Automation of a Respirometry System

Gonçalo André Furtado Ramos de Deus
Departamento de Engenharia Electrotécnica e de Computadores
Instituto Superior Técnico
Lisboa, Portugal
grdeus@live.com

Abstract— **Dynamic modelling of the behaviour of wastewater treatment plants (WWTP) is used as a means to analyse its performance and/or operational control, and it features the specs of a great number of components and interactions. Regarding WWTP per suspended biomass, IWA (International Water Association) Activated Sludge Models (ASM) are frequently applied. By the use of respirometry tests, respirograms measuring the quantity of oxygen consumed per time unit and biological reactor volume (called oxygen uptake rate – OUR) can be obtained. Furthermore, these tests can determine the growth and decay constants for the heterotrophic and autotrophic biomass fractions, as well as the particle substrate hydrolysis constant value, allowing the calibration of ASM models.**

Regarding the current paper, a respirometry system based on the LSS variant (Liquid-phase principle: Static gas, Static liquid) was developed, implemented and automated. The automated respirometry system was developed from scratch in a laboratory environment, with the aim of obtaining real time data reads and to draw respirometric curves for different types of residual water and biomass from different origins. The bench scale system is essentially composed of an airing and mixing tank, where the sample is introduced, and a separate measurement cell where the dissolved oxygen readings take place. The system's actuators are connected to a software managed controller (programmable logic controller – PLC), implemented in LabVIEW environment. The same software will give the user all the obtained readings and will estimate the respiration rate using different methods, the most notable being the Kalman Filter (KF). After the experiment is over, a standard Excel file is created, registering all the acquired data.

Keywords- **respirometry; activated sludge; ASM models; dissolved oxygen; instrumentation and automation; monitoring; estimation; Kalman Filter; identification.**

I. INTRODUCTION

In the world, as we know it, there has never been something as unique and precious as water. Less than 0.5% of Earth's water is in suitable condition for consumption and use in agricultural applications. This small fraction has decreased considerably due to excessive use and urban, agricultural and industrial pollution. Therefore, it is necessary to ensure the continuity of the natural water cycle and human impact on water resources must be limited if disasters is to be avoided.

Central to this is proper treatment of wastewater. In terms of treated raw material, wastewater treatment can now be considered the largest process industry and showing a clear grown tendency.

In the stage of wastewater treatment, by suspended biomass, respirometry appears as a robust variable for characterizing, monitoring and controlling the process. Respirometry is employed, at present, on a regular basis, especially as a tool to aid implementation of different models related to the biochemical processes occurring in wastewater treatment and control methods.

The aim of this thesis is to develop an automation system that allows the characterization of a set of relevant variables in the process and identify respirometric parameters of dynamical systems that describe the evolution of the compounds involved. OUR estimates will be obtained using linear optimal estimation techniques (KF) and other methods. Implementation of these strategies will be performed in LabVIEW environment and resorting to a Schneider Electric PLC.

II. RESPIROMETRY

Respirometry is a technique that allows measurement and interpretation of the biological oxygen consumption rate under well defined experimental conditions. It is used during the biological process of activated sludge, in which aerobic organisms, in the presence of oxygen, oxygenate and mineralize organic material for the synthesis of new cellular material and energy production. Respiration rate is the variable that has raised great interest for application to control such processes, because the oxygen uptake is directly linked to substrate removal and biomass growth.

A. Respirometer

Respirometry is evaluated using a respirometer. Nowadays, the respirometer is a major instrument for optimization of biological processes, assessing the treatability of organic effluents and calibration of models related to the treatment by activated sludge. The respirometers can be classified into eight basic principles of measurement, according to two criteria: the phase where the oxygen concentration is measured – gas (G) or liquid (L) – and whether or not there is input and output of liquid and gas – flowing (F) or static (S). Any technique has its merits, depending on the specific application, provided that the correct measuring conditions are satisfied.

B. Modelling respiration

The model adopted in this paper, which characterizes these processes, is known as Activated Sludge Model No. 1, developed by the IWA. In this model, respiration is associated only with the aerobic growth of heterotrophic and nitrifying biomass and follows the death-regeneration approach. At the present, the model is probably the most widely used to describe the process of treating wastewater, forming an internationally accepted standard, when the biological phosphorus removal is not important.

III. Respirometric apparatus

A. Operative part

The operative part includes the aeration tank and the measuring cell, containing approximately 3.7 L of mixture, together with the actuators (compressor, hydraulic pumps and stirrer) and the dissolved oxygen (DO) and pH sensors, which also monitor the temperature of the mixture inside the two compartments. The actuators operate based on the orders received by the command part and the sensors have the role of tracking the physical quantities, giving information about the state of current operations to the command part.

A sensor is a measuring instrument that converts information from the physical quantity to be measured into an electrical signal proportional to it and which is adapted to the characteristics of the input signal conditioner. It was defined a minimum sampling interval of 1.5 seconds, so that the sending of information is performed with as few gaps as possible. Both sensors are manufactured by Hamilton and communicate with the computer through Modbus protocol.

The DO sensor differs from the conventional membrane sensors due to its optical mode of operation. Despite overcome all the limitations related to the membrane maintenance, this type of sensor has a slower response. The highly dynamic nature of the sensor makes it impossible to neglected its characteristics in the estimation of the OUR. Consequently, the optical Hamilton sensor was modeled by a first-order LTI (linear time-invariant) system. The time constant determined experimentally is about 59.6 seconds, which is clearly an high value.

In the respirometric system designed, the respiration rate is estimated using the DO readings in the sample collected in the measuring cell and it is intended that there is no connection between the latter and the biological reactor. Hence, the respiration rate will be limited by the concentrations of oxygen and substrate in the sample, which in small amounts will lead to the endogenous respiration. In other words, it is a LSS respirometer type. This type of respirometer is distinguished by both simple operation and easy determination of the OUR, but is limited by low frequency of measurement. Over time the DO concentration ($S_O(t)$) will decrease, expected as a steady decline, and thus the respiration rate ($r_O(t)$) is described as follows

$$\frac{dS_O(t)}{dt} = -\,r_O(t) \tag{1}$$

B. Command part

The programmable is the main element of this part. It is responsible for giving orders according to its program and the information it receives from the monitoring of the biochemical process in question. In this case, this device is a PLC manufactured by Schneider Electric. In the present situation, the PLC is operating inside an enclosure, where also all operative components are connected for power supply and control of actuation. This process will be performed in accordance with the software implemented in LabVIEW and PL7 environments.

B. Full system

Figure 1 shows an overall scheme of the connections and, in particular, the link between the parts mentioned above. According to the formulation master/slave, commonly utilized in PLC systems, the computer may be seen as the master of the system, since it is coordinating all the operations and requests information from the slaves. The latter group include both sensors (pH and DO), the PCMCIA communication card (allows parallel operation between the master and the software used – LabVIEW and PL7) and the PLC.

IV. Respirometric software

The program implemented to operate in combination with the respirometric system was developed based on the software package from National Instruments – LabVIEW, version 8.6. The main content focuses on: the acquisition of the information obtained from the sensors and the conversion and verification of that information into profitable measures; the noise filtering; the user interface created for monitoring and control the

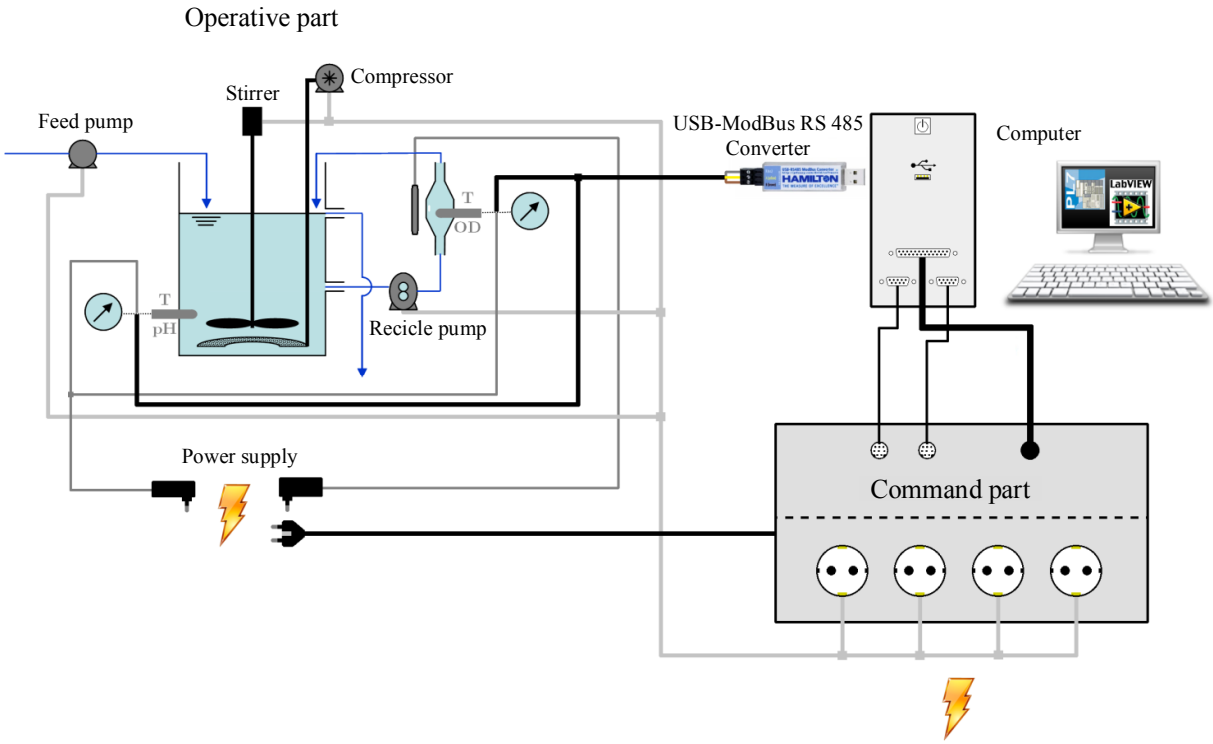

Figure 1. Overview of the respirometric set-up.

process, and finally, on the preparation of a report that contains all the obtained DO, pH, temperature and OUR values in tables and graphs that express the progress of each of these quantities and also the specifications inserted by the operator. The program is also responsible for the communication by Modbus protocol with both the PLC and the sensors. The initial user interface is shown in Figure 2. At this stage the user can choose between manual operation mode and automatic operation mode.

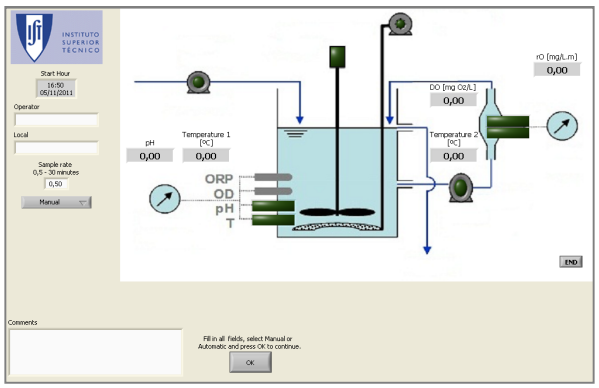

Figure 2. Initial software user interface.

A. *Manual operation mode*

In the manual mode the operator has full control (on/off) on the different actuators of the process at any time. The user interface also allows displaying or hiding of the graphs of the measures acquired by sensors. At the end of the process, the user has the opportunity to create an Excel standard report.

B. *Automatic operation mode*

In the automatic operation mode the user is asked about: the number of sampling cycles to execute; the pause time between each sampling; the number of measurements of OUR ("replicas") in each sample, the pump operating time and the acquisition time of the values of DO contained within the measuring cell. The user can also set a maximum and a minimum value of DO to which the process skips to the next stage.

A typical cycle for a measurement of the respiration rate of a sewage sample includes the following steps:

1 – Feeding of the sewage sample to the aeration tank through the feed pump, during a predetermined period of time in order to completely replace the sample from the previous measurement cycle, if there is any; the agitation turbine, at least, should be in operation during feeding; the liquid level in the tank should be kept constant by way of an overflow line leading back to the sewage drain;

2 – Agitation and aeration of the sample during a predetermined time period to allow the sensor readings to stabilise; these conditions are kept in the aeration tank up to the end of the respirometric measurement and the sensor readings are registered at given time intervals;

3 – Feeding of a representative portion of the tank liquid content to the measurement cell through the recycle pump; the liquid is recycled back to the tank during a predetermined time period in order to completely replace the liquid left in the cell from the previous measurement or until the maximum DO value is achieved; this stage is highlighted in the graphs through a red vertical line;

4 – Interruption of recycle pump operation and start of registration of the readings from the DO electrode located in the measuring cell; DO readings are registered in time during a predetermined period or until they drop below the minimum chosen DO value; DO concentration decreases according to equation (1); the beginning of this stage is highlighted in the graphs through a yellow vertical line;

5 – Repetition of steps *3* and *4* to obtain replicate measurements;

6 – System pause until the following measurement cycle; agitation and aeration can be kept in operation if the pause is short; preparation of an intermediate report concerning the last cycle, with the same structure as mentioned in the step *8*;

7 – Restart of the process in step *3*. When the total number of samples is reached, and the respective measurements associated with each sample, the acquisition cycle procedure finishes;

8 – Preparation of an Excel report. Bearing in mind the manual operation report, this one additionally includes the user input maximum and minimum values of DO and times of operation, the times of the vertical lines, the slopes linked with each sample and the estimated values of DO and OUR obtained by the KF. There will be a new set of tables and charts for each cycle.

An example of the user interface running in the automatic mode of operation can be seen in the Figure 3.

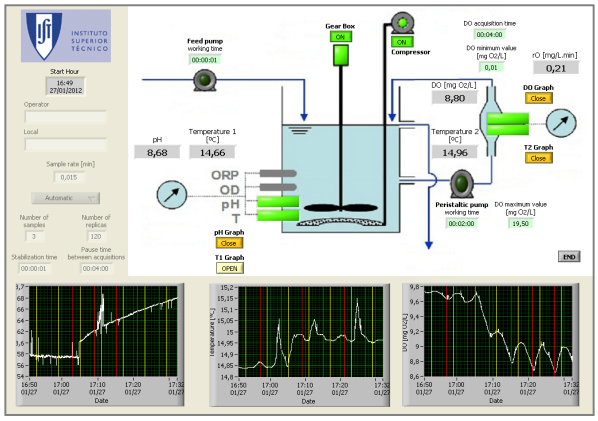

Figure 3. Software user interface during automatic operation mode.

V. OUR ESTIMATION STRATEGIES

In this thesis, the OUR is estimated via three different strategies. These range from the most basic step, obtaining the slope of the acquired signal, to the advanced strategies, which allow estimating of the respiration rate considering the sensors dynamics.

A. Slope of the signal

Taking into account the equation (1), the respiration rate can hence be estimated from the slope of the sensor output. Before that, the signal is filtered in order to suppress the noise and outliers using a median digital filtering technique with a window size of twelve samples. To avoid the slow response of the DO sensor, particularly during the transition from step *3* to step *4*, the program implemented processes only the final 70% of the total measurements obtained in step *4*.

An example of three measurements is shown in the Figure 4. The delimited gray zones reflect the final 70% of the signal acquired during step *4*, from which the slope of the fitted line is calculated. For this example was chosen an interval of four minutes to acquire measures from the measuring cell and two minutes for recirculation of the mixture. Therefore, there is an estimate of OUR every 6 minutes, because the calculation is performed only at the end of the measuring process.

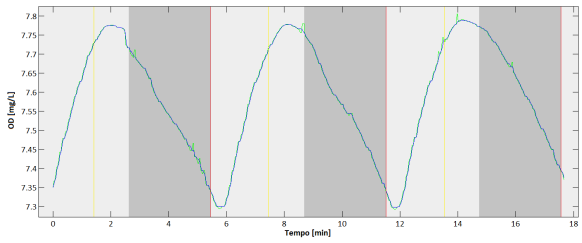

Figure 4. DO signal response (green) and filtered signal (blue).

B. Kalman Filter

The application of a zero-order-hold sampling on DO concentration dynamics given by (1) has previously been made and can be applied in it, which results in

$$S_O[k+1] = S_O[k] - \Delta t \cdot r_O[k] + w[k] \qquad (2)$$

where Δt is the sampling interval, k is the discrete time and $w[k]$ describes sampling and model uncertainties ($\mathbf{w}_k \sim \mathcal{N}(0, \mathbf{Q})$).

The respiration rate can be considered a disturbance input to the DO model and can be modeled using the random walk model

$$r_O[k] = r_O[k-1] + e_w[k] \qquad (3)$$

where $e_w[k]$ is zero mean white noise at time k.

Finally, the expression that models the dynamics of the DO sensor is given by

$$\dot{S}_O^s(t) = \left(S_O(t) - S_O^s(t)\right) \cdot \tau^{-1} \qquad (4)$$

where $S_O^s(t)$ is the measure of sensor output and τ is the time constant, already known.

The last three equations are used in order to get the linear stochastic difference equation addressed by the KF

$$\dot{\mathbf{x}}(t) = \begin{bmatrix} \dot{S}_O(t) \\ \dot{r}_O(t) \\ \dot{S}_O^s(t) \end{bmatrix} = \mathbf{A} \cdot \mathbf{x}(t) + \mathbf{w}(t) \qquad (5)$$

with

$$\mathbf{A} = \begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & 0 \\ 1/\tau & 0 & -1/\tau \end{bmatrix} \quad (6)$$

From the previous result emerges the discretized KF formulation of the process model

$$\mathbf{x}_k = \begin{bmatrix} S_O \\ r_O \\ S_O^s \end{bmatrix}_k = \mathbf{A}_d \cdot \mathbf{x}_{k-1} + \mathbf{w}_k \quad (7)$$

with

$$\mathbf{A}_d = e^{\mathbf{A}\cdot\Delta t} = \mathcal{L}^{-1}\{(s\cdot\mathbf{I} - \mathbf{A})^{-1}\}_{t=\Delta t} \quad (8)$$

and

$$\mathbf{Q} = \mathrm{E}[\mathbf{w}_k \cdot \mathbf{w}_k'] = \begin{bmatrix} \Delta t^2/2 \\ \Delta t \end{bmatrix} \cdot \begin{bmatrix} \Delta t^2/2 \\ \Delta t \end{bmatrix}^{\mathrm{T}} \cdot \sigma_w^2 \quad (9)$$

In the observation model, the measurement is defined as

$$z_k = S_{O_k}^s = \mathbf{H} \cdot \mathbf{x}_k + \mathrm{v}_k \quad (10)$$

where v_k is the random acquisition noise ($\mathbf{v}_k \sim \mathcal{N}(0, \mathrm{r})$) with

$$\mathbf{H} = [0 \quad 0 \quad 1] \text{ and } \mathrm{r} = \sigma_v^2 \quad (11)$$

The Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state, following the steps:

1 – Prediction phase

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F} \cdot \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B} \cdot u_k \quad (12)$$

$$\mathbf{P}_{k|k-1} = \mathbf{F} \cdot \mathbf{P}_{k-1|k-1} \cdot \mathbf{F}^T + \mathbf{Q}_k \quad (13)$$

where $\hat{\mathbf{x}}_{k|k-1}$ is the estimate of $\mathbf{x}_k$ given the measurements z_{k-1}, z_{k-2}, z_{k-3},… and $\mathbf{P}_{k|k-1}$ is the error covariance matrix of the state estimate given z_{k-1}, z_{k-2}, z_{k-3},…

2 – Kalman gain

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \cdot \mathbf{H}^T \cdot \left[\mathbf{H} \cdot \mathbf{P}_{k|k-1} \cdot \mathbf{H}^T + \mathbf{R}_k\right]^{-1} \quad (14)$$

where the matrix $\mathbf{K}_k$ is chosen to be the gain or blending factor that minimizes the *a posteriori* error covariance ($\mathbf{P}_{k|k}$).

3 – Correction phase

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \cdot \left(\mathbf{z}_k - \mathbf{H} \cdot \hat{\mathbf{x}}_{k|k-1}\right) \quad (15)$$

$$\mathbf{P}_{k|k} = [\mathbf{I} - \mathbf{K}_k \cdot \mathbf{H}] \cdot \mathbf{P}_{k|k-1} \quad (16)$$

where **I** is the appropriate size identity matrix.

As the Kalman filtering is only applied during the measurement in the measuring cell (step *4* defined earlier), there is the possibility to use the final values observed during the recirculation phase (step *3*). Therefore $\widehat{S_{O_{0|0}}}$ and $\widehat{S_{O_{0|0}}^s}$ adopt the value of the last obtained reading and $\widehat{r_{O_{0|0}}}$ is approximated through the calculation of the derivative between the latter two acquisitions. In the other hand, the initial values for the covariance matrix were chosen to be $\mathbf{P}_{0|0} = [10^3\ 0\ 0;\ 0\ 10^3\ 0;\ 0\ 0\ 10^2]$. The process noise and the measurement noise were assumed as $\sigma_w = 0.001\ /\ \Delta t$ and $\mathrm{r} = \sigma_v^2 = 0.01$, respectively.

In the Figure 5 are illustrated four samples with estimates corresponding to DO concentration (a) and OUR (b). Each observation acquired during the step *4* means a new iteration of the KF and on-line estimation.

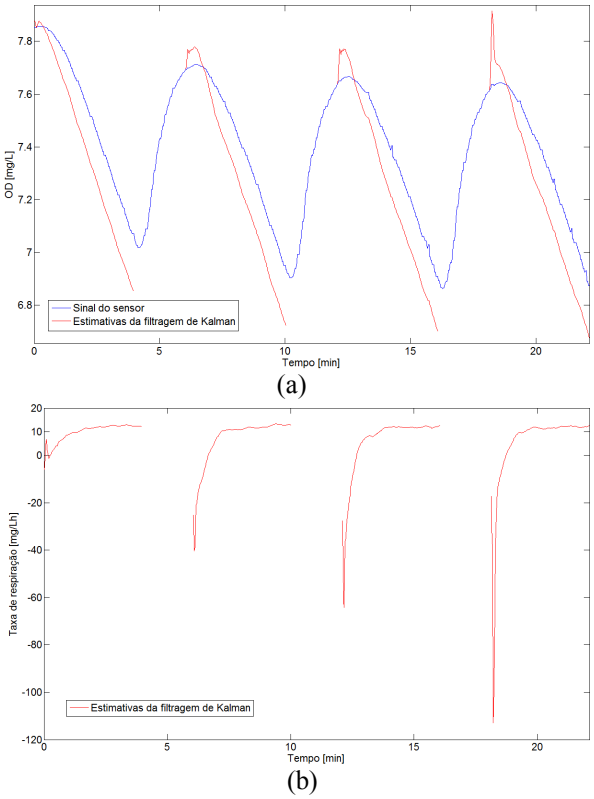

Figure 5. DO signal response (blue) and estimated DO and OUR (red).

C. *Fixed lag smoother*

The third strategy consists in the design of a filter that reduces the influence of the sensor dynamics. A block diagram of the sensor, the input model and the filter is shown in Figure 6. The problem is to find a filter which minimizes the mean square error between the true DO concentration and the filtered DO – $\hat{S}_O(t|t-m)$ – prediction of $S_O(t)$ based on data up to time $t-m$.

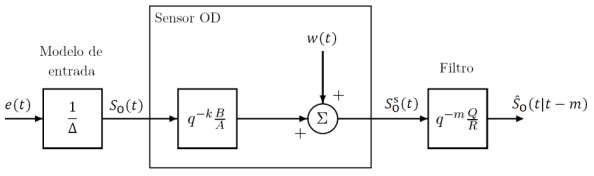

Figure 6. Block diagram of the input signal, the sensor model and the filter.

The sensor is modeled by

$$S_O^s(t) = q^{-k} \cdot \frac{B(q^{-1})}{A(q^{-1})} \cdot S_O(t) + w(t) \qquad (17)$$

where k is a time delay, $A(q^{-1})$ and $B(q^{-1})$ are polynomials in the backward shift operator and $w(t)$ is zero mean white measurement noise.

The filter which minimizes the mean square error is given by

$$\hat{S}_O(t|t-m) = q^{-m} \cdot \frac{Q(q^{-1})}{R(q^{-1})} \cdot S_O^s(t) \qquad (18)$$

where the $Q(q^{-1})$ and $R(q^{-1})$ polynomials are found by solving the following designed equations developed by Ahlén and Sternad (1989), where the argument (q^{-1}) is left out for simplicity

$$r \cdot \beta \cdot \beta_* = B \cdot B_* + \rho \cdot A \cdot \Delta \cdot A_* \cdot \Delta_* \qquad (19)$$

$$q^{m+k} \cdot B_* = r \cdot \beta_* \cdot Q_1 + q \cdot \Delta \cdot L_* \qquad (20)$$

$$Q = Q_1 \cdot A \qquad (21)$$

$$R = \beta \qquad (22)$$

The sensor model can be determined by a least squares method. The data necessary for estimating the sensor dynamics was achieved by moving the DO sensor between waters with different DO concentrations. The following parameters were identified using the system identification toolbox in MATLAB

$$\begin{aligned} A &= A_0 + A_1 q^{-1} = 1 - 0{,}96630 q^{-1} \\ B &= B_0 = 0{,}03202 \qquad\qquad k = 4 \end{aligned} \qquad (23)$$

The parameter ρ is probably easiest to find by trial and error. A small ρ gives a noisy result and a large ρ gives a slow response to changes in the DO concentration.

Using the polynomials (23) in the design equations (19) to (22) with a smoothing lag $m = -7$ and $\rho = 10$ gives the Q_1 and R polynomials

$$\begin{aligned} Q_1 &= 0{,}28330 + 0{,}00735 \cdot q^{-1} \\ &+ 0{,}00530 \cdot q^{-2} + 0{,}00286 \cdot q^{-3} \\ R &= 1 - 1{,}85319 \cdot q^{-1} + 0{,}86275 \cdot q^{-2} \end{aligned} \qquad (24)$$

The filter then becomes

$$\hat{S}_O(t|t+7) = q^7 \cdot \frac{Q_1 \cdot A}{1 - 1{,}85319 \cdot q^{-1} + 0{,}86275 \cdot q^{-2}} \cdot S_O^s(t) \qquad (25)$$

In Figure 6 an example of five samples is shown. The slope or the KF strategies can be applied to the filtered signal in order to obtain an OUR estimation. Unlike the KF, this strategy only allows the estimate of OUR at the end of the process, just like the slope strategy.

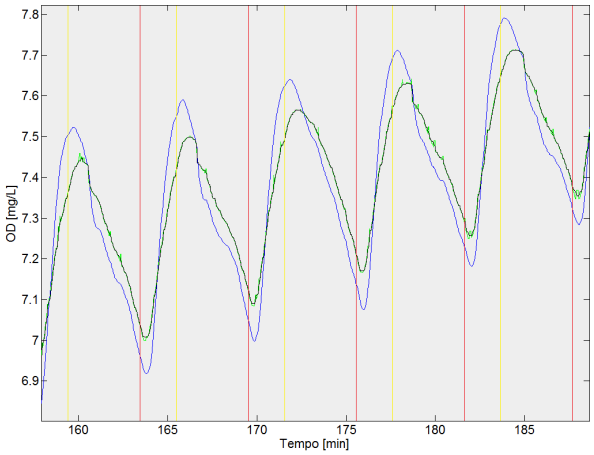

Figure 7. DO signal response (green), DO signal filtered using a median filter (black) and DO signal after filtering with (25) (blue).

VI. ASM No.1 Parameters Estimation

In order to test and validate the respirometer developed, as well as the calculation methods applied, were estimated some coefficients and parameters of the ASM1. The results were compared to values reported in the literature. In all the experimental procedures the subsequent aspects were taken into account: the sludge was taken from an urban WWTP (Beirolas, Loures, Portugal); sodium acetate was supplied as substrate; ATU was not added to the mixture; and the temperature and pH of the mixture were not kept constant.

A. *Heterotrophic yield* - Y_H

A linear relationship between the substrate (S_S) added and the oxygen consumed (OC) allows to calculate biomass yield via

$$\mathrm{OC} = (1 - Y_H) \cdot S_S \qquad (26)$$

by using the slope of the curve. The heterotrophic yield stoichiometric coefficient was evaluated through a respirometric batch experiment with four different pulses of substrate added to endogenous activated sludge sample. Sodium acetate COD (chemical oxygen demand) concentration range from 64 – 1000 mg /L was used in this experiment. A linear increase of OC was observed when increasing amount of substrate was added to the reactor, as seen in Figure 8.

The maximum average yield for this data series is $Y_H \approx 0{,}66$ mg COD/mg COD.

B. *Heterotrophic decay rate* - b_H

The decay kinetic parameter was determined aerating the reactor with endogenous sludge for seven days. Respiration rate was measured at regular time

every day. The decay rate in traditional modeling approach (b'_H) is calculated from the slope of a plot of $\ln(r_O)$ versus time (Figure 9). The following equation is then applied to calculate the value of b_H, adopted in the ASM No.1

$$b_H = \frac{b'_H}{1 - Y_H \cdot (1 - f_p)} \quad (27)$$

where f_p is calculated by

$$f_p = \frac{f'_p \cdot (1 - Y_H)}{1 - f'_p \cdot Y_H} \quad (28)$$

knowing that $f'_p = 0.2$.

The decay rate obtained was $b_H \approx 0.36$ day^{-1}.

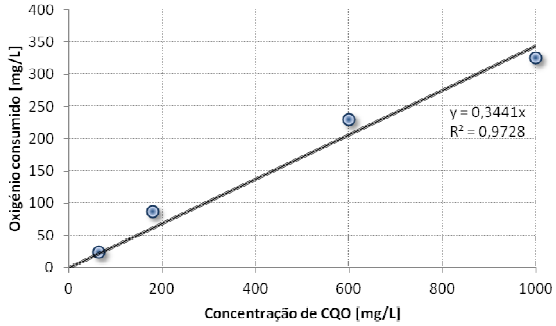

Figure 8. Linear relationship between oxygen consumed and substrate added.

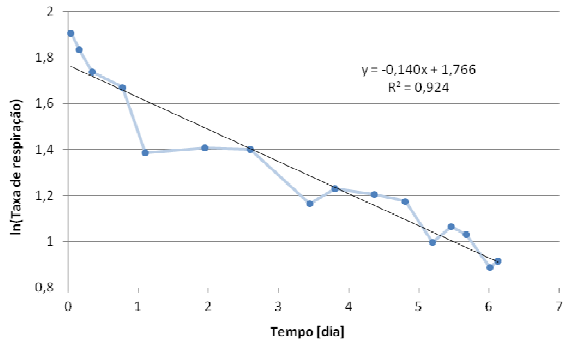

Figure 9. Plot of $\ln(r_O)$ versus time.

C. *Heterotrophic max. specific growth rate - $\hat{\mu}_H$*

The maximum specific growth rate was assessed with the procedure based on adding high readily biodegradable substrate to low concentration of activated sludge with none limiting of DO concentration. A linear increase of OUR was observed when sodium acetate was added to the respirometer. The possibility of assessing $\hat{\mu}_H - b'_H$ is the slope of the plot of $\ln(r_O)$ versus time (Figure 10). The kinetic parameter for this experimental data is $\hat{\mu}_H \approx 2.30$ day^{-1}.

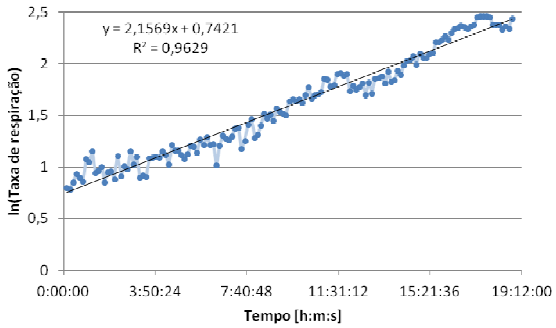

Figure 10. Plot of $\ln(r_O)$ versus time.

D. *Half-saturation coefficient for heterotrophs - K_S*

Saturation constant for substrate is determined following the method based on Monod equation and analysis of the OUR at different substrate concentration. Exogenous OUR was measured as the difference between endogenous OUR and the total OUR registered in every experiment. The exogenous OUR was divided by the maximum value of exogenous OUR registered in the whole experiment to calculate the relative activity, depending on substrate concentration. The resulted of respirometric experimental concurrent with data fitted by a logarithm function is shown in Figure 11. The saturation constant kinetic parameter obtained is $K_S \approx 19.89$ mg COD/L.

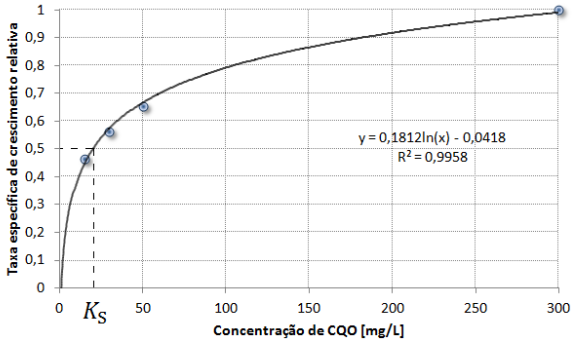

Figure 11. Assessment of saturation constant for substrate.

VII. Conclusion

The obtain experimental results have shown that the used methodologies were successful in estimating OUR, however the fixed lag smoother showed that it is not a robust strategy for studying nonstationary cases. When compared with other methods the proposed KF strategy gave better performance with respect to response time, immunity to noise and steady response. The slope strategy gave also consistent results but the accuracy of the results diminished for low levels of respiration rate.

The respirometric experiments for the determination of ASM No.1 parameters are demonstrated to be sensitive and robust. The results of parameter estimation using respirometric measurements data were close to the default values in ASM No.1 and

other reported values. Even though some parameter was lower than the default value, they were still comparable within the range of values in the literature. The difference of each parameter from default value may be due to some constraints related to temperature and pH variations, sludge sources, location, operating conditions, experimental design and experimental time.

Overall the respirometer designed and the strategies applied in this thesis were successful in estimating both OUR and the ASM No.1 parameters, constituting a valuable tool to monitor and control the activated sludge process and to calibrate its models.

REFERENCES

AHLÉN, A. e STERNAD, M. (1989). Optimal deconvolution based on polynomial methods. IEEE Transactions on Acoustics, Speech and Signal Processing, Vol. 37, No. 2, pp. 217–226.

GERNAEY, A.K., PETERSEN, B., OTTOY, J. e VANROLLEGHEM, P. (2001). Activated sludge monitoring with combined respirometric–titrimetric measurements. Water Research, Vol. 35, No. 5, pp. 1280–1294.

JEPPSSON, U. (1996). Modelling aspects of wastewater treatment processes. Ph.D. dissertation, IEA, Lund Institute of Technology, Sweden.

KLEEMAN, L. (1996). Understanding and applying Kalman filtering. Proceedings of the Second Workshop on "Perceptive Systems", Curtin University of Technology, Perth, Western Australia.

LINDBERG, C.F. (1997). Control and Estimation Strategies Applied to the Activated Sludge Process. Dissertation for the Degree of Doctor of Philosophy, Uppsala University, Sweden.

MAO, H., ZHAO, J., HUA, L. e HU, B. (2011). Determining parameters in Activated Sludge Model No.1 by respirometric experiments with sodium acetate as substrate. IEEE International Symposium on Water Resource and Environmental Protection (ISWREP 2011), Xi'an, Shaanxi Province, China, Vol. 1, pp. 1660–1663.

MOGENS, H., GUJER, W., MINO, T. e VAN LOOSDRECHT, M. (2000). Activated sludge models ASM1, ASM2, ASM2d and ASM3. IWA Publishing, London, UK.

OLIVEIRA, P. (2008). Curso de automação industrial. ETEP, Lisboa, Portugal.

OPPENHEIM, A.V., WILLSKY, A.S. e NAWAB, S.H. (1996). Signals and Systems. Second edition, Prentice Hall International.

SAENSING, P. e KANCHANATAWEE, S. (2009). Development of combined ultimate hybrid respirometer-titrate meter to estimate kinetic parameters of activated sludge. Suranaree Journal of Science and Technology, Vol. 16, No. 3, pp. 221–233.

SILVA, F.J.S., CATUNDA, S.Y.C., NETO, J.V.F. e VAN HAANDEL, A.C. (2010). Dissolved oxygen PWM control and oxygen uptake rate estimation using Kalman Filter in activated sludge systems. IEEE International Instrumentation and Measurement Technology Conference (I2MTC 2010), Austin, Texas, USA, pp. 579–584.

SOTOMAYOR, O.A.Z., PARK, S.W. e GARCIA, C. (2002). Software sensor for on-line estimation of the microbial activity in activated sludge systems. ISA TRANSACTIONS, Vol. 41, pp. 127–143.

SPANJERS, H., VANROLLEGHEM, P.A., OLSSON, G. e DOLD, P.L. (1998). Respirometry in Control of the Activated Sludge Process: Principles. Scientific and Technical Report No. 7. IAWQ, London, UK.

VANROLLEGHEM, P.A., SPANJERS, H., PETERSEN, B., GINESTET, P. e TAKACS, I. (1999). Estimating (combinations of) Activated Sludge Model No. 1 parameters and components by respirometry. Water, Science and Technology, Vol. 39, No. 1, pp. 195–214.

VANROLLEGHEM, P.A. (2002). Principles of respirometry in activated sludge wastewater treatment. Proceedings International Workshop on Recent Development in Respirometry for Wastewater Treatment Plant Monitoring and Control, Taipei, Taiwan, pp. 2/1–20.

WEIJERS, S. (2000). Modelling, identification and control of activated sludge plants for nitrogen removal. Ph.D. Thesis, Eindhoven University of Technology, Netherlands.

WELCH, G. e BISHOP, G. (2001). An introduction to the Kalman filter. Technical Report, TR 95-041, University of North Carolina at Chapel Hill, USA.