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Nonlinear PI control for dissolved oxygen tracking at wastewater treatment plant

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Abstract: The paper addresses design, implementation and simulation of a novel type of softly switched Takagi-Sugeno fuzzy PI control system for dissolved oxygen concentration (*DO*) tracking at wastewater treatment plant (*WWTP*). The proposed control system is designed, including tuning the PI controllers, entirely based on the experimental data. This control system is validated by simulation.

1. INTRODUCTION AND PROBLEM STATEMENT

An activated sludge wastewater treatment plant can be classified as a complex system due to its nonlinear dynamics, large uncertainty in the disturbance inputs, multiple time scales in the internal process dynamics and multivariable structure.
The scheme of the wastewater treatment processes considered in the paper is shown in Fig. 1.

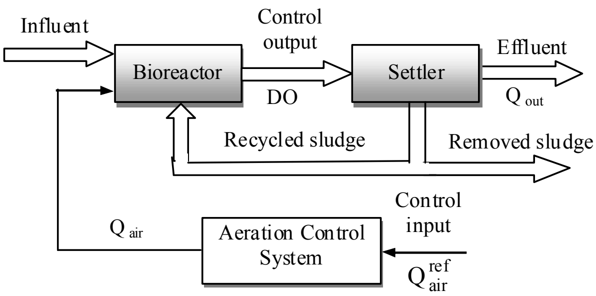

Fig. 1. Scheme of the wastewater treatment system

The bioreactor contains a mixture of liquid and suspended pollutant where a population of microorganism is produced in order to remove the organic substrate from the mixture. The settler is a gravity settlement tank where the sludge and clear out flow are separated. The activated sludge is directly recirculated from the settler to the bioreactor. The excess biological sludge is removed.
During the last years control strategies for the *WWTP* have been intensively investigated. A hierarchical multilayer control structure that utilises multiple time scales in the plant dynamics for robust optimised control of the biological wastewater treatment plants was proposed in (Brdys *et al.,* 2007). The dissolved oxygen concentration in the bioreactor is a key manipulated variable. Its set point trajectory prescribed by the upper control layer is forced in the reactor by an aeration system that delivers an oxygen by blowing airflow $Q_{air}(t)$ into the bioreactor. The aeration in *WWTP* role is twofold. Firstly, the oxygen is provided as a main component for biological processes. Secondly, it supports mixing sludge with the sewage what helps to treat the sewage. Aeration is highly energy consuming and the energy consumption represents more then 60% of the total energy demand in an activated sludge wastewater treatment processes.
As the DO dynamics is nonlinear and typically WWTP operates under high variability of the influent quantity and pollutant parameters an applicability of a conventional fixed parameter PID controller is limited. A fuzzy logic Mamdami type of controllers were proposed in (Ferrer *et al*., 1998) and (Kalker *et al*., 1999). Another Mamdami type of fuzzy logic controller was presented in (Traoré *et al*., 2005) and it was applied to a bath reactor pilot WWTP. The latter work considered the DO controller cascaded with the ammonia concentration controller. This control structure was also considered in (e.g., Gerkšič *et al*., 2006) where the DO controller was designed by applying a deterministic gain scheduling. A neural-fuzzy algorithm was developed in (Rodrigo *et al*., 1999) in order to apply gain scheduling for standard PID controller.
The nonlinear predictive control was proposed by Brdys and Konarczak (2001) for the removal of nitrogen and phosphorus and further developed in (Chotkowski *et al*., 2005).
A hierarchical predictive two - level controller for the optimised *DO* tracking was recently presented in (Piotrowski *et al*., 2007). The upper level controller (*ULC*) prescribes trajectories of desired airflows to be delivered into the aerobic biological reactor zones. The *ULC* uses the manipulated variable $Q_{air}(t)$ as its control outputs forcing $DO(t)$ to follow $DO^{ref}(t)$. A nonlinear multivariable model

predictive control algorithm is applied to design this controller unit. The lower level controller (*LLC*) forces the aeration system to follow these set point trajectories. The *LLC* acts as an actuating system and takes the *ULC* output asthe reference trajectory $Q_{air}^{ref}(t)$ of the airflow to be provided. The *LLC* uses the aeration system control handles in order to produce the airflow trajectories $Q_{air}(t)$ that follow the trajectories $Q_{air}^{ref}(t)$ prescribed by the *ULC* and to minimize the electrical energy cost due to blowing the air. Due to a mixed integer structure of the aeration system blowers a hybrid model predictive controller (*MPC*) at the lower control level has been derived in (Piotrowski *et al.*, 2007).

The *MPC* is very attractive solution, but highly dependent on the accuracy of the plant model and accuracy of the influent flow rate and pollutant concentrations. In reality, complex dynamics of biological processes make the task of model construction and identification and the disturbance input prediction difficult, leading to significant uncertainties. This and a cost of implementation of the hybrid model predictive controller make the use of nonlinear control scheme such as an intelligent fuzzy control the competitive alternative.

The paper is organised as follows. The control problem analysis is presented in Section 2. Section 3 presents the controller design. The simulation results are described in Section 4. Finally, the conclusions are drawn.

2. CONTROL PROBLEM ANALYSIS

The simplified but still realistic mathematical model of the *WWTP* (see Fig. 2) can be given by the following mass balance equations (Nejjari *et. al.*, 1999):

$$\frac{dX}{dt} = \mu(t)\,X(t) - D(t)\,(1+r)\,X(t) + r\,D(t)\,X_r(t) \tag{1}$$

$$\frac{dS}{dt} = -\frac{\mu(t)}{Y}X(t) - D(t)\,(1+r)\,S(t) + D(t)\,S_{in}(t) \tag{2}$$

$$\begin{aligned}\frac{dDO}{dt} = &-\frac{K_0\,\mu(t)\,X(t)}{Y} - D(t)\,(1+r)\,DO(t) + \\ &+\alpha\,Q_{air}(t)\,(DO_{\max} - DO(t)) + D(t)\,DO_{in}(t)\end{aligned} \tag{3}$$

$$\frac{dX_r}{dt} = D(t)\,(1+r)\,X(t) - D(t)\,(\beta + r)\,X_r(t) \tag{4}$$

$$\mu(t) = \mu_{\max}\frac{S(t)}{K_s + S(t)}\cdot\frac{DO(t)}{K_{DO} + DO(t)} \tag{5}$$

with:

$$D(t) = \frac{Q_{in}}{V_a};\quad r = \frac{Q_r}{Q_{in}};\quad \beta = \frac{Q_w}{Q_{in}};\quad V = \frac{V_a}{V_s}$$

where $X(t)$, $S(t)$, $DO_{\max}$, $X_r(t)$, $D(t)$, S_{in}, DO_{in}, Y, μ, $\mu_{\max}$, K_s, K_{DO}, α, Q_{air}, K_0, r, β denote biomass concentration, substrate concentration, maximum dissolved oxygen concentration, recycled biomass concentration, dilution rate, substrate concentration in the influent, dissolved oxygen concentration in the influent, biomass yield factor, biomass growth rate, maximum specific growth rate; affinity constant, saturation constant, oxygen transfer rate, aeration rate, model constant, recycled sludge rate, removed sludge rate, respectively.

Q_{in}, Q_{out}, Q_r, Q_w are the influent, effluent, recycle and waste flow rates, respectively. V_a and V_s represent the aerator and settler volumes. It is assumed that $V = 1$.

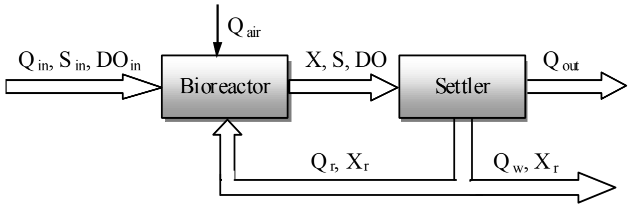

Fig. 2. Scheme of the wastewater treatment plant

The aeration rate $Q_{air}(t)$ is the control input while the dilution rate $D(t)$, influent substrate concentration $S_{in}(t)$ and influent dissolved oxygen concentration $DO_{in}(t)$ are the plant disturbance inputs that can significantly vary in time. This model links these inputs to the dissolved oxygen concentration in the biological reactor $DO(t)$ that is plant controlled output. The dissolved oxygen concentration controller is expected to maintain good tracking of the prescribed trajectory in spite of these unmeasurable and time varying disturbances.

The scheme of the overall control system follows the hierarchical architecture presented in (Piotrowski *et al.*, 2007) and it is shown in Fig. 3, where $DO^{ref}(t)$ and $Q_{air}^{ref}(t)$ denote the set point trajectories of the $DO(t)$ and $Q_{air}(t)$, respectively.

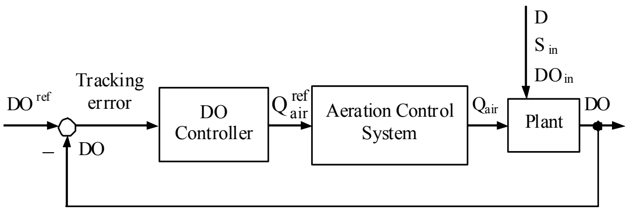

Fig. 3. A structure of the overall control system

In the paper the aeration control system is not investigated and it is considered as an actuator system with the rate and magnitude constraints imposed on the airflow $Q_{air}^{ref}(t)$. As the *DO* dynamics is highly nonlinear a fixed parameter linear controller is not able to maintain a satisfactory tracking performance under the full range of operating conditions. An adaptive PI controller was proposed in (Yoo *et al.*, 2002). The controller parameter adaptation algorithm in spite of its complexity was capable of achieving only limited overall controller performance.

The proposed controller is designed, including off-line tuning the PI controllers, entirely based on the experimental data. A softly switched nonlinear Takagi-Sugeno Fuzzy PI controller for *DO* tracking is derived and validated by simulation using the plant model given by the equations (1)-(5). No on-line explicit controller parameter tuning is required.

3. CONTROLLER DESIGN

Designing an intelligent controller in order to achieve the *DO* tracking at *WWTP* when the accurate model of the plant is unknown and under unknown and time varying disturbance inputs can be approached in different ways. A Fuzzy Expert Control System can be used with Recursive Least Square (*RLS*) on-line training method (Wang, 1994; Qi and Brdys, 2007). This Fuzzy Expert Control System could make decision like a human expert and generate control rules through on-line training. The on-line training is a general method which has been widely applied to automatically generate a fuzzy system online. However, this has been verified not suitable in our case as the RLS algorithm has not been fast enough to follow the time varying disturbances. In the approach employed in the paper a steady – state relationship between the control input and controlled output is piecewise linearized as illustrated in Fig. 4.

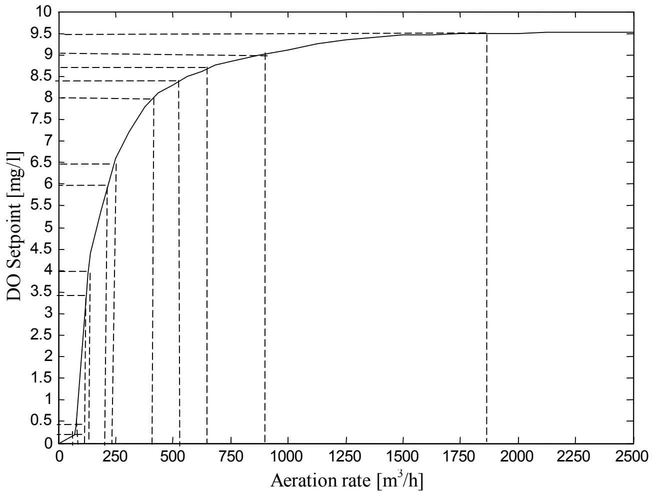

Fig. 4. *DO* concentration versus the aeration rate and piecewise linearization

The intervals are revealed on the *DO* axis over each of which the steady-state plant model can be considered linear. Therefore, the PI controllers would be applied to efficiently control the *DO* over each of the intervals. Tuning of a single PI controller can be done first by locating the *DO* value within the corresponding operating interval and then applying manual adjustment of its parameters so that the desired transient of moving the *DO* to the prescribed set point within the interval (step input response) is achieved. Hence, an overall tuning process can be done experimentally without necessity of employing the plant model.

The experiment performed as described above has shown that suitable PI controller gains are the same for several adjacent intervals produced by geometrical piecewise linearization. Hence, these intevals have been integrated to produce new enlarged intervals. The final results of tuning are illustrated in Table 1.

It is noticed that the *DO* operating region has now been partitioned into seven subregions shown in the Table 1. There are seven associated fixed parameter K_P, K_I PI controllers that are achieving desired tracking performance over each of these subregions. Values of the controller parameters K_P, K_I are shown in the Table 1. The Table 1 can then serve a lookup table to change the controller parameters based on current value of *DO* in the plant. The resulting controller would be the gain scheduled nonlinear PI controller. Changing the PI controller parameters when *DO* is leaving one operating subregion and is entering another one produces unwanted switching transients. In order to smooth these transients the Takagi – Sugeno control system is introduced (Yen and Langari, 1999). First, the crisp *DO* subregions are fuzzified by applying the following membership functions:

Table 1. Selected partitioning of the original experimental data

DO^{ref}	K_P	K_I	DO^{ref}	K_P	K_I
0.05 ~ 0.10 0.10 ~ 0.15	25	300	6.0 ~ 6.5 6.5 ~ 7.0 7.0 ~ 7.5 7.5 ~ 8.0	350	8000
0.15 ~ 0.20 0.20 ~ 0.25 0.25 ~ 0.30 0.30 ~ 0.35	50	650	8.0 ~ 8.2 8.2 ~ 8.4 8.4 ~ 8.6 8.6 ~ 8.8	1000	9000
0.35 ~ 0.40 0.40 ~ 0.45 0.45 ~ 0.50 0.50 ~ 0.60 0.60 ~ 0.70 0.70 ~ 0.80 0.80 ~ 0.90 0.90 ~ 1.00 1.00 ~ 1.50 1.50 ~ 2.00 2.00 ~ 2.50 2.50 ~ 3.00 3.00 ~ 3.50	200	3500	8.8 ~ 9.0 9.0 ~ 9.2 9.2 ~ 9.4 9.4 ~ 9.6 9.6 ~ 9.8 9.8 ~ 10.0	1500	15000
3.50 ~ 4.00 4.00 ~ 4.50 4.50 ~ 5.00 5.00 ~ 5.50 5.50 ~ 6.00	250	7000			

$$
\begin{aligned}
f_1(x) &= e^{((-0.5(x-0.2)^2)/1.0501^2)}\\
f_2(x) &= e^{((-0.5(x-1.0)^2)/1.0501^2)}\\
f_3(x) &= e^{((-0.5(x-3.5)^2)/1.0501^2)}\\
f_4(x) &= e^{((-0.5(x-5.5)^2)/1.0501^2)}\\
f_5(x) &= e^{((-0.5(x-7.5)^2)/1.0501^2)}\\
f_6(x) &= e^{((-0.5(x-8.4)^2)/1.0501^2)}\\
f_7(x) &= e^{((-0.5(x-9.4)^2)/1.0501^2)}
\end{aligned}
\tag{6}
$$

The membership functions are illustrated in Fig. 5.

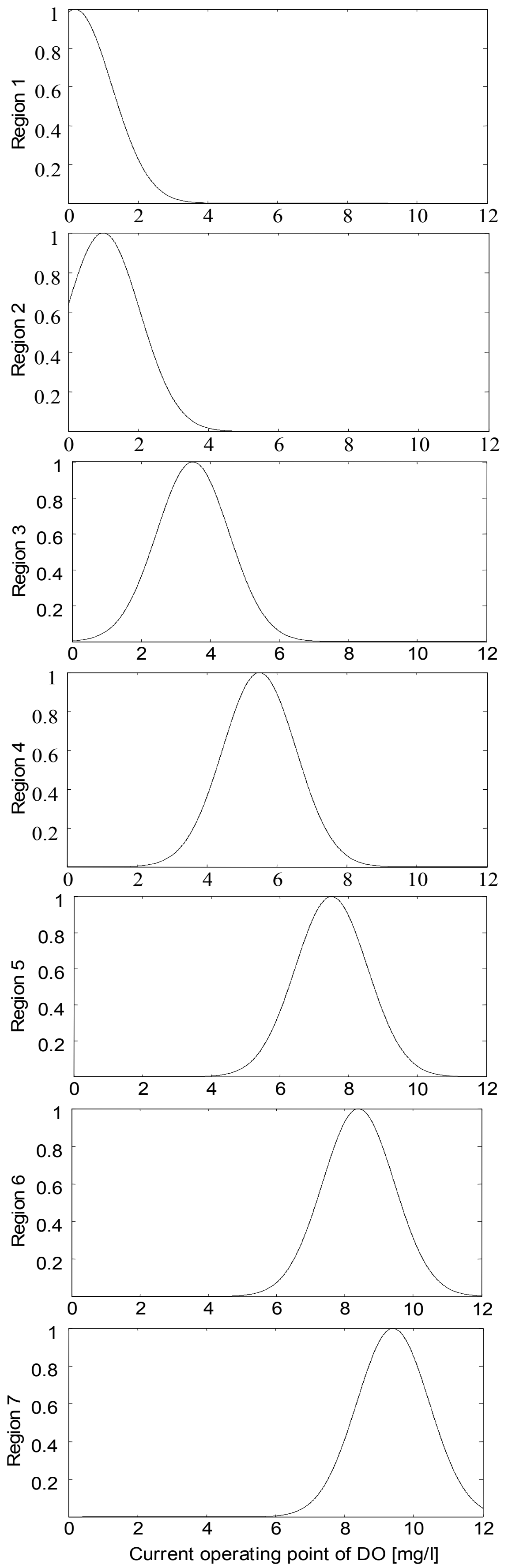

Fig. 5. Graphs of the membership functions $f_1, \ldots, f_7$

The Takagi – Sugeno nonlinear PI controller is shown in Fig. 6. The seven regional PI controllers operate in parallel producing the control input signals $Q_{air}^{ref,i}(t), i = 1,...,7$. These control inputs are fuzzy blended to produce the control input $Q_{air}^{ref}(t)$ that is applied to the plant via the aeration control system. The fuzzy blending operates as follows:

$$Q_{air}^{ref}(t) = \sum_{i=1}^{i=7} f_i(DO(t)) Q_{air}^{ref,i}(t) \tag{7}$$

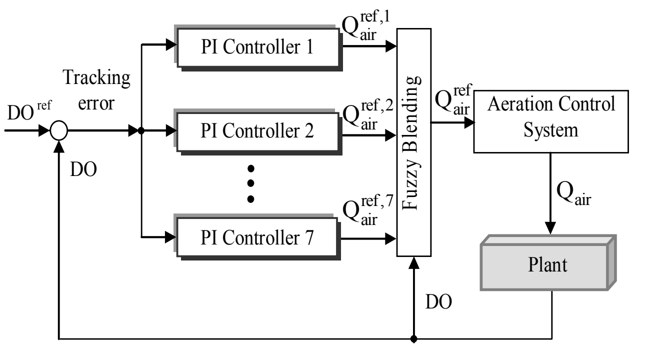

Fig. 6. Softly switched Takagi-Sugeno fuzzy PI control system

Hence, the control input $Q_{air}^{ref}(t)$ is a weighted sum of the control signals produced by the regional PI controllers. Their contribution to the overall control input depends how well the current $DO(t)$ operating point fits into the corresponding subregions. This is evaluated by the grades of memberships of the $DO(t)$ in the fuzzy subregions. Let us notice that a new PI controller is now activated not as in the case of lookup table approach in a hard manner but this is done gradually smoothing the corresponding transients. Indeed, when the $DO(t)$ values are in an overlapping range of a two adjacent subregions both of the regional PI controllers are active and the strengths of contributions of the control signals produced by the PI controller representing the subregion from which the $DO(t)$ values are moving away are decaying while the strengths of contributions of the control signals produced by the PI controller representing the subregion the $DO(t)$ values are moving into gradually increase (see Fig. 5 and (7)). Finally, the new PI becomes the only one active controller in the new subregion and a switching to this controller is soft.

4. SIMULATION RESULTS

The proposed controller was applied to the plant model described in Section 2. The model coefficients have the following values: $DO_{\max} = 10\ mg/l$, $S_{in} = 200\ mg/l$, $DO_{in} = 0.5\ mg/l$, $Y = 0.65$, $\mu_{\max} = 0.15\ mg/l$, $r = 0.6$, $K_s = 100\ mg/l$, $K_{DO} = 2\ mg/l$, $\alpha = 0.018$, $K_0 = 0.5$, $\beta = 0.2$. The digital PI controllers of the pulse transfer function $G_{PI}^{i}\left(z\right)=K_{P}\cdot\left(1+K_{I}\cdot\frac{1}{1-z^{-1}}\right),\ i\in\overline{1,7}$ were tuned manually as described in Section 3. The tuning procedure has started with parameters obtained by digitizing the continuous time PI controllers with the parameters listed in Table 1 by applying the backward rectangular rule of integration. The rate and magnitude limiters were applied to model the aeration control system. Fig. 7 illustrates a performance of the fixed parameter regional PI controller covering the subregion $DO\in[1.5, 3.0]$ where $K_p=200, K_I=3500$.

It can be seen that the regional controller robustly track the set point varying within the subregion in spite of the significant variations of the influent and the tracking performance is good.

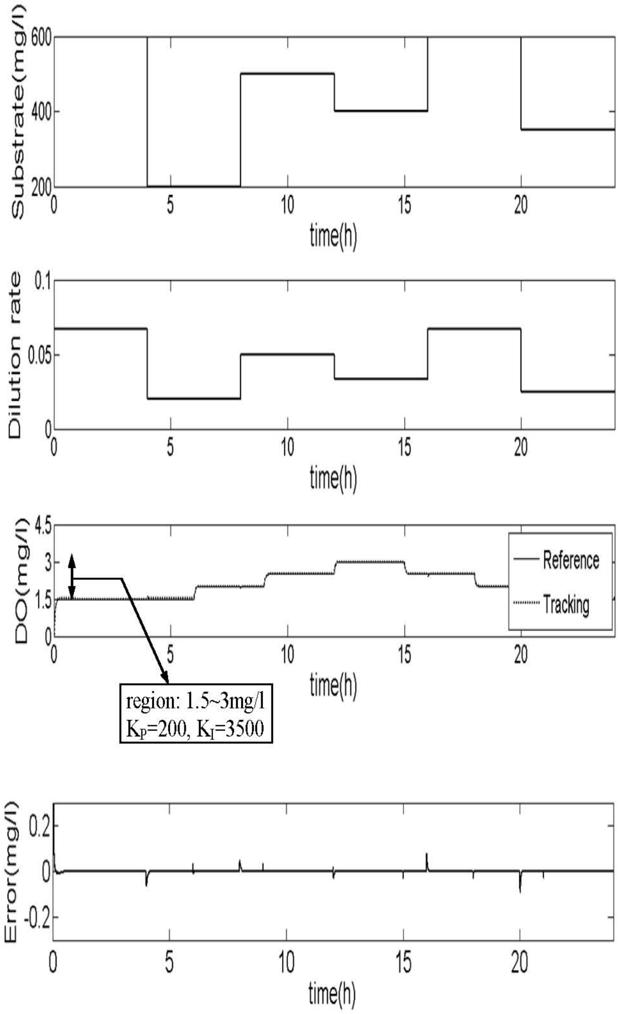

Fig. 7. Simulation results of a regional PI controller under time varying disturbances: a). influent substrate; b). influent dilution rate; c). *DO* set point and the tracking performance; d). tracking error

Performance of the overall multiregional controller is illustrated in Fig. 8 where the *DO* set point varies over a whole operating range. The tracking performance is comparable with the regional PI controller performance.

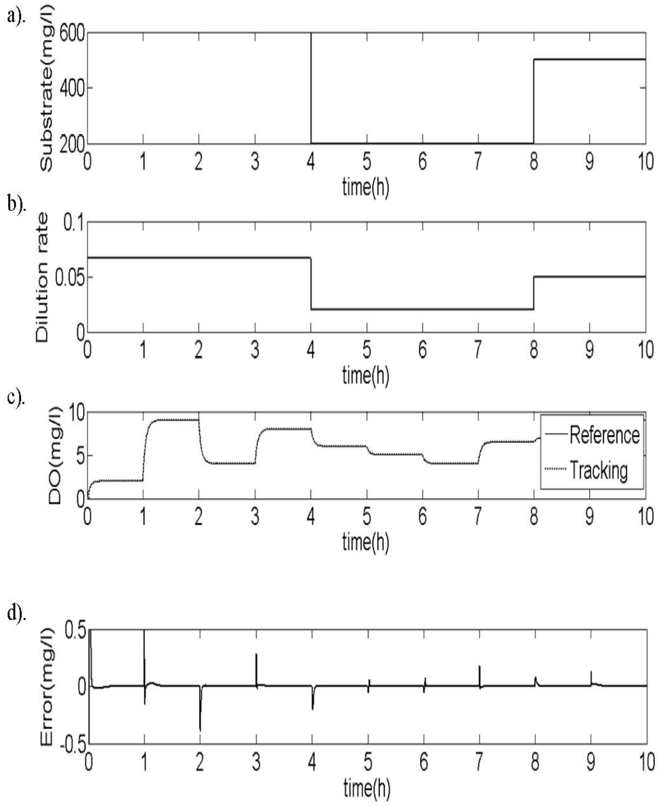

Fig. 8. Simulation results of a multiregional PI controller under time varying disturbances; a). influent substrate; b). influent dilution rate; c). *DO* set point and the tracking performance; d). tracking error

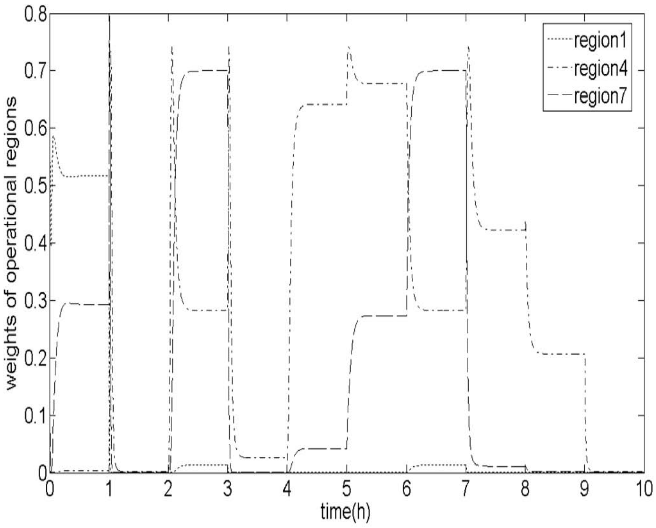

Fig. 9. Changing the weights over time for the subregions 1, 4 and 7 during the multiregional controller operation

An operation of the softly switched mechanism during the controller operation over a whole *DO* operating range is illustrated in Fig. 9 by presenting the regional PI controller weights over time for selected subregions.

5. CONCLUSIONS

The paper has addressed an important and difficult control problem. A novel approach to the dissolved oxygen concentration tracking has been presented. The softly switched Takagi-Sugeno nonlinear PI controller has been derived and its performance has been validated by simulation. Good tracking performance has been observed. The closed loop system stability analysis is under research.

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