Control of an Activated Sludge Process using the Virtual Reference Approach

José David Rojas, Víctor M. Alfaro, and Ramón Vilanova

***Abstract*—In this paper, the Virtual Reference Feedback Tuning is applied to the control of the dissolved oxygen and substrate concentration output in an Activated Sludge Process (ASP) based wastewater treatment using an Internal Model Control structure. This data-driven methodology was found to be easy to implement and gave excellent results when compared to a two degrees of freedom continuous time PI controller, but with the advantage of using only data taken directly from an experiment in open-loop and skipping the modeling step.**

***Index Terms*—Wastewater Treatment Plant, Activated Sludge Process, Data-Driven Control, Virtual Reference Feedback Tuning, Feedforward control.**

I. Introduction

WASTE Water Treatment Plants (WWTP) are an important case of study within the process control area, while an active research area that involves other disciplines as for example chemistry, biology, and instrumentation. Nowadays, the correct treatment of wastewater is critical in all cities due to environmental and human health reasons. That is why the constraint on the level of pollution of the treated water before discharging it into the receiving waters, is becoming more stringent while it is also necessary to maintain low cost of operations and high efficiency [1], [2]. Among the types of WWTP, the Activated Sludge Process (ASP) is one of the most popular methods to biologically remove organic components, nitrogen and phosphorus from the treated water [3]. From the automatic control perspective it has been a widely case of study, for example in [4] a parameter and state non-linear estimator is used in an adaptive linearizing control of the dissolved oxygen and substrate concentration of an ASP but under the assumption that only the dissolved oxygen is available for measurement. In [5], several multivariable PI control method are applied to the ASP by linearizing the nonlinear model and the results are presented, as well as the combination of some of these methods. In [6], predictive control is used to maintain a low concentration of substrate at the output by controlling the dissolved oxygen using the dilution rate. The internal model of the predictive control is a three layer neural network. In [7] the control of the substrate concentration is achieve using an estimation based on the dissolved oxygen measurements, a dynamic controller that cope with the change in reference and a PID controller that corrects the steady state error produced by the use of a linearized model in the first controller. In [8] a decentralized PI approach is presented to show that simple well tuned PI controllers can achieve a similar performance than more complex methodologies for the ASP case. In all the cases, some sort of model (non-linear o linearized) is used to computed the controller. In several cases it is supposed that some parameters are known which may no be the case for a real plant.

Modeling of ASP has been an important research area and several models have appeared in the literature [9]. But from the automatic control perspective, these models are very complex to be used directly to compute a controller, and therefore, a linearization step and possibly a reduction of the model order is needed in order to find an adequate model for control. In those cases, it is desirable to have a method that computes a controller parameters directly from data taken from the plant. It is exactly what data driven control is about: an approach were experimental data is directly used to find a controller, which, generally, is meant to minimize some control performance criterion. Some of the most remarkable methods within this control approach are the Iterative Feedback Tuning (IFT) [10], [11], the Windsurfer Approach [12], [13], the Correlation Approach [14], [15] and the Virtual Reference Feedback Tuning (VRFT) [16]–[18].

The contribution of this work is to use the VRFT approach with an IMC structure in order to be applied to an ASP based WWTP for the tuning of discrete-time restricted-order linear controller in a decentralized control topology. It was found that this methodology provide excellent results, even when compared with an standard two degrees of freedom PI approach.

The rest of the paper is divided in two parts, in section II, a short overview on VRFT is presented as well as the mentioned extension to the IMC control. In section III the results of the application of this data-driven method is presented and compared with a two-degrees of freedom PI controller. The conclusion are presented in section IV.

II. Virtual Reference Feedback Tuning extensions

In this section, an overview on the VRFT is presented as well as some results that extend the capacity of the VRFT for different control strategies and structure of controllers is presented.

A. Virtual Reference Feedback Tunning overview

The Virtual Reference Feedback Tuning (VRFT) is a one-shot data-based method for the design of feedback controllers. The original idea was presented in [16], and then formalized by Lecchini, Campi, Savaresi and Guardabassi

This work has received financial support from the Spanish CICYT program under grant DPI2010-15230 and project AECI - PCI A/025100/09. Research work of J.D. Rojas is done under research grant supported by the Universitat Autònoma de Barcelona.

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ISBN: 978-988-19251-2-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

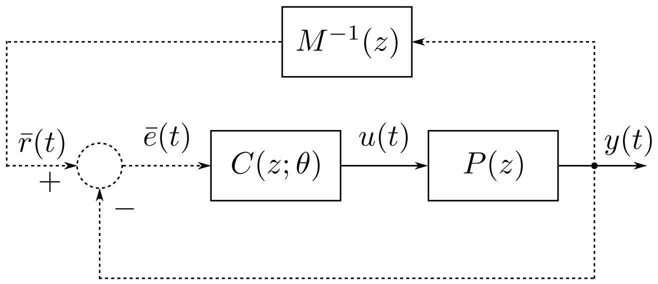


Fig. 1. The VRFT set up. The dashed lines represent the "virtual" part of the method

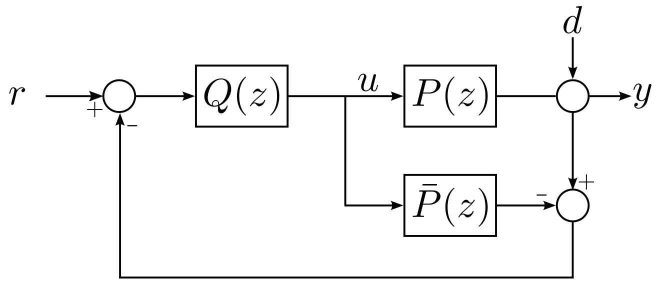


Fig. 2. Standard Structure of the IMC. $\bar{P}$ represents the plant model and Q is the IMC controller

(see [17], [18]). In [17], the method is presented for the tuning of a one degree of freedom feedback controller. If the controller belongs to the controller class $\{C(z;\theta)\}$ given by $C(z;\theta) = \beta^T(z)\theta$, where $\beta(z) = [\beta_1(z) \ \cdots \beta_n(z)]^T$ is a known vector of transfer functions, and $\theta = [\theta_1 \ \theta_2 \ \cdots \theta_n]^T$ is the vector of parameters, then the control objective is to minimize the model-reference criterion given by:

$$J_{MR}(\theta) = \left\| \left(\frac{P(z)C(z;\theta)}{1+P(z)C(z;\theta)} - M(z) \right) W(z) \right\|_2^2 \quad (1)$$

Starting from a batch of open-loop data $\{u(t), y(t)\}$, a "virtual" reference signal $\bar{r}(t)$ is computed in such a way that, if the closed-loop system is feed with this virtual signal and the controllers in the loop were the ideal controllers that would achieve a predefined target transfer function, then the input and output signals of the plant in closed-loop would be the same than the batch of open-loop data. The output of the controller should be equal to $u(t)$ and then, this controller can be found by *identifying* the transfer function which yields the output $u(t)$ when the input $\bar{e}(t) = \bar{r}(t) - y(t)$ is applied to the input as depicted in Fig. 1.

The original VRFT algorithm, as presented by the authors in [17], is as follows: Given a set of measured I/O data $\{u(t), y(t)\}_{t=1,\ldots,N}$

1) Calculate:
   - a virtual reference $\bar{r}(t)$ such that $y(t) = M(z)\bar{r}(t)$, and
   - the corresponding tracking error $\bar{e}(t) = \bar{r} - y(t)$
2) Filter the signals $\bar{e}(t)$ and $u(t)$ with a suitable filter $L(z)$:

$$\bar{e}_L(t) = L(z)\bar{e}(t)$$
$$u_L(t) = L(z)u(t)$$

3) Select the controller parameter vector, say, $\hat{\theta}_N$, that minimizes the following criterion:

$$J_{VR}^N(\theta) = \frac{1}{N}\sum_{t=1}^{N}\left(u_L(t) - C(z;\theta)\bar{e}_L(t)\right)^2 \quad (2)$$

$u_L(t)$ and $\bar{e}_L(t)$ are the filter versions of the signals $u(t)$ and $\bar{e}(t)$ useful to approximate the optimization problem in (2) to the control criterion in (1). If $C(z;\theta) = \beta^T(z)\theta$, the criterion (2) can be given by

$$J_{VR}^N(\theta) = \frac{1}{N}\sum_{t=1}^{N}\left(u_L(t) - \varphi_L^T(t)\theta\right)^2 \quad (3)$$

with $\varphi_L(t) = \beta(z)\bar{e}_L(t)$ and the parameter vector $\hat{\theta}_N$ is given by

$$\hat{\theta}_N = \left[\sum_{t=1}^{N}\varphi_L(t)\varphi_L(t)^T\right]^{-1}\sum_{t=1}^{N}\varphi_L(t)u_L(t) \quad (4)$$

The authors, also showed that, the filter $L(z)$ should be the one that approximates the criterion (2) to (1). This filter should be designed to accomplish the constraint:

$$|L|^2 = |1-M|^2\,|M|\,|W|^2\,\frac{1}{\Phi_u} \quad (5)$$

where Φ_u is the spectral density of $u(t)$
The VRFT framework have been used in several applications and even have been extended for the MIMO case and used for PID tuning, for example see [19]–[23].

B. Internal Model Control using the Virtual Reference Feedback framework

Internal Model Control (IMC) is a popular control method that incorporates the model of the process into the controller [24]. The standard structure is depicted in Fig. 2. $P(z)$ represents the Plant, while $\bar{P}(z)$ is its model. $Q(z)$ is the IMC controller. If the output of the model and the output of the plant are the same, and there is no disturbance, the control system behaves as if it was in open-loop. If this is the case, to have perfect tracking, $Q(z)$ must try to cancel the dynamics of the plant. On the other hand, if there is a mismatch between the plant and its model or if a disturbance acts on the system, the feedback loop enters into play. This characteristics leads to the well know property that an IMC system would be nominally internally stable if $Q(z)$ is stable, in case the model is equal to the plant.

It is possible to find an IMC controller using the VRFT framework without concerning about the modeling of the system. In Fig. 3, the experimental setup for the VRFT applied to the IMC topology is depicted. If the target complementary sensitivity function is given by $M(z)$, then the virtual reference $\bar{r}(t)$ is computed as

$$\bar{r}(t) = M^{-1}(z)y(t) \quad (6)$$

If the ideal controller were in the loop, then one would have $\bar{P}(z) = P(z)$ and the input to the controller $Q(z,\theta)$ would be $\bar{r}(t)$ and its corresponding output would be $u(t)$ in order to have $y(t)$ as the output of the closed-loop system. From Fig 3, it can be found that the ideal controller would be given by

$$Q_0(z) = M(z)P(z)^{-1}$$
$$\bar{P}_0(z) = M(z)Q_0(z)^{-1} \quad (7)$$

ISBN: 978-988-19251-2-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

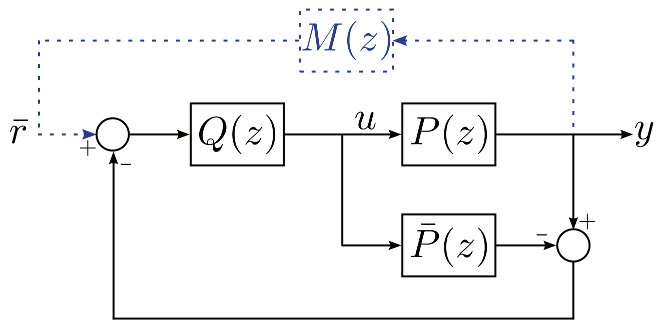


Fig. 3. Disposition for the VRFT experiment using the IMC topology. The dashed line represents the virtual signals and components.

$P_0(z)$ would be the ideal plant model that is derived from the ideal controller. This basic idea leads to the following optimization problem which gives the set of optimal parameters θ^* (in a least square sense):

$$\min_{\theta} J(\theta) = \min_{\theta} \sum_{i=1}^{N} (u(i) - Q(z,\theta)\bar{r}(i))^2 \tag{8}$$

Once $Q(z, \theta^*)$ has been determined, it is easy to compute the approximation of the process model of the plant from (7):

$$\bar{P}(z,\theta) = M(z)Q(z,\theta)^{-1} \tag{9}$$

It is important to note that $\bar{P}(z,\theta)$ is seen just as an "instrumental model", that results from the determination of the optimal controller. In fact, it is only a derived part of the IMC controller that results from the optimization. Of course, if a robust check is performed with the obtained controller, this approximation of the plant can be used as if it were the nominal model. Therefore, it can be stated that both the controller and the nominal model are found at once using this methodology.

III. Application to an ASP based WWTP

In this section a practical example of the IMC-VRFT method exposed above is presented. The plant considered in this paper is the WWTP given in [25]. It comprises an aerated tank where microorganisms act on organic matter by biodegradation, and a settler where the solids are separated from the wastewater and a proportional part is then recycled to the aerator in order to maintain certain amount of biomass in the system. The layout is shown in Fig. 4. For the complete reference of the WWTP model and equations, please see [4], [25], [26].

The component balance for the substrate, biomass, recycled biomass and dissolved oxygen provide the following set of non-linear differential equations:

Biomass	$X(0)$	= 217.79 mg/l
Substrate	$S(0)$	= 41.23 mg/l
Dissolved Oxygen	$DO(0)$	= 6.11 mg/l
Recycled Biomass	$X_r(0)$	= 435.58 mg/l
Influent Substrate	$S_{in}(0)$	= 200.00 mg/l
Influent Dissolved Oxygen	$DO_{in}(0)$	= 0.50 mg/l

TABLE I
Initial Conditions

$\beta = 0.2$	$K_c = 2\text{mg/l}$
$r = 0.6$	$K_s = 100\text{mg/l}$
$\alpha = 0.018$	$K_{DO} = 0.5$
$Y = 0.65$	$DO_s = 0.5\text{mg/l}$
$\mu_{max} = 0.15\ \text{h}^{-1}$	

TABLE II
Kinetic parameters

$$\frac{dX(t)}{dt} = \mu(t)X(t) - D(t)(1+r)X(t) - rD(t)X_r(t) \tag{10}$$

$$\frac{dS(t)}{dt} = -\frac{\mu(t)}{Y}X(t) - D(t)(1+r)S(t) + D(t)S_{in} \tag{11}$$

$$\frac{dDO(t)}{dt} = -\frac{K_o\mu(t)}{Y}X(t) - D(t)(1+r)DO(t) + K_La(DO_s - DO(t)) + DO(t)DO_{in} \tag{12}$$

$$\frac{dX_r(t)}{dt} = D(t)(1+r)X(t) - D(t)(\beta+r)X_r(t) \tag{13}$$

$$\mu(t) = \mu_{max}\frac{S(t)}{k_S + S(t)}\frac{DO(t)}{k_{DO} + DO(t)} \tag{14}$$

$$K_La = \alpha W(t) \tag{15}$$

where $X(t)$ - biomass, $S(t)$ - substrate, $DO(t)$ - dissolved oxygen, DO_s - maximum dissolved oxygen, $X_r(t)$ - recycled biomass, $D(t)$ - dilution rate, $W(t)$ - aeration rate, S_{in} and DO_{in} - substrate and dissolved oxygen concentrations in the influent, Y - biomass yield factor, μ - biomass growth rate in a Monod like form [27], μ_{max} - maximum specific growth rate, k_S and k_{DO} - saturation constants, K_La - oxygen mass transfer coefficient, α - oxygen transfer rate, K_o - model constant, r and β - ratio of recycled and waste flow to the influent. The influent concentrations are set to $S_{in} = 200$ mg/l and $DO_{in} = 0.5$ mg/l.

It is important to note that this equations are used only to get data, as if it were a real plant in the simulation. The equation were not considered for the controllers optimization. The control strategy is a decentralized control as in [8] where the multivariable process is treated as two separate

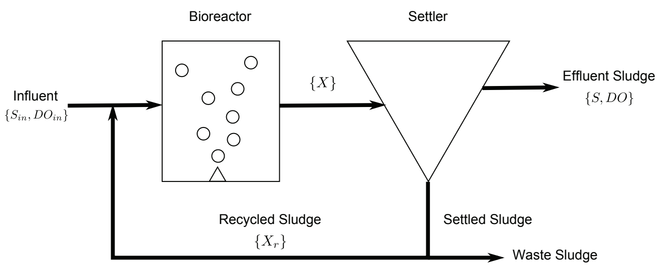


Fig. 4. Wastewater Treatment Process

ISBN: 978-988-19251-2-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

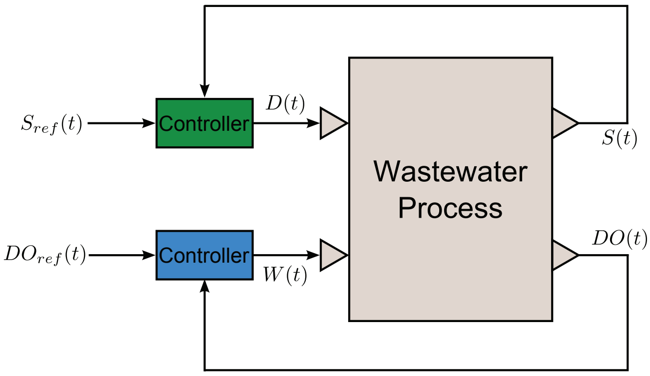


Fig. 5. Control Strategy for the WWTP

single variable process and, it was shown that a simple controller could perform as good as other more complicated methodologies if the controller is well tuned. The strategy is depicted in Fig. 5. With respect to the control problem definition, it is considered that the dissolved oxygen, $DO(t)$, and substrate, $S(t)$, are the controlled outputs of the plant and that are measurable, whereas the dilution rate, $D(t)$, and aeration rate $W(t)$ are the two manipulated variables. The control of DO provides a method to maintain the necessary amount of biomass in the system while controlling S gives a way to keep the pollution at the effluent in an acceptable level [4]. The initial conditions and kinetic parameters are taken as in [8], [25] and presented in Table I and II.

The settings of the VRFT controller are as follows: For both control loops, the sampling time was selected as $Ts = 0.5\text{min}$, the IMC controller $Q(z)$ has the following parameterization:

$$Q(z) = \frac{\alpha_1 + \alpha_2 z^{-1} + \alpha_3 z^{-2}}{\beta_1 + \beta_2 z^{-1} + \beta_3 z^{-2}} \tag{16}$$

the target transfer function for the DO loop is:

$$M_{DO}(z) = \frac{0.02357z^{-1}}{1 - 0.9764z^{-1}} \tag{17}$$

which represents a first order transfer function with a constant time of approximately 20min. For the S loop (controlled by manipulating $D(t)$), the target closed-loop dynamics is a first order transfer function with a constant time of approximately 40min given by:

$$M_S(z) = \frac{0.01382z^{-1}}{1 - 0.9862z^{-1}} \tag{18}$$

The input-output data was selected as an additive random signal of 0 mean and variance 90 for the $W(t)$ and variance 7.5e-4 for the $D(t)$ around the operation points given in Table I. As an example, the data used to find the Dissolved Oxygen controller is depicted in Fig. 6. The resulting controllers were found as:

$$\begin{aligned} Q_{DO}(z) &= \frac{40.69 - 19.35z^{-1} - 19.65z^{-2}}{1 - 0.4683z^{-1} - 0.4792z^{-2}} \\ Q_S(z) &= \frac{0.01236 - 0.006155z^{-1} - 0.006158z^{-2}}{1 - 0.4863z^{-1} - 0.4924z^{-2}} \end{aligned} \tag{19}$$

The results of this controllers are compared to the two-degrees of freedom, continuous time PI controller of [8]. Two different test were performed: a change in the references and a disturbance on the influent substrate S_{in} where it is considered that every 24h, an increase of 10% of the value of S_{in} during 1h takes place.

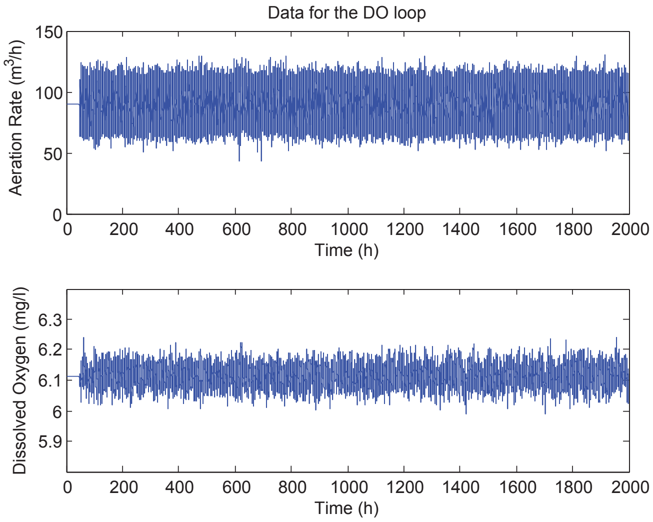


Fig. 6. Data used for the determination of the controllers, above the aeration rate as input and the dissolved oxygen as output.

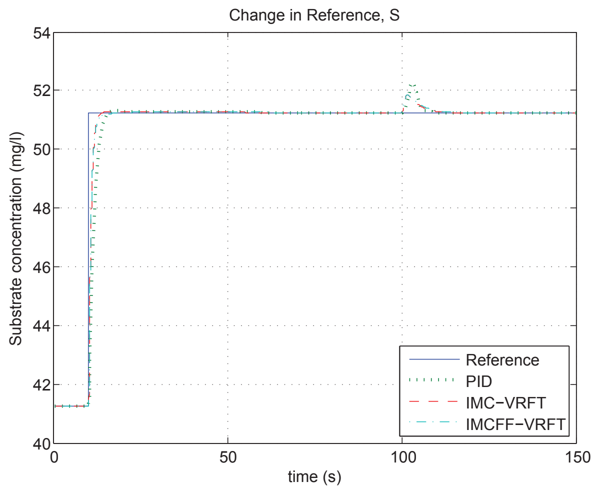
For the change in reference ($S_{ref}(t)$ for the substrate concentration reference and $DO_{ref}(t)$ for the dissolved oxygen reference), the result is as given in Fig. 7. A step change of 10mg/l is applied to $S_{ref}(t)$ at time $t = 10\text{h}$ while a step change of -2mg/l in $DO_{ref}(t)$ is applied at time $t = 100\text{h}$. The effect of one loop change in the other loop, due to the process interaction, can be observed as well. In Table III the values of the integral of the squared errors (ISE) and the Total Variation (TV), which measures the aggressiveness of the control effort, are presented. The Integral of the Absolute Error (IAE) is also presented since it reflects economic considerations of the performance of the controller [28]. These criterion are computed as :

$$\begin{aligned} \text{ISE} &= \int_0^t e(t)^2\, dt \\ \text{IAE} &= \int_0^t |e(t)|\, dt \\ \text{TV} &= \sum_{i=1}^{N} |u(i) - u(i-1)| \end{aligned} \tag{20}$$

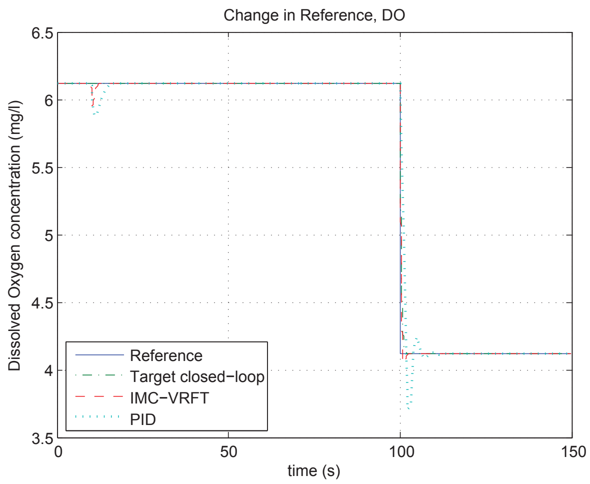
$e(t)$ is the error signal (the reference minus the measured output), and $u(i)$ is the output of the controlled sampled every hour and N is the total number of samples. In the column “Reference Tracking” it can be seen that for the S loop with the application of the IMC-VRFT controller the ISE and the IAE are greatly reduced (near the 57% and 41% respectively) but with almost the same TV. The DO loop is also improved with respect to ISE, IAE and TV, as can be also seen in Fig. 7, it is clear that the response of the PI controller is much worse than the response of the IMC-VRFT, which almost has no overshoot. In Fig. 8, the plot of the control signals is presented for both the dilution rate and the air flow rate.

For the disturbance in the substrate concentration of the influent, the responses are presented in Fig. 9 and Fig. 10. PI control is faster to control the disturbance Fig. 9a, but the overshoot is larger. The response of the DO is greatly

ISBN: 978-988-19251-2-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)



(a) Step change in the S reference at time $t = 10$h



(b) Step change in the DO reference at time $t = 100$h

Fig. 7. Response to a change in the reference for both loops

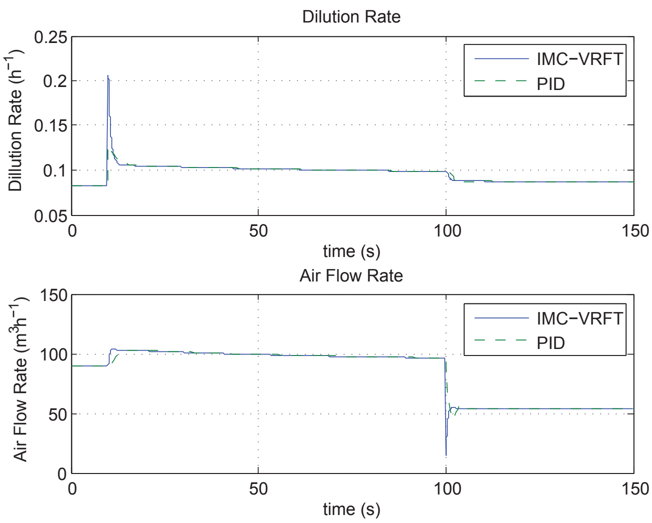
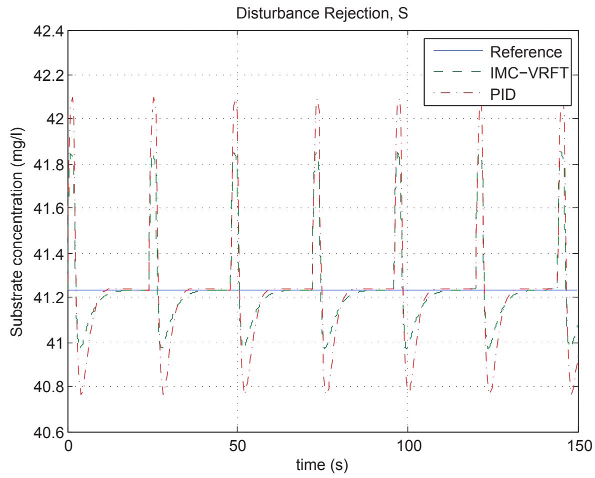


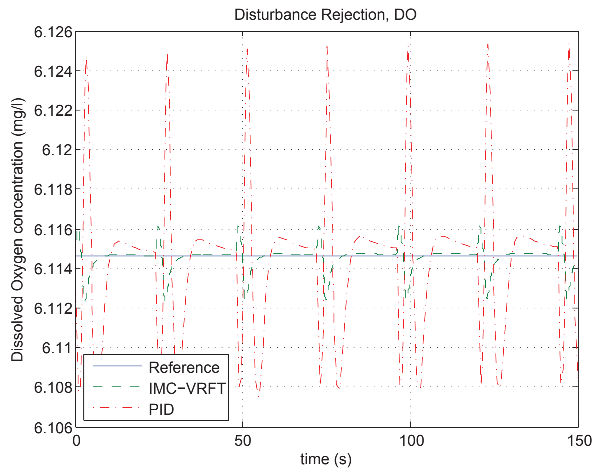
Fig. 8. Control effort during the change in the reference

		Reference tracking		Disturbance rejection	
		S	DO	S	DO
ISE	PI	77.23	2.94	12.05	0.0021
	IMC-VRFT	32.85	0.64	5.56	6e-005
IAE	PI	19.47	3.68	22.92	0.37
	IMC-VRFT	11.56	0.81	15.76	0.052
TV	PI	0.091	89.10	0.15	7.02
	IMC-VRFT	0.083	67.33	0.15	4.69

TABLE III
COMPARISON OF THE RESULTS BETWEEN THE IMC-VRFT, IMCFF-VRFT AND THE PID CONTROL



(a) Effect over the substrate concentration when the substrate input is disturbed



(b) Effect over the dissolved oxygen when the substrate input is disturbed

Fig. 9. Response to a disturbance for both loops

improved with a reduction of almost 97% of ISE and 86% for IMC-VRFT. It is clear that the IMC-VRFT methodology fits perfectly well in the Dissolved Oxygen control in the ASP, which has several implication in both performance and cost.

IV. Conclusions

In this paper, the VRFT method has been studied and extended to an IMC structure. It was successfully applied to a WWTP process, substantially improving the results of a continuous time two-degrees of freedom PI controller using a restricted order discrete time controller in the case of the reference tracking. It was found that, using this methodology

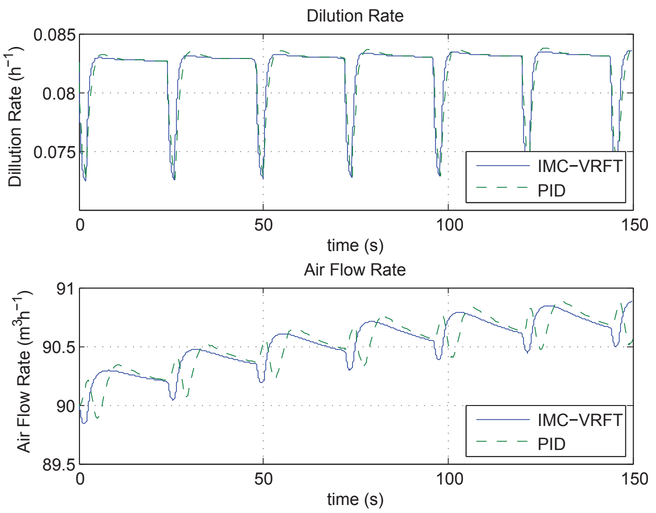


Fig. 10. Control effort during the disturbance in the substrate concentration of the influent

with a simple 4 parameter controller, the dissolved oxygen control greatly improves for both reference tracking and disturbance rejection. From the data-driven control perspective, still it is needed some kind of guidelines, based entirely con data, in such a way that the designer could be able to know the limitations of the closed loop, and the best structure of the controller, before performing the optimization.

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ISBN: 978-988-19251-2-1
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)