeds the limits authorized by the law.

With typical supervision tools (left column), the supervisor gives only basic measurements. To detect the previous described dysfunction the operator may:

- go to the plant (which may be far away from the supervision station), notice sludge appearance (colour, form) and conclude thanks to its experience ;
- wait results of off-line measurements which are usually done every day for COD or even every week for BOD_5 measurement.

In addition, if the biomass decrease is fast and strong the operator may realize the seriousness of the situation far too late to act efficiently and the biomass may be totally washed out.

In comparison, the co-operative supervision system (figure 5, right column), gives not only the basic measurements but also estimates useful unmeasured data and proposes some interpretations on the reactor operating conditions. In addition, to previous informations, the operator can know:

- the on-line estimation of unmeasured data as the biomass concentration and the COD of treated effluent,
- the anticipation of the process behavior and the data tendency,
- the treatment efficiency evaluation,
- the proposal of control actions and their efficiency.

The operator may also introduce his own remarks as sludge appearance, which ideally may be used by the supervisor. In addition, some elements as the cost of the proposed actions may be also included (low cost or efficiency choice). The simulation of new plant configurations and new equipments may also propose information on the associated treatment cost saving, which may facilitate sensor investments.

Through this example, the lack of available information on the process is obvious for common supervisory systems. In these conditions, it is difficult for the human operator to detect a dysfunction and above all to anticipate the phenomenon.

Consequently, the development of an on-line aid in decision task is decisive for a good process operating. Such a tool allows the operator to better understand the process behavior and to detect dysfunctions from the initial stages.

3.2 Co-operative integrated supervision design

For usual industrial processes, the aim of supervision tools is to detect and to localize faults. Different methods are available to solve this problem such as causal graph (Leyval, *et al.*, 1994) or fuzzy set theory and multi-criteria decision (Gentil, *et al.*, 1994; Montmain and Gentil, 1996). Nevertheless, the main difficulty of supervision for wastewater treatment process is to detect dysfunctions on biological and hydrodynamic behaviors and to react as rapidly as possible. Thus, other tools have to be fitted.

The structure of the proposed tool for decision aid will be based on a succession of steps. Each one is sufficiently interesting to be used alone. Proposed steps are the followings:

1) *A model* is developed, and validated with data. The model may be use for simulation purposes and is the basis of all the information treated in the next points.

2) *Unmeasured data estimation*: a model-based nonlinear observer is designed to compensate the lack of sensors. At this step, all the information needed for a complete understanding of the process is available.

3) *Reliability data indicator*: sensor precision, estimation quality.

4) *Tendency extraction*: to anticipate data variations and then to predict the process behavior. Based on the results proposed by Charbonnier, *et al.*, (2004), the method uses a data segmentation algorithm and a classification tool.

5) *Action proposal*: depending on present and future behavior, some actions will be proposed to operator to improve the treatment process by respecting a trade-off between depollution, operating cost and biomass activity.

Different tools mentioned above have been developed and tested in simulation. The next two sections will focus on process modelling and estimation of unmeasured data.

3.3 Model design

For activated sludge processes, a reference model has been proposed by the European group COST Action 624 (Copp *et al.*, 2002) where the biological model corresponds to the Activated Sludge Model (ASM) n°1 developed by the task group of the International Association on Water Quality (IAWQ) (Henze, *et al.*, 1986). Due to the number of state variables and parameters, this model is difficult to handle for estimation purpose, whereas a simplified model is more suitable, always respecting a trade-off between complexity and precision. Thanks to previous works ((Cadet, *et al.*, 2003), (Cadet, *et al.*, 2004)), the design of a new reduced model, for which simplifications are mainly based on biological considerations, is presented. It has been design for industrial effluents (treatment of carbonaceous matter).

1) *Simplification hypothesis.*

- *Hydrodynamics.* The bioreactor corresponds to one well-mixed reactor (instead of five) which provides a large reduction of the number of states;

- *State variables considerations*. Only the components necessary for the main reactions are kept and leads to 5 state variables (instead of 13):
  - 1 fraction of nitrogen (S_{NH})
  - 1 fraction of organic matter (XS_S)
  - 2 types of micro-organisms (heterotrophic biomass X_{BH}, autotrophic biomass X_{BA})
  - 1 fraction of dissolved oxygen (S_O)

- *Biological processes*. Only four processes are considered: the biomasses decays, the carbon oxidation and nitrification. Thus, reduced process rates expressions are:

$$\begin{aligned}
r_{XS_S} &= -\frac{1}{Y_H}.\gamma_H.\frac{XS_S}{K_S + XS_S}.\frac{S_O}{K_{OH} + S_O}.\frac{S_{NH}}{K_{NH} + S_{NH}}.X_{BH} \\
&\quad + (1 - f_p).(b_H.X_{BH} + b_A.X_{BA}) \\
r_{X_{BH}} &= \gamma_H.\frac{XS_S}{K_S + XS_S}.\frac{S_O}{K_{OH} + S_O}.\frac{S_{NH}}{K_{NH} + S_{NH}}.X_{BH} - b_H.X_{BH} \\
r_{X_{BA}} &= \gamma_A.\frac{S_{NH}}{K_{NH} + S_{NH}}.\frac{S_O}{K_{OA} + S_O}.X_{BA} - b_A.X_{BA} \\
r_{S_{NH}} &= -i_{XB}.\gamma_H.\frac{XS_S}{K_S + XS_S}.\frac{S_O}{K_{OH} + S_O}.\frac{S_{NH}}{K_{NH} + S_{NH}}.X_{BH} \\
&\quad - \left(i_{XB} + \frac{1}{Y_A}\right).\gamma_A.\frac{S_{NH}}{K_{NH} + S_{NH}}.\frac{S_O}{K_{OA} + S_O}.X_{BA} \\
r_{S_O} &= -\left(\frac{1 - Y_H}{Y_H}\right).\gamma_H.\frac{XS_S}{K_S + XS_S}.\frac{S_O}{K_{OH} + S_O}.\frac{S_{NH}}{K_{NH} + S_{NH}}.X_{BH} \\
&\quad - \left(\frac{4,57 - Y_A}{Y_A}\right).\gamma_A.\frac{S_{NH}}{K_{NH} + S_{NH}}.\frac{S_O}{K_{OA} + S_O}.X_{BA}
\end{aligned} \tag{1}$$

where γ_H, γ_A and Y_H are reaction rate factors that have to be tuned. These parameters have been selected according to sensitivity functions. Other rate factors keep their reference value (Copp *et al.*, 2002). The obtained reduced model is composed of 5 state variables and 3 parameters to estimate.

Validation. Three urban wastewater databases are available, corresponding to dry, rain and storm weather, which allow simulating realistic operating conditions. The parameters have been adjusted with a quasi-Newton algorithm for dry weather conditions and the model is then validated with different data (rain and storm weathers). Some results in storm conditions at the output of the reactor (aerobic state variables) are shown on figure 6. The reduced model presents an excellent accuracy. During the first day, the steady state point of the reduced model is remarkably close to the reference steady state point. The following 7 days, with dry weather, the model accuracy is excellent. From the day 9, the storm event induces rough disturbances on model inputs which influence hardly output state variables.

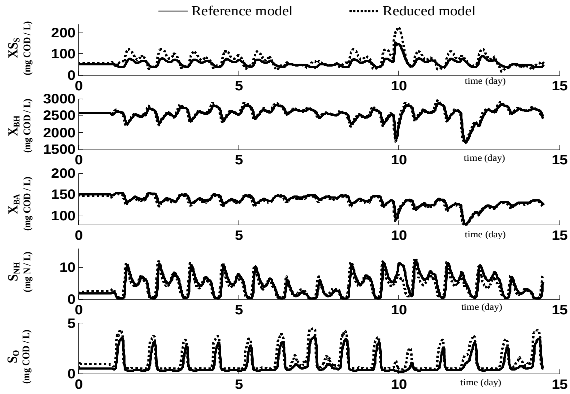

Fig. 6. Reduced model validation on storm weather.

More precisely, the difference on dynamic behavior of the carbon fraction is due to the influence of nitrogen concentration on carbon oxidation processes which is not take into account in the reference model. The biomasses and the dynamic variations of oxygen and nitrogen state variables are very close to the reference model.

Consequently, this model is suitable for our purpose: on one hand, its accuracy is excellent so as to expect good performances for the observer based on that model and, on the other hand, it is sufficiently simple to be validated on a real treatment plant.

3.4 Observer design

A comparative study of the two observers that are most commonly used on actual activated sludge processes, asymptotic observer (Bastin and Dochain, 1990) and extended Kalman filter, has been presented in a previous work (Cadet and Plouzennec, 2003). Several drawbacks (such as convergence rate determined by experimental conditions, model linearization) lead to study an other approach: the Moving Horizon State Observer. Only the principle is presented here, more details may be found in (Alamir, 1999).

1) Moving horizon state observer principle
Considering the nonlinear model:

$$\begin{cases} \dot{x}(t) = f\left(x(t)\right) \\ y(t) = h\left(x(t)\right) \end{cases} \tag{2}$$

where $x \in \Re^n$ is the state vector, and $y \in \Re^p$ is the measured output. The functions f and h are supposed to be continuously differentiable. We denote z the estimate of x.

The method transforms the state estimation of a dynamical system into static optimization problem updated with respect to time. The new problem is to estimate the initial conditions *z(t-T)* which have lead the process to its present state *x(t)* since the beginning of the moving horizon *(t-T)* while producing the measured output. The criterion to be minimized is the integration of the squared difference between the outputs given by the model from the initial conditions at *(t-T)* and the corresponding measured outputs.

The state vector $z(t\text{-}T)$ is adjusted by resolving the model equations (2) modified by adding a correction term. This term decreases with the criterion $J(t)$. Thus an asymptotic observer with a fixed gain γ can be established:

$$\begin{cases} \dot{z}(t-T) = f\left(z(t-T)\right) - \gamma G(t)^T \left[G(t)G(t)^T\right]^{-1} \sqrt{J(t)} \\ \dot{\hat{x}}(t) = f\left(\hat{x}(t)\right)\Big|_{z(t-T)} \end{cases} \quad (3)$$

where $G(t) = \dfrac{\partial J(t)}{\partial z}$.

In order to lighten the computations while keeping a good final precision, the estimation is updated with a period $(t_{n+1}\text{-}\ t_n)$.

2) *Simulation results with respect to reduced model.* Realistic measured state variables have been chosen: S_{NH} and S_O for which on-line sensors exist. For testing purpose, we used the reduced model to generate measurements to be used by the observers. The input flow is decreased of 10% (simulation of an upstream machine dysfunction) between day 0,05 and day 1. This perturbation is unmeasured and therefore not applied to observer inputs. As shown in figure 7, the observer presents a good convergence time even if it is slower for the heterotrophic biomass. There is no bias for steady state conditions. Therefore, the moving horizon observer gives an accurate estimation of the process states.

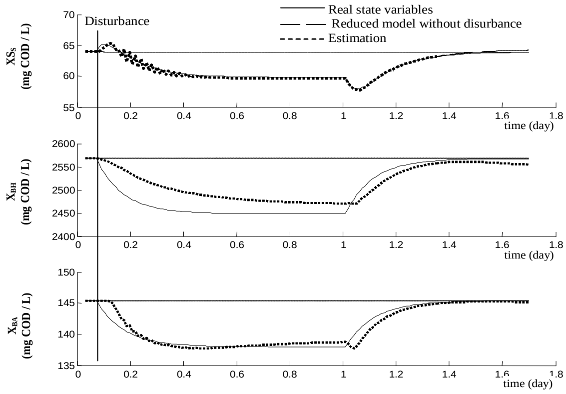

Fig. 7. Observer convergence with dry weather data.

4. CONCLUSION

In this paper, the conception and realization of an activated sludge pilot plant has been described. The pilot plant behavior satisfies the fixed purposes, like modular configuration, and allows scaling-up results. The design of an on-line aid decision tool, dedicated to activated sludge processes, has been developed. First results show the very good accuracy of the reduced model which is sufficiently simple to allow validation on a real effluent. Simulation observer results confirms that the Moving Horizon State Observer approach is relevant for this application. Results are now sufficient to plan further developments: validation on real effluent and other supervisory steps realization to contribute to a better control of activated sludge processes.

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