Data-based modelling and proportional-integral-plus (pip) control of nitrate in an activated sludge benchmark

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Abstract This paper presents the result of an investigation into the Proportional Integral Plus (PIP) control of nitrate in the second zone of an activated sludge benchmark. A data-based reduced order model is used as the control model and identified using the Simplified Refined Instrumental Variable (SRIV) identification and estimation algorithm. The PIP control design is based on the Non Minimum State Space (NMSS) form and State Variable Feedback (SVF) methodology. The PIP controller is tested against dynamic load disturbances and compared with the response of a well tuned PI controller.

Keywords Activated sludge plant; data-based modelling; nitrogen removal; Proportional Integral Plus control

Introduction

Control systems can reduce operational cost and effluent charges in wastewater treatment plants by means of optimising process performance. Automatic control in nitrogen removal systems is even more important since a good balance between nitrification/denitrification processes should be provided in the system. In the nitrification process ammonium is converted to nitrate under aerobic conditions and in denitrification, nitrate is converted to nitrogen gas with the use of organic carbon under anoxic conditions. There are a number of different ways of providing the required conditions for nitrification/denitrification in the reactor. A typical plant layout is to divide the reactor into anoxic and aerobic zones and to recirculate the effluent. In this case the choice of the regulator is limited to the recirculation rate and dissolved oxygen setpoint. However, an improved method of nitrogen removal is to use alternating systems: here, the sludge is alternatively aerated to generate aerobic/anoxic phases in the reactor. A third approach is to maintain DO in the mixed liquor at a level that allows simultaneous nitrification and denitrification. In all cases the activated sludge plant needs to be properly operated in order to optimise the nitrogen removal.

The *WORKING GROUP No.2* within the framework of the European COST Action 682 "Integrated Wastewater Management" has developed a benchmark simulation for evaluating different control strategies for activated sludge plants (e.g. Alex *et al*., 1999). 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 predenitrification (the first two anoxic zones) and nitrification (the last three aerobic zones), together with a settler at the end of the process. Here the benchmark problem is used to introduce the model-based Proportional-Integral-Plus (PIP) control methodology (Young *et al*., 1987; Taylor *et al*., 1994) in the control of wastewater treatment systems. The benchmark was downloaded from the following web site, from which further information may be obtained: www.ensic.u-nancy.fr/COSTWWTP/benchmark.html

The first step in all model-based control strategies is to identify an appropriate model of the system. Mechanistically derived mathematical models of biological systems are usually very complex with many parameters. These models are often not easily identifiable nor suitable for use in control system design, unless they are first simplified and linearised.

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In this paper a data-based modelling procedure is used to estimate the nitrate dynamics for the second anoxic zone of the benchmark system. The input-output data in this study are obtained directly from the benchmark simulation itself and a low order transfer function model is identified using the Simplified Refined Instrumental Variable (SRIV) identification and estimation algorithm (Young, 1991). The resulting model is employed in the subsequent True Digital Control (TDC) design. In TDC control system design, all aspects of the design procedure are digital in nature, thus avoiding the problems associated with the digitisation of the model or controller structure from their continuous time equivalents. In this situation, the sampling interval is usually relatively coarse in comparison with that used in digitised continuous-time systems. This is because the identified discrete-time transfer function (TF) model is often better defined statistically at such coarser sampling intervals, and the resulting TDC system will be more robust to uncertainty.

Over the last few years, PIP control systems have been successfully employed in a range of practical applications (e.g. Young *et al*., 1994; Taylor *et al*., 1999). Ghavipanjeh *et al*. (2000) discuss preliminary results for the PIP control of dissolved oxygen concentration in the aforementioned benchmark system, while the present paper is instead concerned with the control of nitrate concentration.

The benchmark system

The benchmark system (Alex *et al*., 1999) consists of five compartments, including two anoxic zones for predenitrification and three aerobic zones for nitrification processes. The benchmark simulation is based on two previously developed models: the Activated sludge model no. 1 (IAWQ model) (Henze *et al*., 1987) is utilised for the biological part of the process; and the Tackas model (Tackas *et al*., 1991) is chosen for the settler dynamics. The parameters of these models are set to their realistic values at 15°C. In the present research, the equations of the benchmark system are programmed and solved using the MATLAB/SIMULINK™ package. The simulation is verified for both its steady state and dynamic response to various influent flow rates and concentrations.

The control objective here is to maintain the nitrate concentration in the second anoxic zone at 1 mgN/l by regulating the internal recycle flow rate, i.e. the flow feedback from compartment 5 to the influent. Finally, note that the nitrate sensor is assumed to have a delay of 10 minutes, while its performance is further degraded by measurement errors, namely white noise with 0.1 mgN/l standard deviation.

Data-based modelling

As biological processes involve a large number of unknown reaction mechanisms, building a reliable mechanistic model is time consuming and the resulting model is not particularly suitable for control system design. Moreover, the data used to calibrate the model may be noisy and the uncertainty in the model description may be quite high. In these situations, a statistical model provides a more appropriate description since it is able to quantify the level of uncertainty and use this in the control system design. Therefore, it is worthwhile establishing a dynamic model directly from the input/output data measured from the plant. The advantages of data-based modelling methodology, in addition to its simplicity and ability to characterise the dominant modal behaviour of the system, is that it provides parsimonious transfer function models that can be directly employed in control system design. The present paper shows how such an approach combines both linearization and model reduction.

Control model identification

The simulation model of nitrate in the second zone of the benchmark is a high order non-linear model. For the present analysis, a linear TF model is identified around a steady state level of 1 mg/l of nitrate concentration in the second anoxic zone. TF models are usually identified from measured input-output data, collected either from planned experiments or during the normal operation of the plant. Alternatively, as in the present benchmark example, the data are obtained from the simulation experiments. For this purpose, an equilibrium point is first obtained by running the simulation model for a long period of time with constant inputs and no disturbances. Secondly, the simulation model is perturbed about this operating point by an impulse applied to the control input signal and data are collected at a sampling rate of 10 minutes.

The linear discrete time TF model for a single-input, single-output (SISO) system can be described as,

$$y(k) = \frac{b_1 z^{-1} + \cdots + b_m z^{-m}}{1 + a_1 z^{-1} + \cdots + a_n z^{-n}} u(k) = \frac{B(z^{-1})}{A(z^{-1})} u(k) \quad (1)$$

where $A(z^{-1})$ and $B(z^{-1})$ are appropriately defined polynomials in the backward shift operator z^{-1}; i.e., $z^{-i}\,y(k) = y(k-i)$. Here, $y(k)$ and $u(k)$ are the nitrate concentration (mg/l) in the second zone and returned flow rate (m^3/h) from zone 5 to 1 respectively. SRIV estimation coupled with the YIC identification criterion (Young, 1991) and the model fit defined by the Coefficient of Determination, R_T^2, yields the following second order discrete time transfer function:

$$y(k) = \frac{0.014 z^{-1} + 0.011 z^{-2}}{1 - 1.206 z^{-1} + 0.396 z^{-2}} u(k) \quad (2)$$

Figure 1 illustrates the TF model response compared with the simulated output, where it is clear that the dynamics of the benchmark system are adequately represented by the simpler model. In fact, the coefficient of determination R_T^2 = 0.99640, i.e. at this operating point 99.6% of the variation of the non-linear simulation is explained by the TF model.

NMSS/PIP control system design

The structure of the PIP controller is quite simple and similar to conventional Proportional-Integral (PI) controllers, as illustrated in Figure 2. In this diagram f_0 and k_I are the proportional and integral gains respectively. However, the PIP algorithm also utilizes additional feedback of past values of the input and output variables, represented by the $F_1(z^{-1})$ and $G(z^{-1})$ polynomials. Here, $F_1(z^{-1})$ and $G(z^{-1})$ are defined as follows:

$$\begin{aligned} F(z^{-1}) &= f_0 + F_1(z^{-1}) = f_0 + f_1 z^{-1} + \cdots + f_{n-1} z^{-(n-1)} \\ G(z^{-1}) &= 1 + g_1 z^{-1} + \cdots + g_{m-1} z^{-(m-1)} \end{aligned} \quad (3)$$

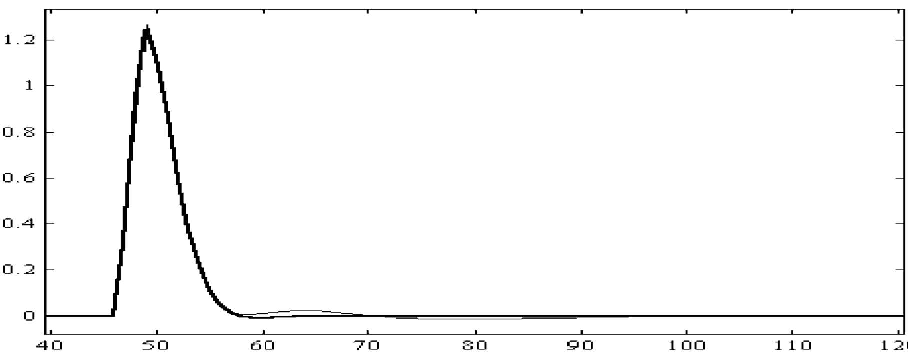

Figure 1 Thin line non-linear model response, thick line reduced order model response. The nitrate concentrations [mg/l] are plotted against time in 10 min samples (based line removed)

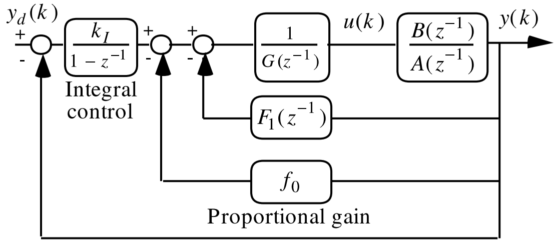

Figure 2 The NMSS/PIP servomechanism system (feedback form)

where n and m are obtained from the order of the transfer function model of the system (1).

The $F_1(z^{-1})$ and $G(z^{-1})$ polynomials will only appear when the system's behaviour has second order or higher order dynamics. Otherwise, for a first order model, the controller structure would be the same as a PI controller. However, in contrast to conventional PI/PID controllers, PIP design has numerous advantages: in particular, its structure exploits the power of State Variable Feedback (SVF) methods, where the vagaries of manual tuning are replaced by pole assignment or Linear Quadratic (LQ) design.

The state variables in this methodology are the present and past sampled values of the input and output variables, together with the "*integral of error*" state. The *integral-of-error* state guarantees type 1 servomechanism performance or steady state tracking. The state vector $\boldsymbol{x}(k)$ is defined as,

$$\mathbf{x}(k) = \begin{bmatrix} y(k) & y(k-1) & \cdots & y(k-n+1) & u(k-1) & \cdots & u(k-m+1) & z(k) \end{bmatrix} \tag{4}$$

where $y(k)$ is the output variable, $u(k)$ the input variable and $z(k)$ is the *integral-of-error* between the reference or command input $y_d(k)$ and the sampled output $y(k)$, defined as follows,

$$z(k) = z(k-1) + \{y_d(k) - y(k)\} \tag{5}$$

Using (4), the TF model (1) can be represented by the following Non-Minimum State-Space (NMSS) equations,

$$\begin{aligned} \boldsymbol{x}(k) &= \boldsymbol{F}\boldsymbol{x}(k-1) + \boldsymbol{g}u(k-1) + \boldsymbol{d}y_d(k) \\ y(k) &= \boldsymbol{h}\boldsymbol{x}(k) \end{aligned} \tag{6}$$

where the state transition matrix $\boldsymbol{F}$, input vector $\boldsymbol{g}$, command input vector $\boldsymbol{d}$, and output vector $\boldsymbol{h}$ of the NMSS system are defined as:

$$\mathbf{F} = \begin{bmatrix} -a_1 & -a_2 & \cdots & -a_{n-1} & -a_n & b_2 & \cdots & b_{m-1} & b_m & 0 \\ 1 & 0 & \cdots & 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & \ldots & 0 & 0 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & \ldots & 1 & 0 & 0 \\ a_1 & a_2 & \cdots & a_{n-1} & a_n & -b_2 & \cdots & -b_{m-1} & -b_m & 1 \end{bmatrix}$$

$$\boldsymbol{g} = \begin{bmatrix} b_1 & 0 & \dots & 0 & 1 & 0 & \dots & 0 & -b_1 \end{bmatrix}^T$$
$$\boldsymbol{d} = \begin{bmatrix} 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 1 \end{bmatrix}^T$$
$$\boldsymbol{h} = \begin{bmatrix} 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix}$$

For the above NMSS model (6), the SVF control law is defined in the normal manner, i.e.,

$$u(k) = -\boldsymbol{k}\,\boldsymbol{x}(k) \tag{7}$$

where $\boldsymbol{k}$ is the $n + m$ dimensional SVF control gain vector,

$$\boldsymbol{k} = \begin{bmatrix} f_0 & f_1 & \cdots & f_{n-1} & g_1 & \cdots & g_{m-1} & -k_I \end{bmatrix} \tag{8}$$

The control gains are determined using the well known SVF strategies, such as closed loop pole assignment, or optimisation in terms of a LQ cost function of the form,

$$J = \tfrac{1}{2}\sum_{i=0}^{\infty}\left\{\boldsymbol{x}(i)^{\mathrm{T}}\boldsymbol{Q}\,\boldsymbol{x}(i) + r\,\boldsymbol{u}^2(i)\right\} \tag{9}$$

where $\boldsymbol{Q}$ is a $n + m$ by $n + m$ matrix and r is a scalar weight on the input. In the NMSS/PIP approach $\boldsymbol{Q}$ can be formed conveniently as a diagonal matrix with elements defined as follows,

$$\boldsymbol{Q} = \mathrm{diag}\begin{bmatrix} q_1 & q_2 & \dots & q_n & q_{n+1} & \dots & q_{n+m-1} & q_{n+m} \end{bmatrix} \tag{10}$$

Here, the user defined output weighting parameters $q_1, q_2, \dots, q_n$ and input weighting parameters $q_{n+1}, q_{n+2}, \dots, q_{n+m-1}$ are generally set equal to common values of q_y and q_u respectively; while q_{m+n} is denoted by q_e to indicate that it provides a weighting constraint on the integral-of-error state variable $z(k)$. In this formulation, the input weight is defined as $r = q_u$. The "default" PIP-LQ controller is then obtained using total optimal control weights of unity, i.e., $q_y = 1/n$, $q_u = 1/m$ and $q_e = 1$. The resulting SVF gains are obtained from the steady state solution of the discrete time matrix Riccati equation.

Results and discussion

Simple experimentation reveals that PIP-LQ weightings of $q_e = 50$, $q_u = 0.1$, $q_y = 1$ yield a good response for the control of nitrate in the 2nd compartment. In this case the PIP-LQ control polynomials are defined as shown below,

$$F(z^{-1}) = 32.02 - 12.91z^{-1}$$
$$G(z^{-1}) = 1 - 0.346z^{-1}$$
$$k_I = 12.93 \tag{11}$$

The PIP-LQ algorithm (11) is applied to the full non-linear simulation for a step change in the set point. The response is illustrated in Figure 3 with neither any noise on the nitrate measurement nor any disturbance inputs. In order to evaluate the performance of the controller in realistic conditions with load disturbances, the 14 days dry-weather file is introduced to the benchmark simulation. The data represents diurnal variations of influent flow rate and the concentration of some of the components in the influent wastewater. Figure 4 shows the variation of the influent flow rate. In Figure 5, the PIP controlled nitrate concentration is shown, while subjected to these load disturbances. Here, the PIP control algorithm attempts to maintain the nitrate concentration at the required level of 1 mg/l,

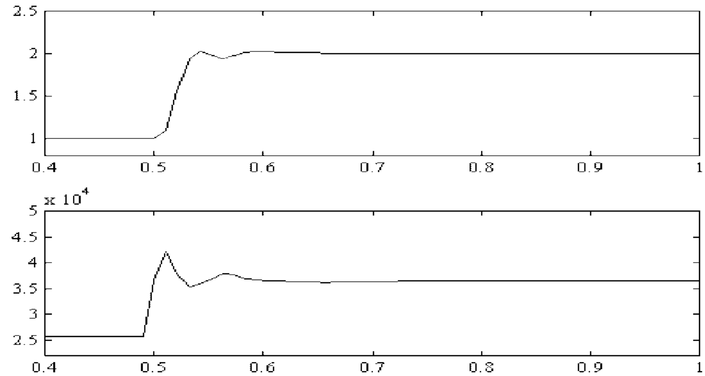

Figure 3 Step response for PIP-LQ control of the non linear benchmark simulation without disturbances. The nitrate concentration (mg/l; top) and returned flow rate (m^3/d) are all plotted against time in days

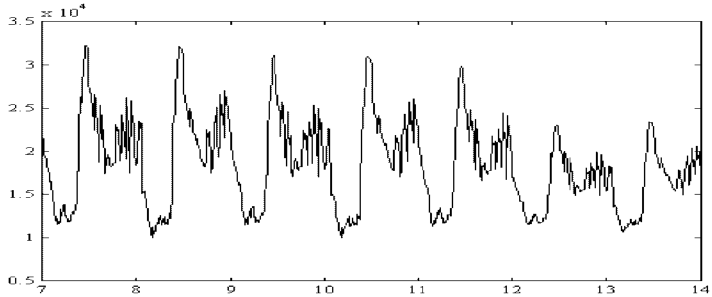

Figure 4 Influent flow rate variations of the dry weather file (m^3/d) plotted against time in days

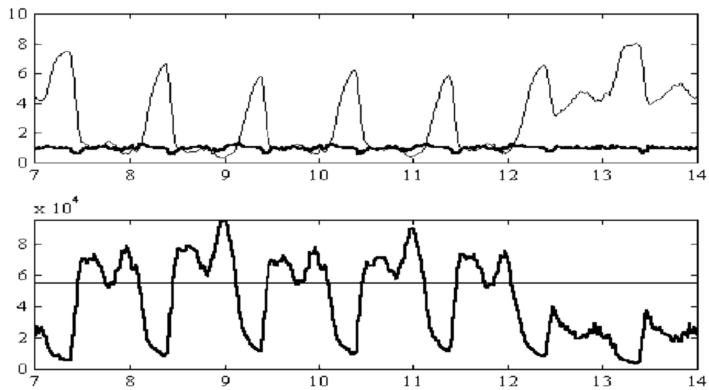

Figure 5 PIP-LQ control of the non linear simulation benchmark with disturbances (solid traces) compared to the open loop response based on a constant control input of 55338 m^3/d (dashed traces); nitrate (mg/l; top) and returned flow rate (m^3/d; bottom) are plotted against time in days

however, because of the high variation in the load disturbances there are variations in the controller response. The open loop response to the same influent disturbances, based on a constant control input of 55338 m^3/h, is also shown as the dashed trace in Figure 5. It is well known that the dissolved oxygen concentration is an important factor in the nitrogen removal system. Hence, the single-input single-output PIP controller for nitrate concentration in the second zone of the benchmark is simultaneously implemented with a PIP controller for dissolved oxygen in the third aeration tank (see Ghavipanjeh *et al.*, 2000). The

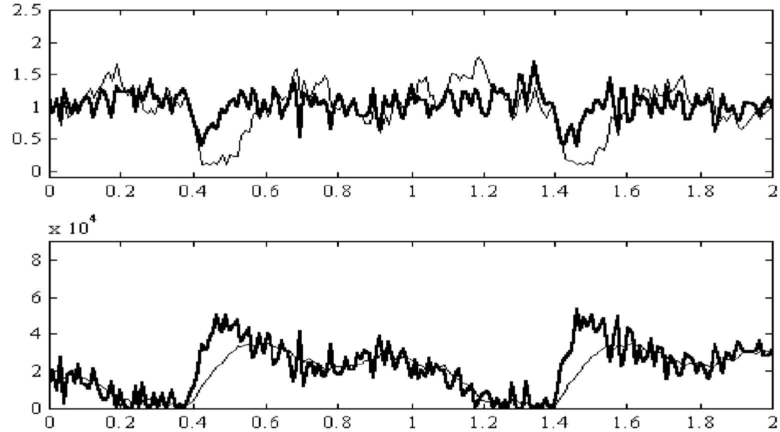

Figure 6 PIP (solid line) and PI (dashed line) controller response of nitrate concentration in the second anoxic zone in the presence of noise (top), and returned flow rate variations (bottom) are plotted against time in days

nitrate response to load disturbances while both controllers are employed is shown in Figure 6. In this case, nitrate measurement noise is also simulated.

The combined DO and nitrate controller yields moderately better control of nitrate in the 2nd chamber, when compared to the case without DO control. However, the main benefit of the multiple loop controller is in terms of the overall performance of the wastewater treatment plant, as shown in Table 1. Here, although there is a small increase in the percent of time that the total nitrogen concentration violates the benchmark specifications, there is a significant reduction in the proportion of time that ammonium violates the limits, from 63% to 17%.

The PIP controller yields an improved performance compared with a well tuned PI design, albeit at the expense of increased activity in the input. However, this variation in the input is not of a particularly high frequency (note that Figure 6 shows a period of two days) and is within the practical limits that can be implemented in practice. Nonetheless, the authors are presently investigating the application of multi-objective optimisation techniques (Chotai *et al.*, 1998), with the aim of simultaneously improving treatment performance and reducing costs.

Conclusions

This paper has presented the initial results obtained in a design exercise aimed at producing a Proportional-Integral-Plus (PIP) controller for activated sludge plants. The paper has concentrated on the application of the univariate PIP methodology to control nitrate concentration in a well known benchmark system. The PIP control algorithm successfully maintains nitrate concentration at the required level, despite the presence of significant disturbances to the influent. This has involved a very simple design procedure, with the weights in the LQ cost function used to straightforwardly tune the closed loop response.

However, if other more difficult design objectives are required, the algorithm may be

Table 1 Ammonium and nitrogen concentration in effluent of the benchmark simulation

	Total Nitrogen		Ammonium	
	No. of Violation	% of time	No. of Violation	% of time
NO3 controller	5	8.74	7	63.1
NO3 & DO controllers	7	16.5	5	16.8

tuned still further by more computationally intensive, multi-objective optimisation methods and research is ongoing in this regard. This will become particularly important as the research moves towards the full multivariate PIP control (see e.g. Young *et al*., 1994) of other variables, such as dissolved oxygen, rather than the multiple loop univariate controllers considered in the present paper.

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