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Study of Two Input Fuzzy PID Control for Dissolved Oxygen Concentration in the Activated Sludge Process

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Abstract- In this paper, Fuzzy PID controller is developed to improve the performance of the activated sludge process (ASP). The ASP is described by a nonlinear multivariable model with multi inputs multi outputs. The main objective of ASP is to obtain a substrate concentration in the effluent within the standard limits by legislation on wastewater treatment; this goal is achieved by controlling the dissolved oxygen (DO) concentration in aeration tank to set point value. The Fuzzy PID controller is designed based on the mathematical model of the activated sludge process. Simulations are carried out on the nonlinear model to show the effectiveness of fuzzy PID control method. It also discusses the activated sludge process response results obtained for a range of hydraulic and organic input disturbances.

Keywords- wastewater treatment, fuzzy PID controller, dissolved oxygen concentration, Activated sludge process

1. Introduction

The activated sludge process is the most widely used biological wastewater treatment process in treating both domestic and industrial wastewater. In the activated sludge process, the organic matter in the influent wastewater is utilized by microorganisms for synthesis of new cells in the aerator. Oxygen required is supplied for respiration and to maintain microorganism activity. Settling of the microbial flocs in the clarifier/settler purifies the effluent from the aerator. A portion of the settled sludge is recycled to the aerator to maintain enough microorganism amounts in the system. Part of the excess sludge is regularly removed. Correct operation of the process requires the following three items: First, the influent sewage entering the process has to be mixed intimately with recycled sludge. In principle there exist ranges of desirable proportions in which substrate (organic matter) and microorganism should be mixed to fully oxidize the wastewater during the period of retention within the aeration tank. Second, air is blown into the mixed liquor through diffusers or surface aerator; this gives the required agitation of the mixed liquor, provides the necessary aerobic environment for growth of the microorganism. Third, the settler must secure good separation between the biological floc (sludge) and the clarified effluent; excess sludge may be manipulated by the removal of waste sludge.

In recent years, improvement of the quality of treated water, discharged to nature and reduction of plant investment and operating costs become a subject of increasing concern. But, compared to other industrial processes the activated sludge process is characterized by frequent variations in environmental conditions such as the feed flow rate and the influent substrate concentration. The variation in the operational parameters, especially shock loading (Couillard, 1990; Couillard and Tyagi, 1988, 1990), affects the process performance significantly, sometimes even resulting in process failure (Berthouex et al., 1985). Therefore, careful design of the control strategy becomes necessary to maintain the process operation and to improve the effluent quality.

Fuzzy set theory was first proposed by (Zadeh, 1965) and has wide study areas and applications. Since Mamdani’s pioneering work (Mamdani, 1974) on fuzzy control motivated by Zadeh’s approach, there have been more than 100 works reported in control engineering so far. Recently there have also been some developed or developing applications of fuzzy control theory (Sugeno and Kang, 1986; Ono et al., 1989; Tobi et al., 1992). Most of them adopted a group of “IF...THEN...ELSE....” linguistic rules to obtain the control strategies. This is suitable for ill-defined systems or for systems where no accurate mathematical models exist which can describe them well (Pedrycz, 1981) because all linguistic rules are fuzzified and expressed by a membership function, and then uncertainties of the system are involved.

Fuzzy control strategy has been applied to activated sludge process for many years. For examples, the preliminary results for a fuzzy controller for coordination of closed loop dissolved oxygen and sludge recycle controls with sludge wastage control have been developed (Tong et al., 1980; Beck, 1984). There are several points concerning the structure of this controller: (i) a linguistic control rule cover a certain process operating conditions. (ii) Most of rules are concerned with change in waste sludge flow rate. (iii) There are no rules concerning the status of the air flow rate or recycle sludge flow rate.

Significant improvement of the activated sludge process performance, which is adequate to amortize the effect of the shock loading due to the application of the two-hierarchical-level control strategy have been reported (Couillar and Shucai, 1992). The goal of this control strategy is focused on maintaining the concentration of the dissolved oxygen and the height of the sludge blanket at the set points. But there is no mathematical relation between the height of the sludge blanket and the suspended solids concentration in the clarifier in the above-mentioned paper. However, in the case of hydraulic shock loading this controller is unable to stabilize the height of the sludge blanket and the dissolved oxygen level. Application fuzzy control strategy has been proven effective to handle non-linearity, high dimensionality and uncertainty existence in the process model (Tasi et al., 1994; Tasi et al., 1993).

In the following sections, activated sludge process model is described in section 2, fuzzy PID controller (PFC) is explained in section 3, and design of fuzzy PID application for dissolved oxygen is introduced in section 4. Section 5 and section 6 shows evaluation of this approach and simulation results respectively. This study focuses on dissolved oxygen concentration which is taken as controlled variables while air flow rate are taken as manipulated variables, using Matlab-Simulink.

2. Activated Sludge Process Modeling

The process scheme adopted for this study in figure 1. The dynamic model of the process under consideration is focused on carbonaceous substrate degradation which represents the main objective of this process and thickens the biomass for recycle to the aerator and clarifies the treated effluent. The dynamic equations of the biological treatment in the aerator related to the main objective, which mentioned early, are derived from material balance for substrate S concentration, dissolved oxygen C concentration and biomass X concentration. With assuming zero decay coefficients of microorganisms, then according to the general material balance equation:

Substrate balance equation:

$$\dot{S} = -\frac{F_i}{V}S - \frac{F_r}{V}S + \frac{F_i}{V}S_i - K_1\mu X \tag{1}$$

Dissolved oxygen balance equation:

$$\dot{C} = -\frac{F_i}{V}C - \frac{F_r}{V}C + K_{La}U_a(C_s - C) - K_2\mu X \tag{2}$$

Biomass balance equation:

$$\dot{X} = -\frac{F_i}{V}X - \frac{F_r}{V}X + \frac{F_r}{V}X_r - \mu X \tag{3}$$

The dynamics of the settler can be described by the following mass balance equation:

$$\dot{X}_r = \frac{F_i}{V_s}X + \frac{F_r}{V_s}X - \frac{F_r}{V_s}X_r - \frac{F_w}{V_s}X_r \tag{4}$$

Equations (1- 4) form the basic dynamically model that will be used for controller design. Where μ is the specific growth rate, F_i is the influent flow rate, S_i is the influent substrate concentration, V is the aerator volume, K_{La} is the oxygen mass transfer coefficient, C_s is the saturation dissolved oxygen concentration, X_r is the recycled biomass concentration, U_a is the air flow rate, and V_s is the settler/clarifier volume.

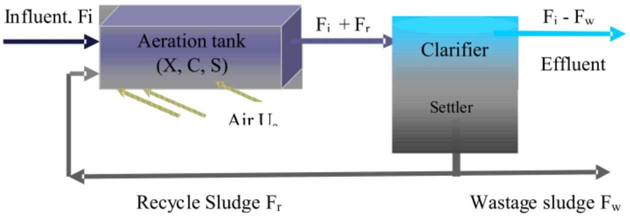

Fig 1 General overview of the ASP

3. Two input Fuzzy PID Controller

Despite the many sophisticated control theories and techniques that have been devised in the last few decades, PID controllers continue to be the most commonly used in the industrial processes [7, 8]. In practice, most physical systems have inherently intractable characteristics such as high order and non-linearity. Therefore, the manner of obtaining the parameters of PID controllers that satisfy the performance requirement has been addressed in many studies [9, 10]. The well-known method, Ziegler–Nichols method [10], provides a systematic tuning method for the PID parameters; this method has good load disturbance attenuation but shows unsatisfactory performance, with a large overshoot and long settling time.

For improving systems' performance, e.g., rise time, overshoot, and integral of the absolute error, many studies are attempting to incorporate features on the basis of the experiences of experts with regard to PID gain scheduling, and the use of fuzzy logic seems to be particularly appropriate.

Recently, fuzzy PID controllers have been presented and investigated, and their satisfactory performance in various plants has been revealed. The principle structure of the PID Fuzzy controlled system consists of PID controller and Fuzzy controller as follow:

If two inputs are used in forming a fuzzy PID controller then one can obtain either fuzzy PD or fuzzy PI controller. For instance, if the inputs are chosen as error (e) and derivative of error (de/dt) then one ends up with a fuzzy PD controller as shown in Figure 2.

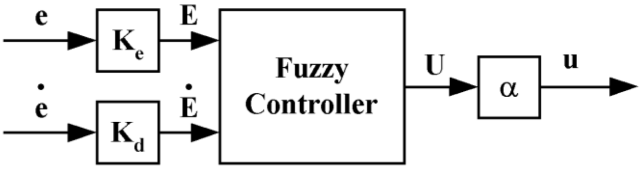

Fig 2 Fuzzy PD-type controller structure

When the two inputs are chosen as error (e) and the integral (or the sum) of error then the controller becomes absolute form fuzzy PI controller. If the inputs are chosen as error (e) and derivative (or change) of error (de/dt) then an incremental form fuzzy PI controller can be obtain, but the output is achieved as the derivative (or the change) of control signal as shown in Figure 3 [11].

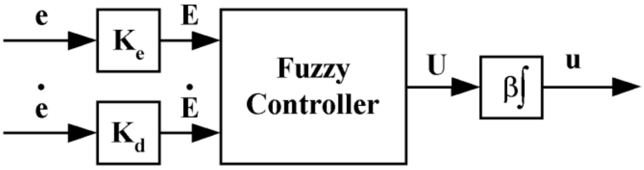

Fig 3 Fuzzy PI-type controller structure

The equivalence of fuzzy PD and conventional PD controllers has been established under special conditions [12-14]. Fuzzy PI control is known to be more practical than fuzzy PD because it is difficult for the fuzzy PD to remove steady state error. The fuzzy PI control, however, is known to give poor performance in transient response for higher order processes due to the internal integration operation.

To obtain proportional, integral and derivative control action all together, it is intuitive and convenient to combine PI and PD actions together to form a fuzzy PID-type controller [9]. Therefore, the formulation of fuzzy PID controller can be achieved by combining fuzzy PI and PD controllers with two distinct rule-bases. Another and a simpler way of construction a fuzzy PID controller is combining fuzzy PD controller with an integrator and a summation unit at the output.

These two cases are given in Figure 4 and in Figure 5, respectively. It is obvious that the fuzzy PID controller given in Figure 5 has less number of rules and scaling factors compared to the fuzzy PID that is given in Figure 4 [15].

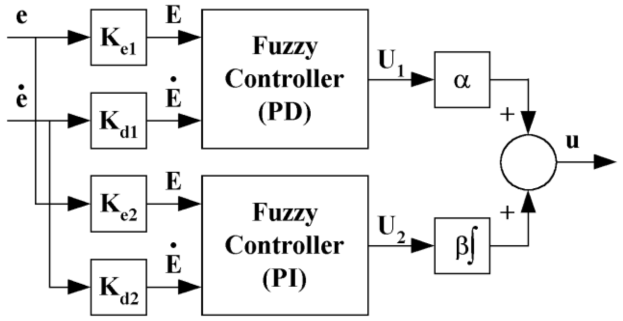

Fig 4: Fuzzy PID-type controller structure formed of combining fuzzy PD-type and PI-type controllers

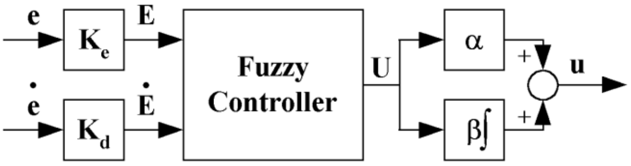

Fig 5: Fuzzy PID-type controller structure with one rule-base

4. Structures of Fuzzy PID controller for Dissolved Oxygen Concentration

Fuzzy PID controller used in this paper is based on two inputs and one output. The overall structure of used controller is shown in Fig. 5. Construction a fuzzy PID controller is combining fuzzy PD controller with an integrator and a summation unit at the output is adopted in the activated sludge process as shown in figure 5. The error $E(k)$ between the set point of dissolved oxygen and the actual value of dissolved oxygen is the first input to the fuzzy PID controller while the value of its derivative $\dot{E}(k)$ is second input.

FLC has two inputs and one output. These are error (E), change of error (CE) and control signal (Ua), respectively. A linguistic variable which implies inputs have been classified as: NB, NS, Z, PS, PB. Inputs are all normalized in the interval of [-1, 1] as shown in Fig. 6. While a linguistic variable which implies inputs have been classified as: CL, CM, CS, NC, OS, OM, OL. Output is normalized in the interval of [-0.5, 0.5] as shown in Figure 6 and 7 respectively.

The linguistic labels used to describe the Fuzzy sets were "Negative Big" (NB), "Negative Small" (NS), "Zero" (ZE), "Positive Small" (PS), "Positive Big" (PB), and “Close Large” (CL), “Close Medium” (CM), “Close Small” (CS), “No Change” (NC), “Open Large” (OL), “Open Medium” (OM), “Open Small” (OS). It is possible to assign the set of decision rules as shown in Table 1. The fuzzy rules are extracted from fundamental knowledge and human experience about the process. These rules contain the input/the output relationships that define the control strategy. Each control input has five fuzzy sets so that there are at most 25 fuzzy rules.

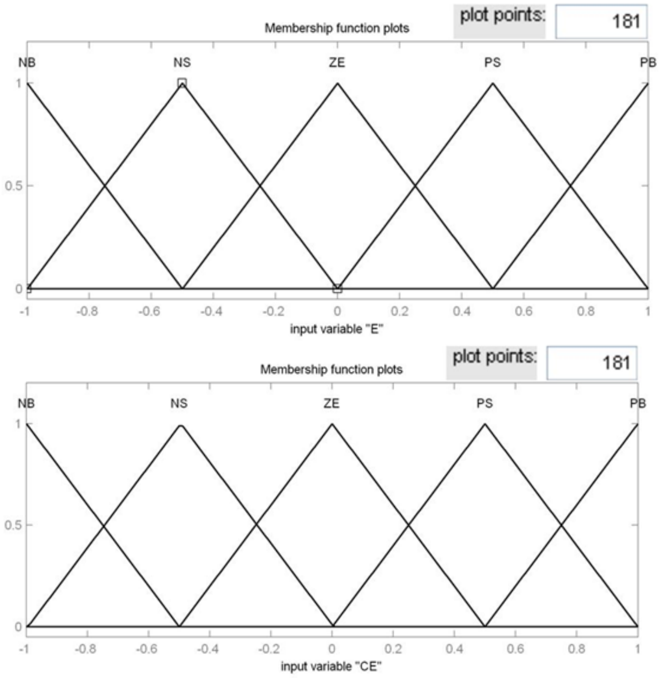

Fig 6: Membership functions of error (E) and change of error (CE)

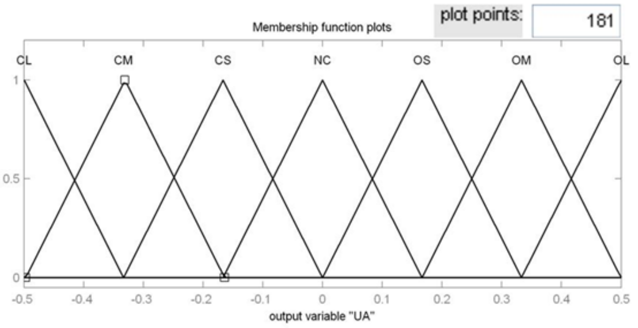

Fig 7: Membership functions of the output (Ua)

Table 1: fuzzy rule

Error (E)	Change of error (CE)				
	NB	**NS**	**ZE**	**PS**	**PB**
NB	*CL*	*CL*	*CM*	*CS*	*NC*
NS	*CL*	*CM*	*CS*	*NC*	*OS*
ZE	*CM*	*CS*	*NC*	*OS*	*OM*
PS	*CS*	*NC*	*OS*	*OM*	*OL*
PB	*NC*	*OS*	*OM*	*OL*	*OL*

5. Controller Performance Evaluation

The objective of the control strategy is the effectively manipulate the flow rates of air such that dissolved oxygen in aerator is kept at specified value (C = 6 mg/l) as well as the organic pollutants in the effluent, (S = 5 mg/l). Simulation studies were conducted using the model described above for the behavior of the activated sludge process; the model was initialized in reference to the listed values in (D. Do chain and M. Perrier, 1992) with the following (monod-type) model for the specific growth rate:

$$\mu = \mu_{max} \frac{S}{K_s + S} \frac{C}{K_c + C}$$

The following model parameters and its nominal values have been considered in the simulation:

$\mu_{max} = 0.2\,h^{-1}$, $K_s = 75\,{}^{mg}\!/_{L}$, $K_c = 2\,{}^{mg}\!/_{L}$, $K_1 = 1.2$, $K_2 = 0.565$, $S_i = 150\,{}^{mg}\!/_{L}$,
$a_o = 0.018\,m^{-3}$, $C_s = 10\,{}^{mg}\!/_{L}$, $V = 100\,m^3$, $V_s = 50\,m^3$, $F_i = F_r = 10\,{}^{m^3}\!/_{h}$,
$F_w = 0.5\,{}^{m^3}\!/_{h}$, $S = 5\,{}^{mg}\!/_{L}$, $C = 6\,{}^{mg}\!/_{L}$, $X = 1225\,{}^{mg}\!/_{L}$, $X_r = 2333\,{}^{mg}\!/_{L}$, $U_a = 100\,{}^{m^3}\!/_{h}$.

The fuzzy PID controller described was tested under a range of hydraulic disturbance and organic disturbance inputs. A simulation program was used in the implementation of the ASP model on a SIMULINK/MATLB program. The nonlinear ASP model is expressed using SIMULINK block diagram and control structure is expressed in Fuzzy Logic Toolbox. The following examples are presented to explain the proposed control strategy and demonstrate its potential. The simulated responses of the fuzzy PID control system are shown in Figures 8-11.

6. Simulation Results and Discussion

The results for the simulations described are given in different cases.

Firstly, Figure 8 shows the fuzzy PID responses under normal hydraulic load (F_i is set at 10 m^3/hr) and normal organic load (S_i is set at 150 mg/l), the controlled variable is close to the set point (6 mg/l) and the manipulated variable is around 100 m^3/hr (nominal value) while the treated water is secured at the target value of substrate concentration (5 mg/l).

Secondly, organic load S_i is set at 150 mg/l and held constant during the simulation, whereas hydraulic load F_i increases by + 25% about its nominal value at simulation time equal 100 hr, over twenty days as shown in Fig. 9. Figure 9 shows a sudden change in substrate concentration up to 7 mg/l at the instant of hydraulic disturbance. The fuzzy PID effort secure the target value of dissolved oxygen (6 mg/l) lead to improve and decrease the value of substrate concentration but the decreasing in dilution time due to hydraulic disturbance lead to the steady state error in substrate concentration equal 1 mg/l (at the final time of simulation, S = 6 mg/l) while the air flow rate is increased to (125 m3/hr) above the nominal value by 25%.

Thirdly, hydraulic load F_i is hold at 10 m^3/hr and held constant during the simulation, while organic load S_i increases by + 25% about its nominal value over twenty days as shown in Fig. 10. At instant of organic disturbance (100 hr), figure 10 shows that increasing in substrate concentration (S = 6.5 mg/l) and with time substrate concentration lead to decreasing (around 5.5 mg/l). These result secured by maintain the dissolved oxygen at 6 mg/l by diffused air (125 m^3/hr).

Lastly, the system is imposed to hydraulic load disturbance (+25%) and organic load (+25%) in the same time as shown in figure 11. In this figure show that more increasing in substrate concentration at the instant of disturbance (8.5 mg/l) and decreasing in dissolved oxygen concentration (4 mg/l) so more air is diffused to manipulated the deviation of dissolved oxygen and the correct the trend of substrate concentration, at final time of simulation, substrate concentration close to 6 mg/l while dissolved oxygen close to 6 mg/l with steady state error around 0.1, in other side the air flow rate is close to 150 m3/hr with increasing rate by +50% above nominal value and with +25% above hydraulic disturbance only (second case) or organic disturbance only (third case)

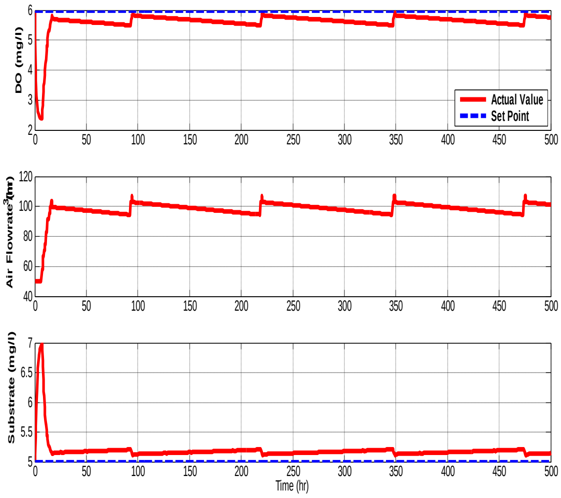

Fig. 8: Simulation results under normal hydraulic Load and normal substrate load

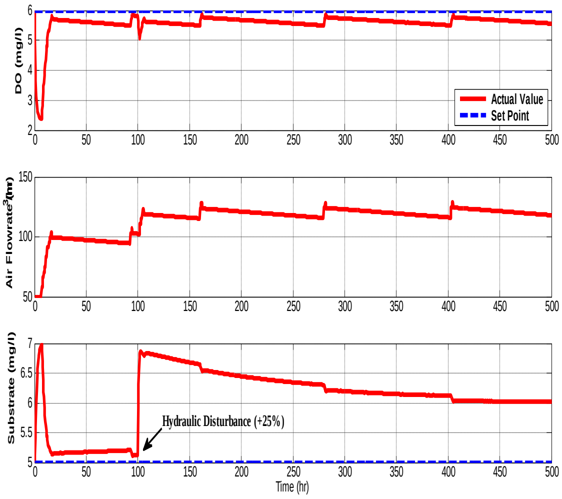

Fig. 9: Simulation results under normal substrate load and +25% Hydraulic Load

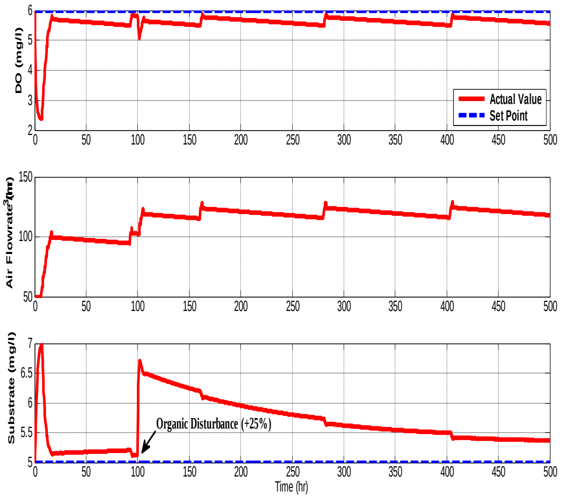

Fig. 10: Simulation results under normal Hydraulic Load and +25% Organic Load

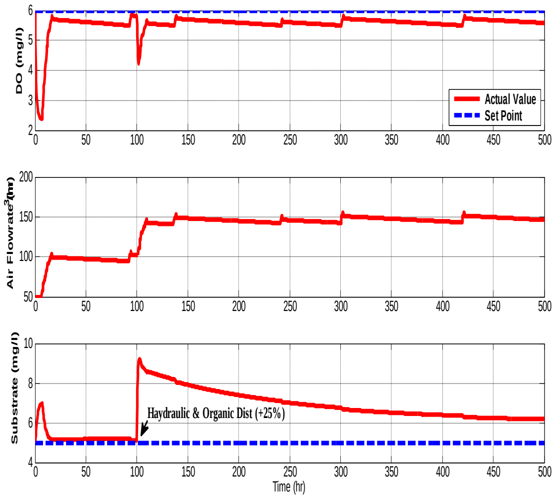

Fig. 11: Simulation results under +25% Hydraulic Load and +25% Organic Load

7. Conclusions

The paper has proposed and validated by simulation a fuzzy PID controller for the dissolved oxygen concentration tracking in an activated sludge process. The controller maintains good performance achieving by previously proposed controller that was based on an original nonlinear dynamics of the activated sludge process. On the other hand it is much more computationally efficient, hence is able to respond in time to fast changes of hydraulic and organic disturbances.

- The results concerning the hydraulic disturbance inputs show that the change in dissolved oxygen concentration variable is eliminated and the change of the substrate concentration variable is more reduced. The controller manipulates the dilution rate and forces the dissolved oxygen concentration to follow the imposed set point.
- The results concerning the organic disturbance inputs show that the change in dissolved oxygen concentration variable is very close to the nominal value and the change of the substrate concentration variable is more reduced and closer to the target value. Moreover, it is able to reject disturbances that might appear on the substrate concentration in the inflow
- The results from the hydraulic disturbance and the organic disturbance inputs show that the fuzzy PID amortizes the more deviations in dissolved oxygen concentration and the change of the substrate concentration. This is maintained within the limits established by law.

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