Annual Report Work Package 6

November 2004 -October 2005

1. Participants

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2. Activities

Taking into account the goals of WP6 and the second annual report in which the selection of faults in actuators and sensors was discussed and the data issues to match the analytical model given by WP2 with the abnormal condition in the POLIMI reactor was pointed out, the efforts during the semester [Nov-04, April-05] were concentrated in the following activities:

1. Improvement of the detection method for faults in the valve using Dynamic Principal Component Analysis and considering the physical constraints of industrial valves specified in the operation manuals.
2. Adjusted of the parameters in the identification algorithm to detect a change in the time constant of the DOx sensor.
3. Final analysis of the abnormal condition (nitrite accumulation) in the POLIMI reactor considering all the stored history of the reactor during the experiments defined by EOLI in the first meeting.
4. Search of a redundancy relation for the in situ respiration rate *r(t)* and a sensitivity analysis o the patterns with respect to nominal values of the parameters of the EM1 and EM2 model given in WP2.

The interactions activities of WP6 were related with WP4 and WP1

- To get a respiration rate redundancy relation which is necessary to solve a FDI issue with analytical methods, the deliverables of WP4 were considered. In particular the idea was to estimate the internal behavior of the EM1 reactor and from them to build the required respiration rate.

- To establish the causal model for the POLIMI reactor, participants of WP6 established a communication with POLIMI. The data reported in WP1 for the POLIMI reactor were analysis together.

3. Summarized Results in term of Objectives and Milestones

Results & Task Objectives	Progress towards achieving objectives
WP6.1 Specifications of the FDI system	• The FDI system for EOLI assumes three cause of faults: 1) damage in the sensor of *DOx* membrane, 2) damage in a generic valve with control 3) fault in the aeration system 4) diverse ab-normal conditions in the process during the reaction time. • The specific abnormal conditions are: 1. The case of nitrification/denitrification

	problem for the POLIMI reactor was one of the selected case. 2. Deviations of the parameters *Ki* and *Ks* from the normal values given by WP2 are considered as abnormal conditions. 3. Incomplete reaction cycle when a open loop control is implemented. • The first milestone of WP6 has been achieved.
WP6.2 FDI System Design	• The monitoreability of the process by the model given in WP2 with the measured variables is very sensitive, even by simulations. Then, only some part of the cycles and subset of variables of the process can be monitored. • A fault detection algorithm for a damage in the *DOx* membrane has been tested and adjusted by simulations. This design is presented in the master thesis of Juventino Cuellar at the UNAM. • A fault in the aeration system of the reactor can be detected estimating the parameter *Kla* online, each cycle of the process. The description of the method will be presented at the IFAC Congress July 05. • A The existence of substrate at the end of the reaction cycle is considered as a fault in the process and can be detected on-line using the pattern of the *DOx*. More details will be presented at the IFAC Congress, July 05. • The DPCA has been used to detect faults in a generic valve. The adjust of an adaptive threshold is under developed. • Qualitative Pattern recognition methods for abnormal conditions are been considered as the only way to supervise the evolution of the reactor during a set of cycles. Particular procedures are under developed for *Ki* and *K*s values. • The second milestone of the WP6 and D6.1 are partially achieved
WP6.3 FDI Validation	• The detection of faults in the *DOx* sensor has been validated by simulation. Real experiments has not been carried on, because of the absence of an unoccupied

	sensor in which hardware modification could be feasible. • The detection of substrate as an abnormal condition at the end of the reaction cycle has been tested by simulation and with data off line. • The detection of faults in the valve has been partially tested by simulation and the improvement of the algorithm is under developed. • The rest of the validation results to achieve the third milestone of WP6 and D6.2 are scheduled for the last semester of the project.

4. Problems encountered

The sensitivity of the SS with respect to a deviation in the initial conditions and error in the input of the observer *mo(t).*

The impossibility to recover all the data of the POLIMI experiments to get a qualitative cause effect model for the nitrification problem in the reactor.

The limitation of the model developed by WP2 to reproduce faults conditions. As consequence, the solid FDI framework with analytical models cannot be applied for the process of EOLI.

As it is usual in FDI issues the absence of hardware faults emulators to validate the scheme in the real word.

The absence of an unoccupied sensor in which hardware modification could be feasible.

5. Publications and Papers

16th IFAC World Congress, 2005. D. Wimberger and C. Verde. Online Monitoring of an Aerobic SBR Process Based on Dissolved Oxygen Measurement (accepted regular paper)

6. Planning

The design of the FDI algorithm based on DPCA and adaptive threshold to detect and isolate a valve clogging, a valve plug or set sedimentation and a valve set erosion will be finished and the validation will be done by simulation of artificial faults.

All the FDI methods for the abnormal conditions will be integrated to have a simple tool for the operator of a SBR which can be used by the supervision system WP7.

Validation of the tool for the operator using artificial faults.

Write the final report and the finish the Deliverables of the WP6.

7. Specific Reports

7.1 Self Faults Diagnosis for the Valve

The part of the report is focused in the fault detection analysis for a generic valve via DPCA. As it was explained in the last report, for the simulation of the proposed detection algorithm it is used the DAMADICS (Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems) benchmark [1]. With this simulator it has been possible to characterize the most common operating scenarios which are *valve not closing or opening fully*. The faults considered as causes in both cases are: Valve Clogging (*f1*), Valve Plug or Valve Seat Sedimentation (*f2*) and Valve Plug or Valve Seat Erosion (*f3*). As input signal is considered the position set-point *CV* and, as output the valve plug displacement *x* and the media volume flow rate *F*.

Considering the fault *f1*, a reference pattern of the normal condition is defined from the time series assuming stationary and considering the auto-correlation and the cross-correlation of the series. For this fault it is taken into account as input signal to *CV* and *x* as the only output signal standardizing the data around the corresponding means standard deviations. To include the serial correlation, it is constructed the so called *trajectory matrix* or *Hankel matrix* applying a time lag shift of order *l* in the data

$$\underline{X}(l) = \left[\underline{X}(k) \quad \underline{X}(k-1) \quad \cdots \quad \underline{X}(k-l)\right] \tag{1}$$

Thus, the principal components are a set of variables $\underline{X}(l)$ transformed into a new set of variables which are uncorrelated to each other, this is

$$\underline{Y} = V_t \underline{X}(l) \tag{2}$$

Where V_t is composed of the eigenvectors associated to the correlation matrix *R* of the trajectory matrix. On the base of the PCA $\underline{Y}$ it is possible to define the univariate statistic $T_{\underline{y}}^{\,2}$ (*Hotelling parameter*) for each component

$$T_{\underline{y}}^{\,2} = \underline{y} S_{\underline{Y}}^{\,-1} \underline{y}' \tag{3}$$

With $S_{\underline{Y}}$ the covariance matrix of $\underline{Y}$. Finally, it is defined a threshold of normal condition from the probability density function of $T_{\underline{Y}}^{\,2}$.

The implementation of this detection algorithm is then reduced to

- take an observation $\underline{x}_a(l)$ standarized around the means and standard deviations of pattern,
- transform it through V_t, to evaluate the parameter $T_{\underline{y}_a}^{\,2}$ and if a deviation of the threshold is an indication of the presence of a fault.

[1] http://diag.mchtr.pw.edu.pl/damadics/

To validate the FD algorithm the simulator shown in Fig. 1 was used. The input data associated to control signal *CV* and other required signals are obtained from available real information of the DAMADICS project (file *OneourTestData_ExampleII.mat*).

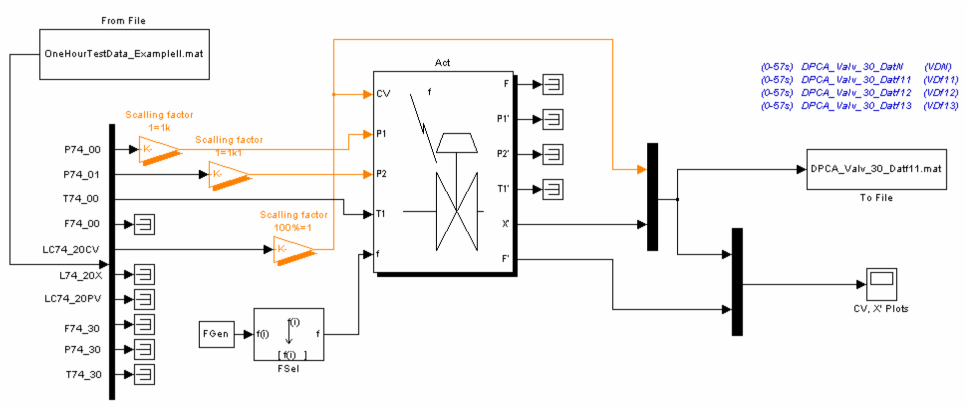

Fig. 1 Valve Simulator.

The upper plot of Fig. 2 shows the behavior of displacement *x* under fault *f1* for different magnitudes (0.25, 0.5 and 1), where *f1*- 0.25 doesn't explain any variation in behavior compared with the displacement signal under normal condition. The lower plot of Fig. 2 shows the detection capacity of the algorithm, where it was possible to detect the faults of magnitude 0.5 and 1, but not that of magnitude 0.25 of which Hotelling parameters stay under the threshold of normal condition.

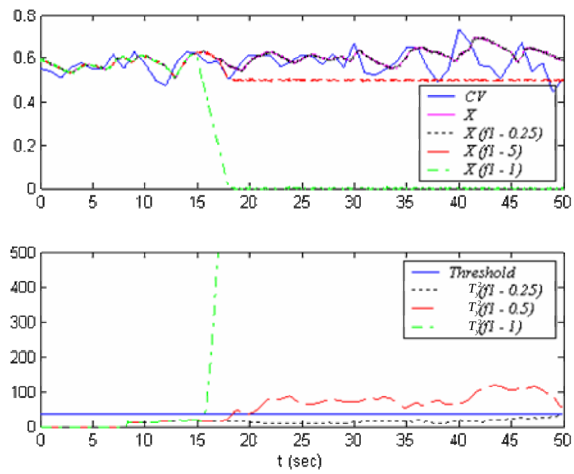

Fig. 2 Upper plot: Behavior of displacement *x* for different magnitudes of *f1;* Lower plot faults detection comparing T_y^2 against the threshold.

As second test we analyzed how the algorithm responds to step changes in the control signal *CV* in normal condition. The For this case s proposed positive and negative step changes non higher than the *maximum step size* permitted for a valve $(\cong 10\%)$[2], the sequence is as follows: positive step change $(18s \le t \le 43s)$ and negative step change from $(93s \le t \le 143s)$.

[2] *Control Valve Dynamic Specification*, Version 3.0, 11/98, EnTech Control Engineering Inc.

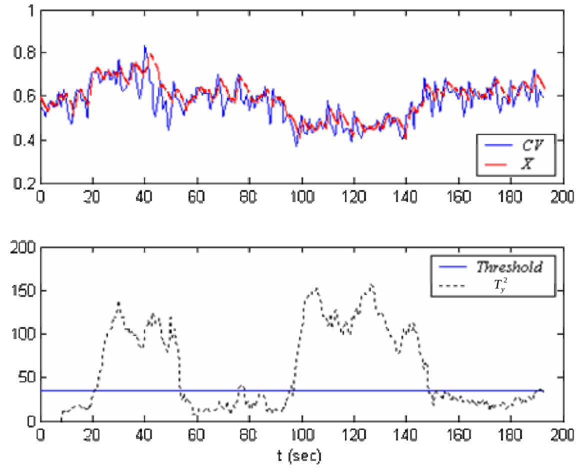

Fig. 3 Step changes in *CV* and response of the detection algorithm.

As it can be seen from Fig. 3 the detection algorithm generates false alarms exactly during the step changes in *CV* even with the valve operating under normal condition, this phenomenon is due to the break of stationary property in both *CV* and *X* time series. Additionally, given that the data vector $\underline{X}$ used for characterization is standardized which means that both X_1 and X_2 have zero mean and unit standard deviation, it causes that during the standardization process of an actual observation $\underline{x}_a(l)$ if this has values out of the zero mean then it will be invariably considered as a fault.

To overcome the described problem it has been proposed a modified algorithm in where the standardization process can be taken according to on-line appropriate averages of the input signal *CV* and the output signal *X*. For this, it is required a kind of output estimation $\hat{X}$ with not necessarily exact estimates because we are interested just in the average $\overline{\hat{X}}$ of the output signal.

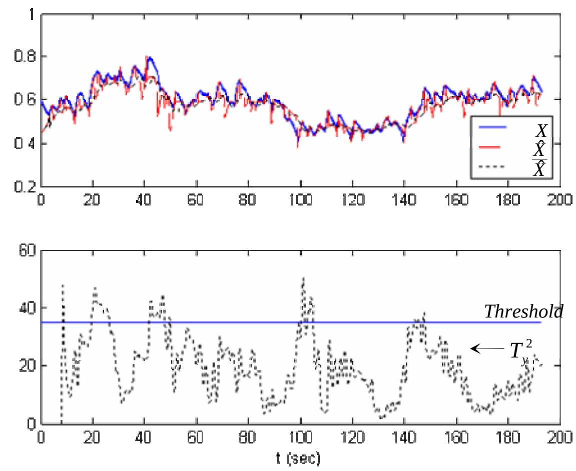

Fig. 4 Upper Plot: Plug displacement *X*, displacement estimation $\hat{X}$ and displacement estimation average $\overline{\hat{X}}$.
Lower Plot: Response of the modified detection algorithm.

In the lower plot of Fig. 4 it is shown the improvement in the response of the fault detection algorithm compared with that obtained in Fig. 3, however, it still results some false alarms, but these arise during the transient behavior of the step changes.

Conclusions: It is possible to get an improvement in the fault detection algorithm via DPCA for small magnitude faults, if we take into account not only the displacement signal *X* but also the media volume flow rate *F* and even other signals available inside the actuator like control current of electro-pneumatic transducer *CVI* and electro-pneumatic transducer output *Ps*. Even the improvement in the fault detection algorithm with the appropriate standardization with regard to on-line averages of the input signal and the output signal estimation, they still result some false alarms during the transient behavior of the step changes. To attempt overcome the transient false alarms, in the following experiments we will implement an adaptive threshold as a function of the input signal.

7.2. Calibration of the Algorithm for the Self FD in the DOx sensor

On the base the current and its integral produced by the *Dox* membrane given in the second annual report and written in a compact way as a nolinear function

$$\int_{h_1}^{h_2} i(t)\,dt = i_{ss} \sum_{n=1}^{\infty} f_{nl}(\tau, n, h_1, h_2) \qquad (4)$$

The integral parameters *h1* and *h2* together with the number of terms *n* used in the summation of equation (4) has been adjusted considering the error in the time constant τ. For the *DOx*, a time variant signal has been assumed with the control and synchronization signals given in Fig 5 with *h=h1* and *h2=2h1*

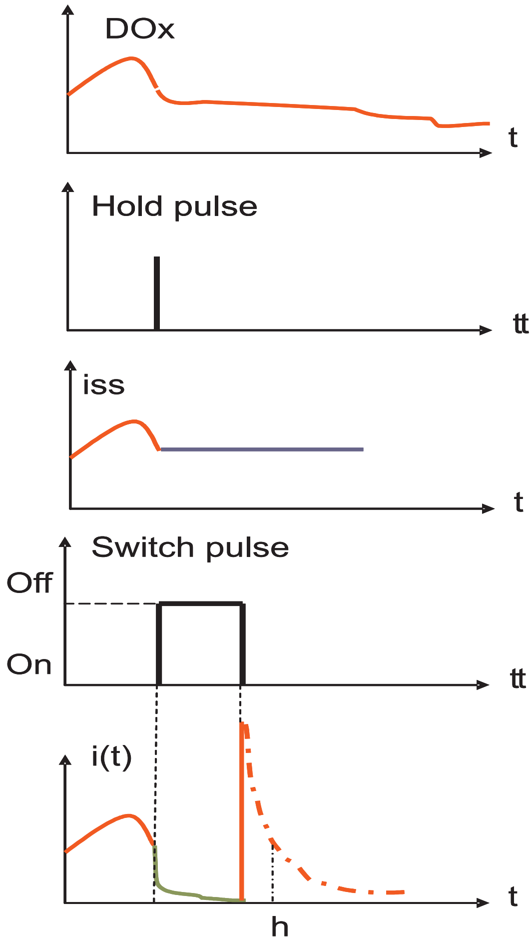

Fig. 5 Control and Syncroniztion signals for the FD algorithm of DOx

The Table 1 shown the results and then we suggest a time for the integration evaluation between 6 and 8 s.

h1 (s)	I/iss	Estimated value	% estimation error
2	5.1198	59-9988	0.0033
4	7.2421	59.9985	0.0025
6	8.9001	59.9990	0.0016
7	9.6578	59.9997	0.0005
8	10.4019	60.0002	0.0003
10	11.8980	60.0011	0.0018
12	13.4554	60.0025	0.0045

Table 1. Evaluation of the estimation error for a set of initial value in the integration time.

7.3. Milan and Nitrification/Denitrification Process Fault

For collaboration with POLIMI, Dieter Wimberger has stayed in Milan for two days of discussions with Dr. Elena Ficara. As a result they have defined the following TODO list items:

1. Sensor Model & Filter Design
2. Evaluation of cyclic data, specifically before and after excessive Nitrite outflow
3. Evaluation of the application of the in-situ respiration in the Milan process

Each of these points has been worked on; results of this work are summarized in the following sections.

7.3.1 Sensor Model & Filter Design

A simple dissolve oxygen (DO) sensor experiment has been performed by Milan, which consisted of recording step responses of the laboratory sensor, produced by passing it from a liquid with 0 [mg/l DO] to a liquid with saturation concentration (about 8.73 [mg/l DO]) and vice versa. Figure 5 shows the input (DO concentration at 0 [mg/l] and 8.73 [mg/l]) and the output signal (measured DO concentration).

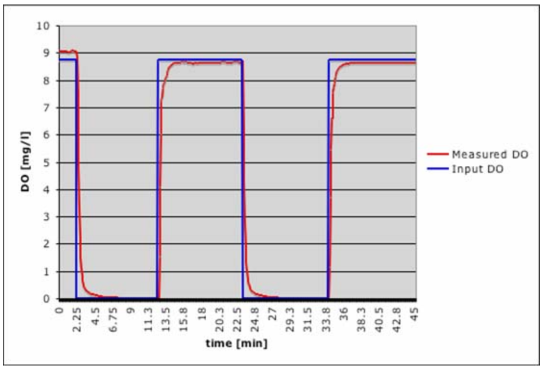

Fig. 5 Behavior of the *DOx* sensor

From the provided data set of the sensor experiment, a simple low-order parametric sensor model has been obtained. The best fit was an arx112, where the parameters are identified using a least squares estimate on a selected part of the experiment data (the second step response). The sensor model is:

$$\frac{0.25z^{-2}}{1-0.75z^{-1}} \qquad (5)$$

identified as a transfer function that can be used directly in MATLAB and SIMULINK. Fig. 6 allows to verify the model output verified the measurements of the complete experiment data.

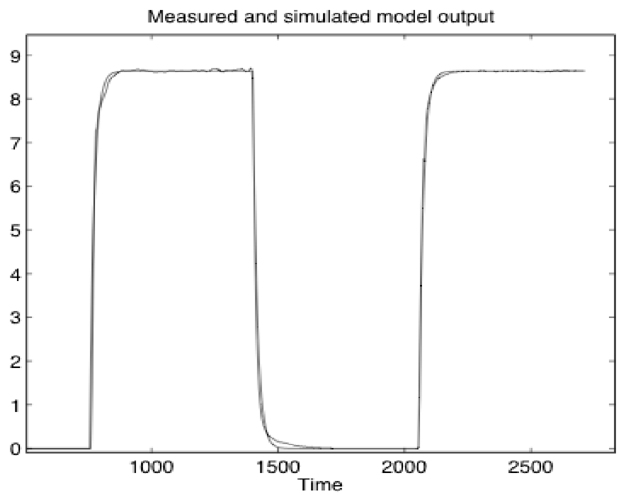

Fig. 6 Response of the *DOx* sensor (Time in [s], *DOx* in [mg/l])

The sensor response can be reasonably well predicted and the established model allows to give an estimate for the sensor delay with about 80[s] from an impulse response, presented in Figure 7.

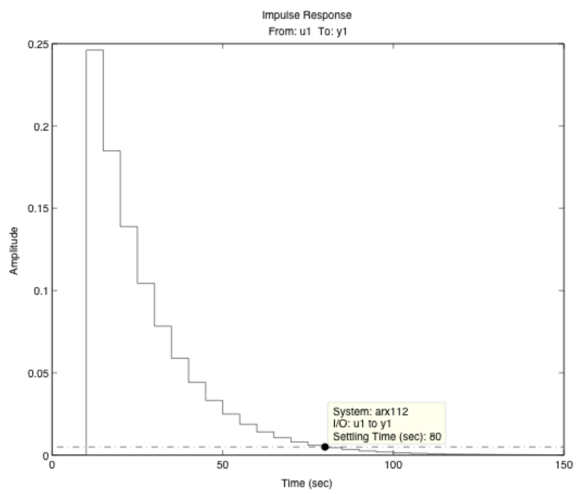

Fig. 7 Impulse response of the *DOx* sensor

The next step performed was the design of a lag-smooth filter using the procedure presented at the meeting in Milan [1]. In particular, for the given experimental data a low noise design parameter was chosen (i.e. ρ=0.01; represents a noise variance ratio). The filter equation is given by

$$\frac{0.7 + 1.97z^{-1} - 1.88z^{-2}}{1 - 0.285z^{-1} + 0.075z^{-2}} \quad (6)$$

Which can be used to improve the measurement of the sensor. Given the experimental data and the sensor specific delay the effect of the filter is not very dramatic. This is illustrated in Figure 8, where a comparison of real, sensor and filter value in a simulated re-aeration is given.

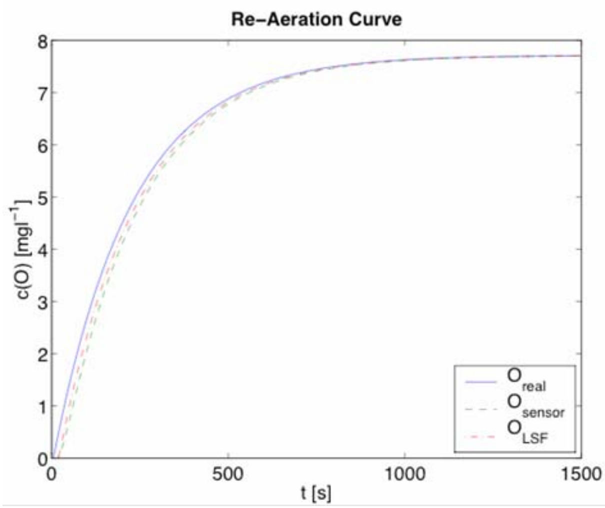

Fig. 8 Recover signal during the re-aeration phase

To summarize and conclude the results:

1. It is possible to obtain a sensor and a filter model for the DO sensor in Milan. However, given the much lower sensor delay (compared to the sensor used in México), the recuperation is not dramatic. It would only be possible to try a higher order filter but with lower pure delay (i.e. k=one instead of 2).
2. The filter could be useful at faster sampling rates to smooth noise; however, it would need to be adjusted accordingly by changing the design parameterρ.

7.3.2 Evaluation of cyclic experiment data

A lot of experimental data has been provided by POLIMI for evaluation. The idea discussed and planted in Milan, was to isolate changes in process trends with regard to the defined process fault of excessive nitrite outflow.

In the range of provided online data, following cyclic tests with excessive Nitrite outflow were available:

1. 24/09/2003
2. 06/10/2003
3. 16/10/2003

Thus we started to extract the online data from Excel sheets stored per week into a MATLAB digestable form (CSV per day). We tried to obtain a range of days that includes some days before and some days after a measured outflow:

1. 24/09/2003 →20/09/2003-26/09/2003
2. 06/10/2003→03/10/2003-09/10/2003
3. 16/10/2003→12/10/2003-19/10/2003

Unfortunately the data is partially incomplete:

1. 21/09/2003 (gap), 23/09/2003 (gaps), 26/09/2003 (gaps)
2. 05/10/2003 (last cycle), 06/10/2003 (gaps), 08/10/2003 (gaps)
3. 12/10/2003 (gap), 13/10/2003 (missing?)

and what is even more problematic: no offline data (i.e. concentration measurements) except for the EOLI reported cyclic tests is available according to the operation diary. This leads us to the conclusion, that it is not possible to establish a causal relationship from the recorded online data, that could be used for detecting the excessive nitrite concentration.

7.3.3 Evaluation of In-Situ Respiration

The third item on the TODO list was the observation of the in-situ respiration from the recorded online DO measurement in the aerobic phase. Given the conclusion from section 3.3.2, WP6 leader have decided to work with the EOLI identification experiments, because there are corresponding offline concentration measurements available:

- influent concentrations
- effluent concentrations and
- at least 5 concentrations in the reactor during the reaction phases of the cycle

In various of the identification experiments excessive nitrite concentration has been measured in the effluent, specifically:

1. 02/07/2003 -35% COD/N
2. 09/07/2003 -50% COD/N
3. 24/09/2003 -20% COD/N

The excessive nitrite concentration in the effluent has been defined as the process fault, thus all of the above mentioned experiments were faulty. It became evident that the fault occurred in all experiments with reduced (compared to the standard condition) carbon to nitrogen content ratio (COD/N) in the influent. This fact allows us to suppose a causal link between the COD/N ratio of the influent as cause and the process fault as effect.

Subsequently, we established the hypothesis that a change in the COD/N ratio would as well have an effect on the respiration rate profile in the aerobic phase. To prove this hypothesis we applied our in-situ respiration rate observer (about to be published [2] and presented at the second annual meeting in Milan) to the online DO concentration measurements of the same decreased COD/N ratio experiments.

Figure 9 presents the observed respiration rate profile for three selected experiments (standard condition experiment and two experiments with decreased COD/N ratio)

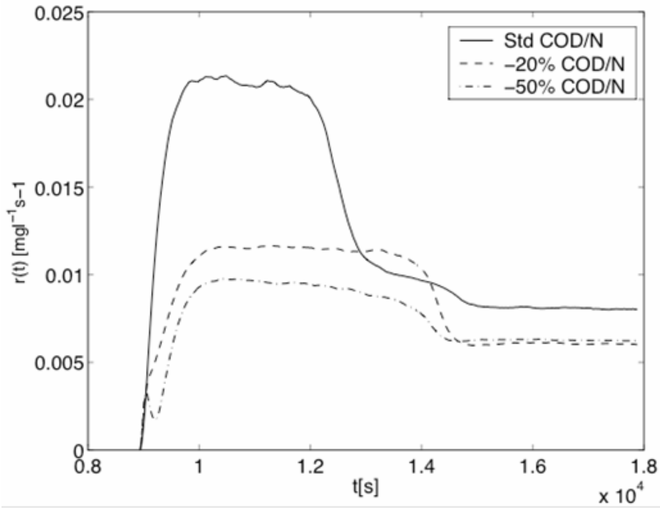

Fig. 9 Evolution of the respiration rate

The -20% and -50% COD/N ratio experiments are faulty experiments and exhibit a visually perceptible pattern, different from the standard condition experiment data. This result confirms our hypothesis that implies a causal link between the COD/N ratio in the influent and the respiration rate profile during the aerobic phase. This link can be exploited for monitoring purposes: detect and inform the process operator of unfavorable COD/N ratios in the influent (affecting the actual reaction) and forewarn that under such conditions excessive nitrite outflow is likely to occur.

Conclusions: The presented results have been sent to POLIMI with a request for comments. One of the questions for the requested comments was, if it wouldn't be possible to obtain more information from the in-situ respirogram (area below the curve might represent the BOD etc.) or even with respect to [3]. More detailed comments have not been received from POLIMI so far.

7.4. Search of a Redundancy Relation by Software Sensors

To define a redundancy relation for the in-situ respiration rate the WP6 leader decides to continue working with the in-situ respiration rate and to integrate the results from WP 4 (Software Sensor for estimating the biomass). Before the design of the software sensor, we proposed to apply a model transformation to the EM1 concentration based model to obtain mass balance equations for conserved extensive quantities [4]. The following set of equations (7) corresponds to this model and it has not been given before in EOLI project:

$$
\begin{aligned}
\frac{dm_x}{dt} &= \mu(V, m_s)\, m_x \\
\frac{dm_s}{dt} &= -k_1 \mu(V, m_s)\, m_x + q_{in} c_{s,in} \\
\frac{dm_o}{dt} &= -k_2 \mu(V, m_s)\, m_x - b m_x + q_{in} c_{o,in} + K_{la}(m_{o,sat}(V) - m_o) \\
\frac{dV}{dt} &= q_{in}
\end{aligned} \qquad (7)
$$

where m_x, m_s, m_o, V, $\mu(V, m_s)$, k_1, q_{in}, $c_{s,in}$, k_2, b, $c_{o,in}$, K_{la}, q_{in}, $m_{o,sat}(V)$ are the biomass, the substrate mass, the mass of dissolved oxygen, the liquid phase volume, the growth rate as a function of the volume, the conversion coefficient from substrate to biomass, the inflow rate, the substrate concentration in the inflow, the conversion coefficient oxygen to biomass, the endogenous respiration coefficient, the oxygen concentration in the inflow, the oxygen mass transfer coefficient and the oxygen saturation mass as a function of the volume respectively.

The growth rate is described by the Andrews Model [5], transformed into the following equation

$$\mu = \frac{\mu_0 m_s}{K_s(V) + m_s + \frac{m_s^2}{K_i(V)}} \tag{8}$$

This new model allowed us to extend the procedure for obtaining the respiration rate to phases with filling and reaction at the same time.

Based on the mass balance model, we have evaluated the asymptotic observer proposed by WP4 respectively Bastin and Dochain 1990 [6] for estimation of biomass and substrate for unknown μ using the observer states z_1, z_2 given in equations (9) and (10)

$$z_1 = m_o + k_2 m_x \tag{9}$$

$$z_2 = m_o - \frac{k_2}{k_1} m_s \tag{10}$$

Unfortunately the resulting observer given by

$$\frac{dz_1}{dt} = -b\frac{z_1 - m_o}{k_2} + K_{la}(m_{o,sat} - m_o) + q_{in}c_{o,in} \tag{11}$$

$$\frac{dz_2}{dt} = -b\frac{z_1 - m_o}{k_2} + K_{la}(m_{o,sat} - m_o) + q_{in}c_{o,in} - q_{in}c_{s,in}\frac{k_2}{k_1} \tag{12}$$

is very sensitive with respect to an error in the initial condition of the biomass $m_x(0)$ that is used to calculate the initial conditions $z_1(0)$, $z_2(0)$ for the observer. Fig 10 shows the block diagram used to test the sensitivity of the software sensor.

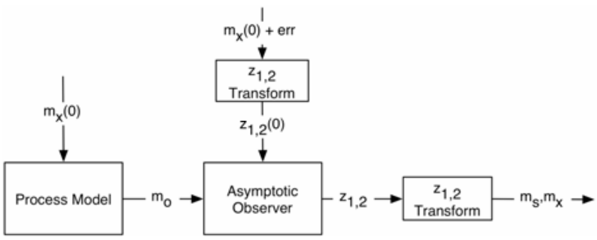

Fig. 10 Validation Scheme for the SS

Figure 11 presents m_s obtained from the asymptotic observer for a given $m_x(0)$ equal to the one used for simulation of the process, as well as for a deviation of +/- 5% of the $m_x(0)$ used for simulation.

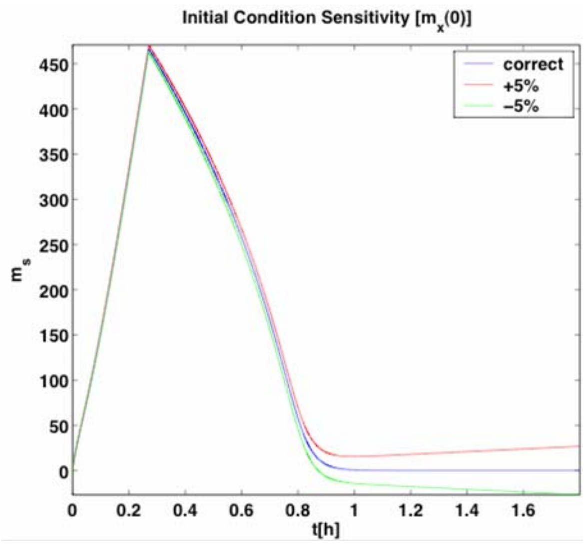

Fig. 11 Evolution of the estimated ms(t) for initial conditions deviations

Conclusion: Our conclusion from these results is that the asymptotic observer cannot be used for the sequential batch process, as a deviation of only 5% in the initial biomass will impede the asymptotic observer to converge to useful estimates for substrate and biomass concentrations, especially when considering that a common error in the measurement of the biomass concentration is already about 10%. Therefore there not exists a satisfactory redundancy relation for the model EM1 and then any analytical procedure based on a redundancy in the system cannot be applied to detect abnormal conditions. As consequence the only way to detect abnormal conditions is looking for patterns of the measurements and their combination. It means the only robust option to detect any abnormal conditions in the process and may be isolate them is to search patterns for the *r(t,) DOx,* and *PH*. As a particular case, the INRA-LBE has developed a method based on the EM2 model using the PCA and it is described in the second annual report, WP7.

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