MODEL BASED PREDICTIVE CONTROL FOR WASTEWATER APPLICATIONS

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Abstract: The aim of this paper is to demonstrate dissolved oxygen and nitrate control in a wastewater treatment-plant, and an integrated wastewater system, using model predictive control. This control is of importance in maintaining the conditions required for aquatic organisms and so, the entire dynamics must be considered: the urban sewer system, water treatment plant, and river itself. The integrated system is highly nonlinear and therefore the control is implemented using multiple models. Using this method, nonlinear control is obtained based on local linearisations, which are scheduled using Takagi-Sugeno-Kang methods. Results demonstrate the advantages of predictive control in water treatment control.

Keywords: Predictive Control, Waste Treatment, Environmental Engineering, Nonlinear Control

1. INTRODUCTION

In the past, extensive research has been done to optimise the performance of wastewater systems by implementation of control based on wastewater treatment plant models. The focus in recent years has now moved towards the integrated water system itself, to include control of both the treatment plant and the receiving waters affected by it.

Model Based Predictive Control (MBPC) can be used in the control and optimisation of the behaviour of a process, in the presence of constraints, by using models of the process to predict future behaviour. This is the requirement in control of integrated wastewater systems, which must be constrained to within governmental regulatory limits, and thus MBPC is an appropriate control methodology.

This paper demonstrates the application of predictive control methods in two systems: the linear control of a wastewater treatment plant, and fuzzy-nonlinear control of an integrated wastewater system (consisting of a sewer network, a treatment plant, and the receiving waters).

For the most part, there has been little work on control of the latter systems; the majority of research has concentrated on the treatment plant alone. A similar approach to that described here was developed by Marsili-Libelli *et al.* (2002) and by Brdys *et al.* (2002) where fuzzy predictive control was applied to the case of treatment plant system, without modelling the effect on the receiving waters.

Predictive control methods are generally popular in industry in their linear form. This is due to the complexity of the nonlinear forms. In recent years, however, progress has been made in the use of linear predictive methods with fuzzy logic methods, as a form of nonlinear control. Skrjanc *et al.* (1994) developed a form of fuzzy predictive controller, using Takagi-Sugeno (TS) models, with a GPC algorithm.

A fuzzy predictive controller for MBPC was described by Roubos *et al.* (1999) using a TS model. A similar approach is used here, with a Takagi-Sugeno-Kang (TSK) model as described by Pinto *et al.* (2004). A methodology similar to that used here was presented in Sanchez *et al.* (2002), where the TSK algorithm with predictive control was implemented on an electric power plant.

The structure of the paper is as follows: the methodology for both MBPC and for fuzzy gain scheduling is introduced, after which the application of both these methods is shown. Finally, the results are discussed, and conclusions are presented.

2. MODEL BASED PREDICTIVE CONTROL

Predictive control is one of the most widely used advanced forms of control used in industry. The reason for this is due to the fact that predictive control algorithms can easily be adjusted to allow constraint handling, that it allows for multivariable control without any extra complexity and that it can be intuitively tuned. Feedforward control is also easily accommodated, by using the model-based aspect of the control.

The control method used was that presented by Krauss *et al.* (1994), a predictive controller based on a system model as follows, requiring the standard state vector $x(k)$, found by identification, to be augmented to include $u(k)$:

$$\begin{aligned} x(k+1) &= Ax(k) + B\Delta u(k) + B_d d(k) \\ y(k) &= Cx(k) + D\Delta u(k) + D_d d(k) \end{aligned} \tag{1}$$

This form allows for the inclusion of measured disturbance $d(k)$, allowing the controller to take into account system inputs that are uncontrolled.

Further disturbance modelling by the inclusion of a constant disturbance state allows the controller to compensate for the plant-model mismatch and reject disturbances in the system, for example, changes in influent or river characteristics due to storm conditions, as shown in Maciejowski (2002). In Krauss *et al.* (1994), the equation for the predicted output is shown to be

$$\hat{y}(k) = F\hat{x}(k) + H\Delta u(k) \tag{2}$$

The matrices F and H in the above prediction equation are found by iteration of the linear model over the controller prediction horizon, H_p, and are of the following form, where H_u is the control horizon:

$$F = C * \begin{bmatrix} A \\ . \\ . \\ A^{H_p} \end{bmatrix} \quad H = C * \begin{bmatrix} B & . & . & 0 \\ . & . & & \\ . & & . & \\ \sum_{i=0}^{H_p-1} A^i B & & & \sum_{i=0}^{H_p-H_u} A^i B \end{bmatrix} \tag{3}$$

The error, upon which the controller must act, is calculated using the estimated augmented states, the setpoint $R(k)$, and the input and measured disturbance $d(k)$ values:

$$E(k) = R(k) - F\hat{x}(k) - \Xi d(k) \tag{4}$$

It can be seen therefore that state estimation is required, and so a simple pole-placement estimator calculates the states. By optimisation of the process cost function

$$V = \left\| H\Delta U(k) - E(k) \right\|_Q^2 + \left\| \Delta U(k) \right\|_\lambda^2 \tag{5}$$

with respect to $\Delta u(k)$, where Q and λ are the error and control change weights respectively, the optimal control input $\Delta u(k)$ is found.

In constraint handling, Maciejowski (2002) shows the method of implementing constraints defined by inequalities (on the input changes, the input range, and the output range, respectively):

$$E\begin{bmatrix} \Delta U(k) \\ 1 \end{bmatrix} \le 0 \quad F\begin{bmatrix} U(k) \\ 1 \end{bmatrix} \le 0 \quad G\begin{bmatrix} Z(k) \\ 1 \end{bmatrix} \le 0 \tag{6}$$

These constraints are implemented during the cost function minimisation, as constraints on the optimisation problem. The control of parameters in the wastewater treatment plant requires only linear predictive control methods. However, with the addition of the river dynamics to the control objective, significant nonlinearity is introduced, requiring nonlinear control methodology.

3. GAIN SCHEDULING USING FLC

There are various methods of nonlinear control, which however have yet to become widely used in industry, due to the already widespread use of the linear form of MBPC, and the complexity of nonlinear methods. There is, however, a method that bridges the gap between the linear and nonlinear control methods. The use of multiple models for various operating points can allow the user the benefit of nonlinear control, without the added financial or time cost of implementing nonlinear MBPC.

The method used here is called gain scheduling using Takagi-Sugeno-Kang Fuzzy Logic Control (TSKFLC), based on fuzzy theory proposed by Takagi *et al.* (1985). In this format an operating point can belong entirely to one set (one controller), or partially to two sets (two controllers weighted according to operating point). That is, the control is gain-scheduled, where the scheduling variable is that on which the choice of controllers is based (in this particular case study, the scheduling variable is Q, the input flow of the treatment plant).

For TSKFLC, the overall output of the composite controller (that is, the combined linear controllers) is the weighted mean of the outputs of each individual controller, according to the following form:

$$u = \frac{\sum_{i=1}^{K} w_i . u_i}{\sum_{i=1}^{K} w_i} \tag{7}$$

where u is the output of the composite controller, and u_i are the individual outputs of each controller in the gain scheduler. The weighting vector w_i is defined here as being within the bounds of $0 \leq w_i \leq 1$and that the sum of the weights should be equal to 1.

4. SIMULATION RESULTS

The problem of controlling both oxygen and nitrate levels in a wastewater treatment system is considered in this paper. The initial system to be controlled is that presented in the COST 624 benchmark for the Activated Sludge Model (ASM) 1 model. This demonstrates that MBPC linear predictive control is possible for a treatment system, which consists of only the water treatment plant. ASM1 is a comprehensive model based on real data, and is widely used as a benchmark for control evaluation.

However, it is also necessary to demonstrate predictive control on the integrated system, that is, including the sewer and the receiving waters, as well as the treatment plant. The majority of control research in the area of wastewater treatment has concentrated on the effluent from the plant, and meeting regulatory requirements at this point.

The research now has begun to concentrate on the effect this effluent has on the receiving waters. To this end, a simple model of an urban wastewater system (UWS) is used for the controller implementation, for the latter case study.

The aim therefore of first study was to control the nitrate and the oxygen to a specified setpoint. The control of these concentrations was investigated using multivariable predictive control. The control of the integrated wastewater system includes the gain scheduling methods with the application of Fuzzy Logic, in controlling the dissolved oxygen.

4.1 Cost 624 Benchmark Control

The COST 624 research group developed a benchmark model of wastewater treatment, using the ASM1 model developed by Henze *et al.* (Copp, 2002), in order to effectively compare different control strategies.

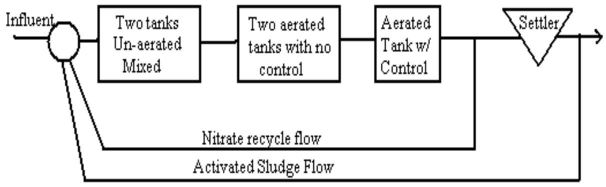

Fig. 1. COST 624 benchmark system model, comprised of five tanks, settler and recycled internal flow

Unless a general model is used for control design purposes, then the effectiveness of different controllers cannot be determined. The COST 624 benchmark plant model shown in Figure 1 is comprised of:

- five biological tanks in series, each using the ASM1 model, the first two tanks are unaerated, and the other three are aerated (with air flow control on the final tank for dissolved oxygen, and optional plant flow control on the second tank for nitrate)
- one non reactive secondary settler based on the settling function by Takacs *et al.* (1991)
- two internal recycles, nitrate from 5^{th} tank to 1^{st}, and sludge from settler to front end of plant

This system considers only the treatment plant dynamics, that is the influent into the plant is that of the average statistics for given rain events, but does not take into account any sewer dynamics. Similarly, the control implemented only considers the effluent, and not the effect downriver. The downriver effects are considered in Section 4.2

The system as presented in Copp (2002) uses low level control in the form of PID control, on the DO (dissolved oxygen) levels of the 5^{th} tank, and nitrate levels in the 2^{nd} tank. The control aim therefore is to improve on this, by implementing predictive control around these PID loops, thereby feeding a variable setpoint to them.

For this MBPC format used here a linear state space model is required, which is found by implementation of Subspace Identification, developed by Van Overschee *et al.* (1996). Implementing the linear MBPC methods, the system is run to control a DO setpoint of $2gm^{-3}$, and the nitrate level is controlled to a setpoint of $1gm^{-3}$. Tuning of the controller is done by trial-and-error, adjusting the cost function weightings according to the required response.

It can be seen that for the dissolved oxygen levels, the predictive control (dotted line) response is considerably better than that of the original PID control (full line). For the nitrate, the improvement is even more obvious. The reason for this is the fact that the predictive controller is a cascaded controller, around the inner PID loop, and therefore can vary the setpoint of the inner loop, avoiding the error due to tuning.

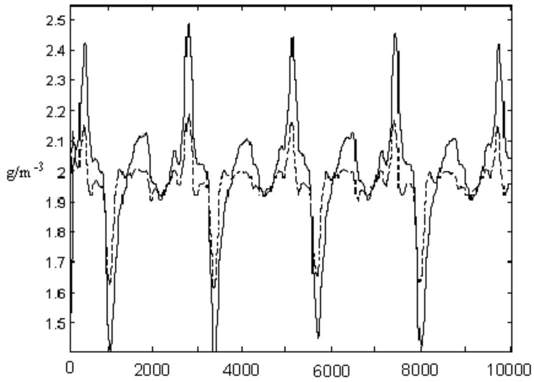

Fig. 2. a) Predictive (cascaded around PID) control (dotted line) vs. PID control only

In constraint handling, the system demonstrates the above response for the output constraint of 2.5gm^{-3}, Figure 3 shows the unconstrained and constrained case respectively for a setpoint step of 0.75gm^{-3} to 2.5gm^{-3} for dissolved oxygen. It can be seen by Figure 3 that the constraints are implemented on the output functions, though they operate strictly.

4.2 Gain Scheduling for Integrated UWS

The system considered as an integrated urban waste water system consists of a sewer network model, a treatment plant model, and the model of the receiving waters (which in this case is a river model). The input to the sewer network is that of the influent from the catchment areas, which consist of human urban wastewater, and other influents from runoff.

It can be seen from figure 4, that the sewer network affects the receiving waters in two ways, the first being the effects of the effluent of the sewer network, which is in turn the influent to the treatment plant. It also affects the receiving waters through overflows. In storm conditions, overflows occur in the sewer network, causing fluctuations of the fractions (such as dissolved oxygen) in the river.

The control objective here is to show the possibility of control of the quality of the receiving water using the treatment plant effluent dynamics. Research has been done by Cembrano *et al.* (2004) in the use of MBPC in reducing overflows, so this paper does not consider this area.

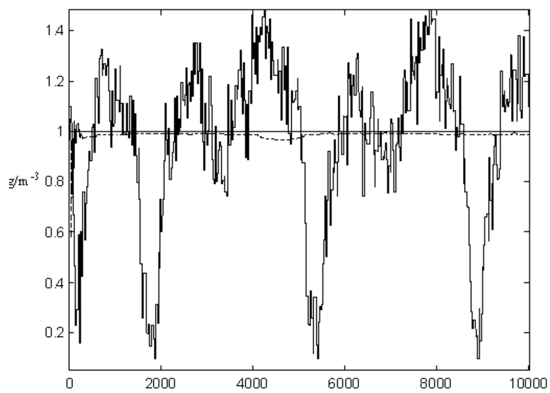

Fig. 2 b) Predictive Nitrate Control cascaded around PID (dotted line) vs. PID only

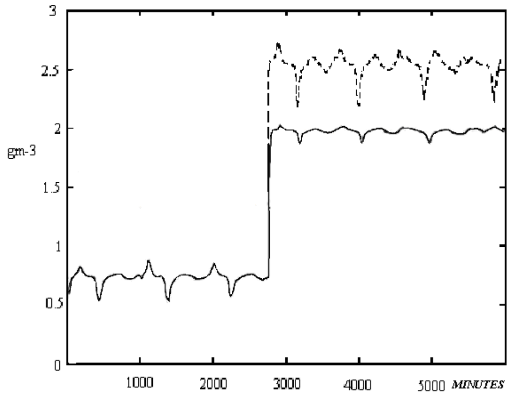

Fig. 3. dotted line: unconstrained case, full line: constrained case (for constraint of 2.5gm^{-3} for DO)

As shown in section 3, the gain scheduling implemented on this system was Takagi-Sugeno Fuzzy Logic Control. This was implemented for the integrated model shown in Figure 4. The subspace identification algorithm used previously in identification of the treatment plant model is used again in this case to also obtain a multivariable model. This model however is of the form of a measured disturbance, as the model input of upstream river dynamics is not controllable here. There is also the difference here that the predictive controller, whilst still applying a variable setpoint to a PID, does not cascade around this PID loop, but around the entire system.

There exists only one controlled input, the setpoint of the dissolved oxygen levels in the treatment plant. Due to this, and the fact that there are three models, for low flow, medium flow and high flow, there are three fuzzy rules for the model of the Nonlinear Predictive Controller using a T-S-K model. The structure of the Nonlinear Predictive Controller is shown in the Figure 5. The formula that describes the Nonlinear Predictive Controller output u is:

$$u = w_1 * C_1 + w_2 * C_2 + w_3 * C_3 \qquad (8)$$

where the degree of memberships (weighting) is represented by w_1, w_2 and w_3, and the individual control signals are represented by C_1, C_2 and C_3, (i.e. the outputs of the local linear predictive controllers). The scheduling variable, that is the variable upon which the ranges are based, is the input flow to the treatment plant, Q. By choosing three models that cover a range from 0 to 12,000m^3 of flow, then the nonlinear control should take into account both the normal flow (in the region of 1000m^3) and the storm weather flow (the maximum 12,000m^3).

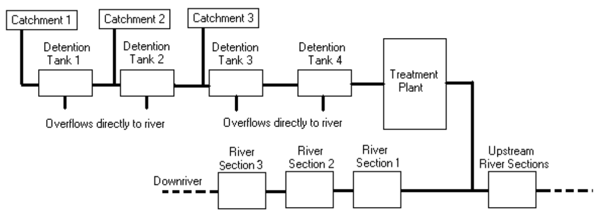

Fig. 4 Integrated Urban Wastewater System consisting of sewer network, treatment plant and receiving waters (usually river)

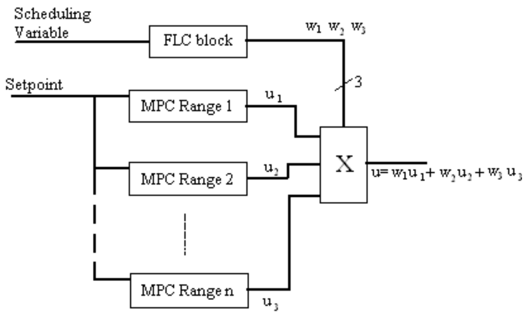

Fig. 5. Fuzzy Predictive Controller, with multiple model predictive controllers, weighted using the FLC function as described by Figure 6.

The membership functions are therefore defined as shown here in equation 9, and subject to the constraints defined by inequalities:

$$u = \begin{Bmatrix} w_1 + w_2 = 1, \, for & 0 \leq Q \leq 6000 \\ w_2 = 1, \, for & 6000 \leq Q \leq 6500 \\ w_2 + w_3 = 1, \, for & 6500 \leq Q \leq 12000 \end{Bmatrix} \quad (9)$$

The T-S-K model allows for operating ranges to be defined for each linear predictive controller in order to cover the nonlinear operating range of the system. The operation range was divided in the form shown in Figure 6, using triangular and trapezoidal membership functions, chosen due to their characteristic of having a unity weighting sum.

To demonstrate the improvement resulting from the use of a Gain-Scheduled MBPC, the following tests were run on the system. Firstly, as in figure 7, the fuzzy controller was tested at a step flow from 4000m^3 to a flow of 9000m^3, for which the setpoint to be reached in the river was a value of 8.2gm^{-3}. Both systems were tuned in order that their maximum values would reach the setpoint. The linear controller was tuned for the flow range of 5000m^3 to 7000m^3.

The fuzzy controller is tuned to reach a given setpoint for all flow ranges, and any flow change results only in a minor transient dip in dissolved oxygen levels. In comparison, it can be seen that the response for a single linear predictive controller, without gain scheduling, is erroneous at both flows and has a considerably larger transient dip during the flow change.

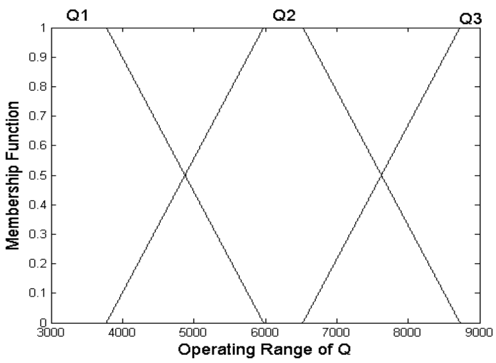

Fig. 6. The definition of the FLC membership functions according to the range of Flow, Q

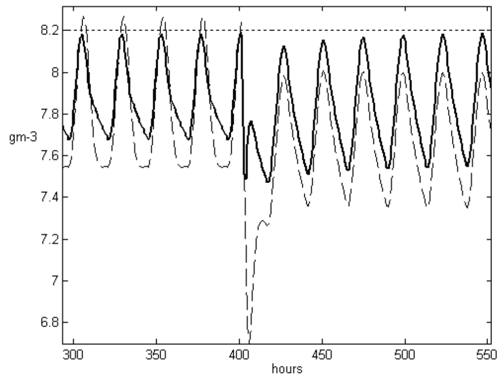

Fig 7. Fuzzy Gain Scheduled Control, FLC (full line) vs. linear MBPC (large dotted line), with respect to setpoint (small dotted line)

There is, therefore, an improvement in the response of an integrated wastewater system when a sudden flow change is applied. This is significant, as the most likely significant change in the system would be an increase in flow, due to storm weather. Using a nonlinear controller, such as a gain scheduler, allows for the system to react to such a transient.

In summary, the output constraints demonstrated in Figure 3 show the significant advantage of using MBPC. Lower control methods, such as PID control, do not allow for constraint handling. The responses in Figure 2 also show the distinct improvement of MBPC over PID in terms of setpoint tracking. This is because the PID controller does not allow for intuitive tuning of multivariable controllers. Figure 7 demonstrates the advantage of using a gain-scheduled controller for the more nonlinear integrated system.

5. CONCLUSION AND DISCUSSION

The majority of control approaches until recently have been focussed on control of the treatment plant. However, the more realistic approach is to focus instead on the effect of the effluent on the river, and to use this knowledge to attempt to control the river dynamics. Thus the effect of overflows on dissolved oxygen, and nutrients could be negated by the control of the WWTP effluent with respect to river dynamics.

The predictive control method used in this paper was outlined in Section 2. It is seen by Section 3 that it is possible to develop nonlinear predictive control using linear methods with fuzzy gain scheduling. The control implemented in Section 4 demonstrates: the ability to control a waste water treatment plant for dissolved oxygen and nitrate levels, and also the control of an integrated urban wastewater system by the use of gain-scheduled MBPC. The latter was implemented for dissolved oxygen.

The research in this paper presents the control of wastewater systems with the use of MBPC, and demonstrates how even nonlinear wastewater systems are controllable with linear techniques, with the use of gain-scheduled control.

Further work could be done to implement this control for nutrients such as nitrates or phosphates, therefore requiring more complex nonlinear predictive control methods, as well as progression to the use of a more complicated integrated system model.

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