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Disturbance Rejection Problem in the Control of Wastewater Treatment Systems

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Wastewater treatment systems are unreliable in terms of their performance. Many parameters could affect their efficiency in which load disturbances are the major cause of large perturbations in the system and the consequent deterioration in the effluent quality. It is known that the variation of the influent flow rate is more important than variations of the various components of the influent. In this paper, the effect of influent flow variation on the system has been modeled and added to the control system structure, in order to alleviate the performance problem. The control system is based on PIP/TDC methodology, which has been published in numerous papers since 1987 and also described briefly here. This kind of control system could bring some advantages to wastewater treatment systems, compared to other more well-known control systems. All experiments have been applied to an activated sludge simulation benchmark and the results show an improvement in the control performance.

INTRODUCTION

The nonlinearity of wastewater treatment systems, together with variable environmental conditions, makes their performance highly variable. This leads to understandard run-times of the systems, which, in turn, causes environmental damage as well as legislation charges. In order to alleviate the problem and, also, to cope with new-hardened regulations, much research has been conducted to enhance the reliability of wastewater treatment systems and improve their performance. Some have focused on upgrading the systems and on alternative system layouts, as well as searching for new treatment methods and technologies [1,2]. However, some studies have concentrated on improving control strategies and systems [3,4].

One of the major problems related to a wastewater system, which makes the treatment performance highly variable, is tackling with disturbances [5]. In fact, there are usually high variations of composition, concentration and flow rate of influent wastewater in daily, weekly and monthly periods. This causes enormous load disturbances on the treatment plant and, thus, violations in the treatment performance and environmental charges.

Biological systems are usually sensitive to variations, causing them to react poorly in these situations and, so, they tend to take time to readapt themselves. Sometimes, indeed, toxic materials enter the treatment plant and cause the bacteria to fail completely. In such situations, it may take more than a month for the system to recover [6]. These reasons are why coping with input disturbances is the major control objective in wastewater treatment systems [5]. However, dealing with these load variations using an automatic control system is not an easy task.

In this paper, it is intended to deal with the problem of disturbance rejection in the control of wastewater treatment systems. A previously developed control system, the so-called PIP (Proportional-Integral-Plus) controller, within the concept of TDC (True Digital Control) methodology, has been used as the control system (see [7,8]).

Over the last few years, PIP control systems have been successfully employed in a range of practical applications (e.g. [9,10]). The application of this control methodology for the control of wastewater treatment systems has already been investigated in [11], in which the advantages of a PIP control system for the control of wastewater treatment systems are brought to attention.

Despite the improvements achieved in the control of wastewater treatment systems using a PIP controller, which is shown in [12-14], there are still deficiencies in the case of disturbance rejection. In other words, the control system is not capable of maintaining the desired setpoint and permissible effluent values.

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Therefore, this paper aims at modifying the control system structure, in order to enhance its ability to overcome the disturbance rejection problem. This is achieved by modifying the applied PIP feedback control structure, in which the disturbance model is introduced into the control loop.

The present research has been implemented on a simulated wastewater treatment benchmark problem. The benchmark problem has been developed by WORKING GROUP No. 2, within the framework of the European COST 682 "Integrated Wastewater Management". The benchmark is a platform-independent simulation environment defining wastewater treatment plant layout, simulation model, influent data, test procedures and evaluating criteria for comparing control performance [15,16].

Control of wastewater treatment systems is usually made by indirect control of the system, through direct control of operational parameters. Dissolved oxygen is one of the operational parameters, which is not the ultimate purpose of the system but is controlled in aerobic systems to ensure good performance. This is also the case in a benchmark problem where there is aeration to the system. Therefore, this paper has focused on the good control of DO in the benchmark system, despite suffering input disturbances.

TDC CONTROL METHODOLOGY

In True Digital Control (TDC) methodology, a discrete-time model is directly identified, based on analysis of either planned experimental data or via model reduction from data generated by (usually high order) continuous or discrete-time simulation models. The model is utilized as the control model in the control design procedure.

The control system in the TDC methodology is called the Proportional-Integral-Plus (PIP) controller. The control design procedure, which is based on a Non-Minimum-State-Space form of the control model, utilizes State Variable Feedback (SVF) control design methods. The SVF control design consists of pole assignment and Linear Quadratic (LQ) optimal methods.

The NMSS representation of the control model and the PIP control design procedure are explained in [7] and programmed by the MATLAB/ SIMULINK$^{\mathrm{TM}}$ software, which is known as CAPTAIN toolbox (For information on the toolbox contact Prof. P. Young, email: p.young@lancaster.ac.uk). Having input-output data of a plant at regular intervals, it is possible to design a PIP control system using CAPTAIN.

There are two main forms of PIP controller; standard form and forward-path structure. Although both structures are identical at the piece-wise linear design stage, they may yield very different closed loop characteristics, particularly when applied to the nonlinear system. Previous research reveals that the feedback form of PIP is faster in response than forward-path PIP control in disturbance rejection, since less deviation from the operating point occurs.

The research implemented by [17,18] implies that the forward-path structure is useful when the output measurements are noisy, so that the noises are not amplified within the controller function, thus, providing a smoother control input. However, when the system is suffering from high amplitude and frequency of disturbances, which is the case in wastewater treatment systems, the forward-path PIP is unable to provide a good closed loop performance (see [11]). In other words, the forward-path PIP controller cannot provide a fast response in terms of disturbance rejection, but it can attenuate the noise effects considerably, resulting in smoother control input. Therefore, since the main objective with the wastewater treatment system is to reject the disturbances of the plant and, also, as the data obtained from these systems are often noisy, it would be worthwhile improving the performance of this structure to disturbance rejection.

One possible action could be to add the influent flow rate model (which is the more important load effect) into the block diagram of the controller. In this way, the effect of the load is added to the control loop in the forward-path.

In this paper, an improvement in the forward-path structure of PIP is suggested by adding the disturbance model into the control loop, in order to anticipate the output variations more accurately.

DATA-BASED MODELLING

The data-based modeling approach that was developed in 1987 within the context of TDC system design is used here to produce a linearized control model of the system. In this method, a reduced-order transfer function model is directly identified from the input-output data obtained either from a real system or from a complex simulation model of the system using statistical identification and estimation algorithms. The model is then employed in the control design procedure.

This modeling methodology could bring some advantages to wastewater treatment systems. Since biological wastewater treatment systems are nonlinear processes with enormously complex reactions, building a reliable mechanistic model of the system is difficult. Also, identifying such a mechanistic model, due to the unavailability of all the state variables of biological treatment systems, is difficult and time consuming. Therefore, the data-based modeling technique could be more favorable in the viewpoint of model identification and parameter estimation. Indeed, this technique seems a practical, simple, cheap and less time-consuming method to identify a proper model, because only input-output data are needed.

Statistical modeling has also been used by other researchers [7-10], but, these models were mainly developed for the purpose of forecasting and fault diagnosis, rather than utilization directly in the control problem. In this regard, this paper utilizes the data-based modeling technique to identify the disturbance model.

BENCHMARK PROBLEM

The benchmark system is based on the layout of a typical activated sludge plant for nitrogen removal. It is composed of a five-compartment bioreactor for pre-denitrification (the first two anoxic zones) and nitrification (the last three aerobic zones), together with a settler at the end of the process. The benchmark was downloaded from the following web site, from which further information may be obtained: www.ensic.u-nancy.fr/COSTWWTP/benchmark.html.

Figure 1 shows the general layout of the benchmark system. The first two zones have no aeration and provide denitrification processes, while the last three zones are aerated and provide nitrification reactions. The benchmark simulation is based on two well-known models; the Activated Sludge Model no. 1 (ASM no.1 or IAWQ model) [19] for modeling the biological part of the process and the Tackas model, for modeling the settler dynamics [20]. The ASM model consists of 13 state variables and 19 parameters. In this model, the wastewater and biomass are structured into a number of different variables to represent the effect of different groups of bacteria on the different components of the wastewater.

The benchmark model is simulated using the MATLAB/SIMULINK$^{\text{TM}}$ software system. A verification routine was applied, in order to check the consistency of the simulation with the benchmark model. This involved the line by line check of the model with the SIMULINK diagram and, also, comparing the static and dynamic response of the simulation subject to constant and dynamic inputs with the results released by the WORKING GROUP. The dynamic input files provided by the WORKING GROUP contain the diurnal variation of some of the input components, such as influent flow rate for a period of 14 days and under different weather conditions. These files are supplied by the WORKING GROUP in order to verify the simulation and also to evaluate the proposed operation or control strategy.

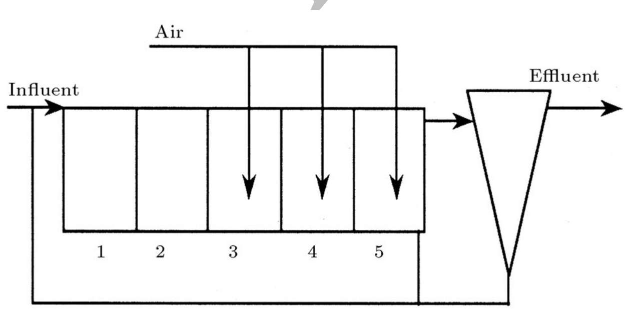

Figure 1. Layout of the activated sludge benchmark system.

CONTROL OBJECTIVES

There are two common objectives for the benchmark system; control of dissolved oxygen in the last zone and control of nitrate in the second zone by means of the aeration rate to the last zone and the returned flow rate from zone 5, respectively. The application of PIP/TDC methodology on the benchmark system has already been released in [12-14]. Also, it is shown in [11] that the forward-path PIP control of DO and nitrate produces a much less noisy control input than the standard form. However, the output variation is higher and less stable. In this paper, it is shown that the dissolved oxygen control loop with the forward-path PIP controller can be improved by introducing the disturbance model into the control loop. Here, the control objective is to maintain the DO level at 2 mg/l, which is a previously defined value of the DO controller in the benchmark system.

DISTURBANCE MODEL

The influents of wastewater treatment systems are usually highly variable in terms of their rate, concentration and composition. Figure 2 shows the variation of an influent flow rate of a dry weather data file of the benchmark. The data resembles the real situation [15].

It is shown in [11] that the influent flow rate is, mainly, the most important variable that largely affects the systems performance rather than the concentration and composition of the influents. Therefore, here, the

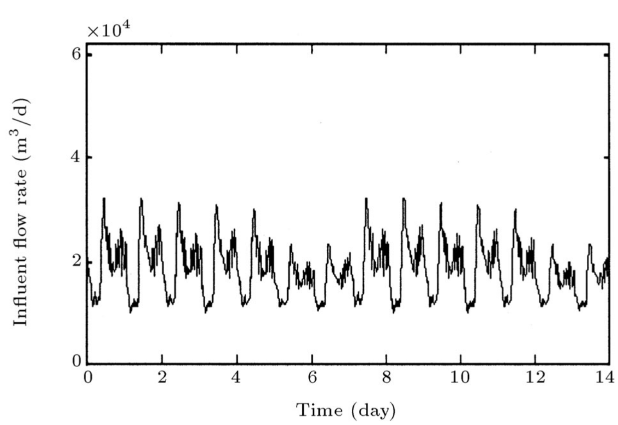

Figure 2. Influent flow rate of dry weather file.

influent flow rate variation is considered as the major disturbance influencing the system and its effect on dissolved oxygen concentration in the last zone of the benchmark is modeled using the data-based modeling technique. It will be shown that this relationship can be well approximated by a simple linear Transfer Function (TF) model.

For a linear, Single-Input Single-Output (SISO) discrete-time system:

$$y(k)=\frac{b_1z^{-1}+\cdots+b_mz^{-m}}{1+a_1z^{-1}+\cdots+a_nz^{-n}}u(k)=\frac{B(z^{-1})}{A(z^{-1})}u(k), \tag{1}$$

where, $A(z^{-1})$ and $B(z^{-1})$ are appropriately defined polynomials in the backward shift operator z^{-1} i.e., $z^{-i}y(k)=y(k-i)$. For convenience, any pure time delay of $\delta>1$ samples is accounted for by setting the $\delta-1$ leading parameters of the $B(z^{-1})$ polynomial to zero, i.e. $b_1\dots b_{\delta-1}=0$. Here, $y(k)$ and $u(k)$ are the dissolved oxygen concentration (mg/l) and influent flow rate (l/d), respectively.

In the present benchmark example, the data are obtained from simulation experiments conducted on the high order nonlinear model of the system. For the present analysis, an equilibrium point is first obtained by running the simulation model for a long period of time with constant inputs. Secondly, the simulation model is perturbed about this operating point by a step applied to the control input signal. Finally, the resulting input-output data are used as the basis for statistical model identification and estimation.

Here, the input-output data are collected in a one-minute sampling rate. The statistical Simplified Refined Instrumental Variable (SRIV) identification and estimation algorithm [21] is used here, which gives the different models sorted, based on some predefined identification criteria as shown in Table 1.

The coefficient of determination, R_T^2, together with the Young Identification Criterion (YIC) [21], determines the best-identified model that is shown by the first row of Table 1. A value of R_T^2 close to unity and a large negative YIC are normally desired that guarantee goodness of fit and not over-parameterizing of the model. The values of R_T^2 and YIC for the obtained second order model are 0.998 and -16.53, respectively. The SRIV algorithm then estimates the values of the model parameters, resulting in a discrete-time transfer function model, as below:

Table 1. The 10 best models proposed by the SRIV algorithm.

Den.	Num.	Delay	YIC	R_T^2
2	2	1	-16.5361	0.998358
1	1	1	-14.9128	0.986154
1	1	2	-14.8935	0.986082
1	1	3	-14.8746	0.986007
1	1	4	-14.8561	0.985929
1	1	5	-14.8377	0.985847
1	2	5	-10.6521	0.987393
1	2	4	-10.5704	0.987361
1	2	3	-10.4884	0.987331
1	2	2	-10.4064	0.987303

$$y(k)=\frac{-0.001935z^{-1}+0.001933z^{-2}}{1-1.9914z^{-1}+0.9914z^{-2}}u(k). \tag{2}$$

As is clear, also, from Figure 3, a very good model fit is obtained.

PIP CONTROL SYSTEM

The TDC control design methodology is based on the definition of a suitable non-minimum state space (NMSS) form for the discrete-time model. Here, the state variables are defined as the present and past sampled values of the input and output variables, together with the 'integral of error'. The control methodology is called Proportional-Integral-Plus (PIP) control design, because the structure is the same as a PI controller for a first-order model, but involves additional feedback terms for higher-order models. Figure 4 shows the standard structure of the PIP controller.

Here, $\frac{B(z^{-1})}{A(z^{-1})}$ is the process transfer function model of the system in terms of backward shift operator $(z^{-1}), K_I$ is the integral action of the controller and $F_1(z^{-1})$ and $G(z^{-1})$ are defined as follows:

$$F(z^{-1})=F_1(z^{-1})+f_0=f_0+f_1z^{-1}+\cdots+f_{n-1}z^{-(n-1)},$$

$$G(z^{-1})=1+g_1z^{-1}+\cdots+g_{m-1}z^{-(m-1)}. \tag{3}$$

The control design problem is, then, to define the values of K_I, $F_1(z^{-1})$ and $G(z^{-1})$ polynomials. The

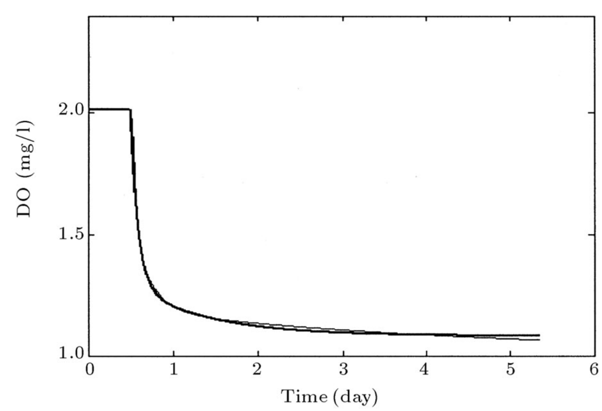

Figure 3. Simulation output (thick trace) compared with the response of the TF model (thin trace).

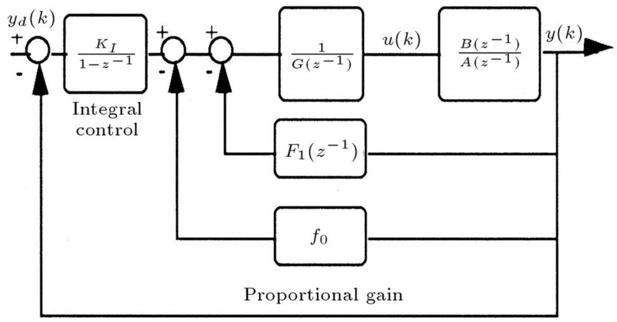

Figure 4. The PIP/NMSS controller structure in the standard feedback form.

PIP control design algorithm utilizes the State Variable Feedback (SVF) design strategies within the NMSS setting, such as: Closed loop pole assignment or optimization, in terms of a Linear-Quadratic (LQ) cost function (see [7]).

MODIFIED FORWARD-PATH PIP

The forward-path structure is shown in Figure 5, in which $\frac{\hat{B}(z^{-1})}{\hat{A}(z^{-1})}$ denotes the model of the system in terms of backward shift operator and $\hat{y}(k)$ is the model output at kth instance. In this control structure, the output is being fed back from the model of the system instead of the real system. This avoids the output noise being amplified within the controller function. But, when there are disturbances, the model of the system in the forward-path control loop does not acquire the effects of the disturbances, which affect the real system. In other words, these effects are only being fed to the integrator, not the other compensators of the forward-path control loop. In the modified forward-path PIP structure, the disturbance model has been included into the control loop and its output has been added to the model output, in order to generate the more accurate output response. Figure 6 shows the modified forward-path PIP structure.

In Figure 6, $\frac{\hat{B}_D(z^{-1})}{\hat{A}_D(z^{-1})}$ is the disturbance transfer function model of the system in terms of backward shift operator and $F_{\text{in}}(k)$ and $\hat{y}_D(k)$ denote the influent flow rate and disturbance model output, respectively.

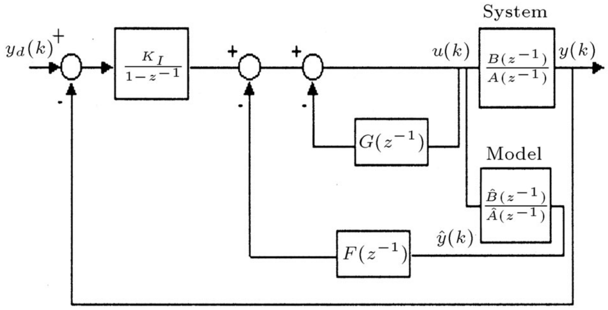

Figure 5. Forward-path structure of the PIP controller.

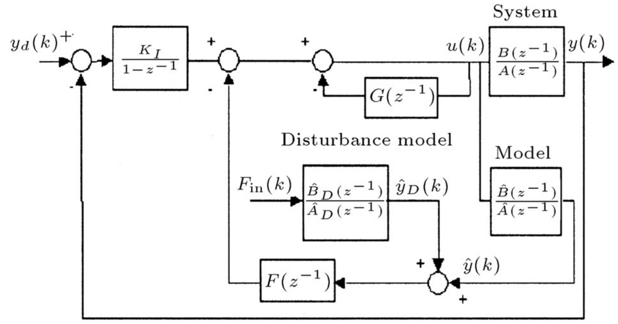

Figure 6. Forward-path PIP control structure with disturbance model (modified forward-path PIP).

IMPLEMENTATION

In order to implement the modified forward-path PIP control of DO in the last zone of the benchmark problem, it is necessary, first, to design a forward-path PIP controller. As previously noted, the design is based on the identification of a control model for DO using the data-based modeling technique and, then, NMSS/PIP control design, based on SVF control design methods.

In [13], PIP control of dissolved oxygen concentration in the aforementioned benchmark system is discussed. The present paper makes use of the PIP control settings stated in that paper to examine the modified forward-path PIP control of DO in the last zone of the benchmark system by means of aeration to the zone.

As mentioned, the PIP control design problem refers to identifying the values of PIP control polynomials, i.e., $F(z^{-1})$ and $G(z^{-1})$ (see Figure 5). The PIP control polynomials for DO, which were obtained using an optimal linear quadratic method, as given in [13], are as follows:

$$F(z^{-1}) = 281.0 - 176.1z^{-1},$$

$$G(z^{-1}) = 1 - 0.9878z^{-1},$$

$$K_I = 26.35. \tag{4}$$

These PIP control settings are used to investigate the performance of the forward-path PIP controller, while the disturbance model in the control loop and system is suffering from influent flow rate disturbances.

RESULTS AND DISCUSSION

The performance of the above PIP controller (Equations 4) in the modified forward-path PIP control loop (Figure 6) is examined using the dry weather data file and implemented on the benchmark problem. The result is then compared with the ordinary forward-path PIP control loop (with no disturbance model), as shown in Figure 7.

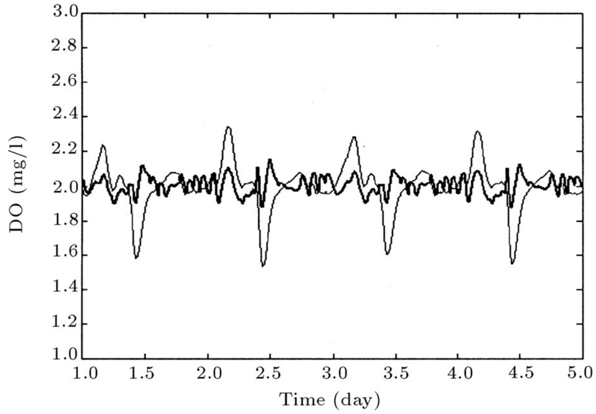

Figure 7. Forward-path PIP control of DO (thin trace) and modified forward-path PIP control of DO (thick trace).

As clear from this figure, the output variations of the modified PIP forward-path control loop has decreased notably showing a better performance of the controller than the ordinary forward-path PIP. The control input variations for both controllers are shown in Figure 8, where it can be seen that the control input oscillations have increased, in the case of the modified forward-path PIP. This implies that the improvement in the output behavior is gained by compensation of loosing a smoother response of input.

CONCLUSIONS

Load disturbances are the major cause of large perturbations in wastewater treatment systems and consequent deterioration in the effluent quality. This paper has presented an improvement in the application of the univariate PIP methodology to disturbance rejection. Dissolved oxygen concentration in a well-known benchmark system is controlled at 2 mg/l in the case of influent flow variations.

A modification is being made in the forward-path PIP control algorithm that successfully maintains DO concentration at the required level, despite the presence of significant disturbances to the influent. This is achieved by introducing the disturbance model into the forward-path PIP control loop. The disturbance model is a data-based model, identified and estimated using the well proven SRIV statistical identification and estimation algorithm. Implementation of the modified forward-path PIP on the benchmark problem shows an improvement in the output response with less deviation from the set point than the ordinary forward-path PIP controller.

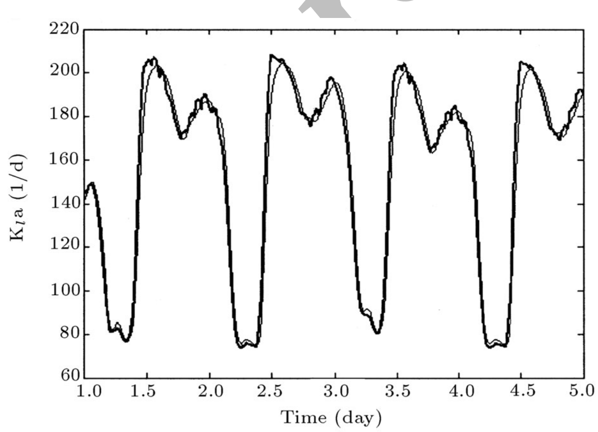

Figure 8. Control input responses of modified forward-path PIP (thick trace) and ordinary forward-path PIP (thin trace).

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