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APPLICATION OF FUZZY MODEL PREDICTIVE CONTROL TO THE DISSOLVED OXYGEN CONCENTRATION TRACKING IN AN ACTIVATED SLUDGE PROCESS

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Abstract: Maintaining desired concentration of the dissolved oxygen (DO) in an activated sludge process is crucial for feasible and efficient operation of a wastewater treatment plant. The dissolved oxygen dynamics is nonlinear and of high dimension. The available models involve many parameters that are very difficult to estimate. Utilising the dynamics structure and its multiple time scale a simplified nonlinear SISO model was recently adopted with a disturbance inputs that can be efficiently and sufficiently accurately predicted over short time period. Based on this model a nonlinear model predictive controller was designed showing good performance. However, necessity of solving a nonliner optimisation task during the controller operation limits its performance under large and fast changes of disturbances or reference trajectories. In the paper a fuzzy Takagi - Sugeno type model of the nonlinear dynamics is produced based on its local linearisations. The recently proposed fuzzy predictive control strategy is then applied to obtain a nonlinear fuzzy predictive controller. The controller is tested and validated on physical data sets showing substantial savings in computing time with negligible loss on its performance. *Copyright © 2002 IFAC*

Keywords: bio-technical processes, nonlinear systems, set-point control, predictive control, fuzzy control.

1. INTRODUCTION

An activated sludge wastewater treatment plant can be classified as a complex system due to its nonlinear dynamics, large uncertainty in uncontrolled inputs and in the model parameters and structure, multiple time scale of the dynamics, and multi input-output structure. In addition, rather scarce measurements are available during plant operation; hence using the mathematical models is essential in designing the controller. However, there is significant uncertainty in these models and their identification is still an open problem. Hence, until recently an intensive work on physical modelling wastewater plant was rather separated from using these models for a controller design. Recent developments in control technology and particular in model predictive control, handling an uncertainty, estimation, trajectory tracking in nonlinear systems and intelligent control triggered out new research and applications in this field (e.g., Barros and Carlsson, 1997; Bechmann, et al., 1998; Brdys and Zhang, 1999, 2001; Brdys and Konarczak, 2001, Hadj-Sadok and Gouze, 2001; Katebi, et al., 1999; Keesman, et al., 1999; Haarsma and Keesman 1995; Kim, et al., 2000, 2001a, b; Lindberg and Carlsson, 1996; Lukasse, et al., 1998; Nielsen, 2001; Olsson and Newell, 1999; Puta, et al., 1999; Sorensen, et al., 1995; Steffens and Lant, 1999; Van der Veen, et al., 1999; Weijers, et al., 1997; Zhao, et al., 1995). A hierarchical three level control structure that utilises multiple time scale in the plant dynamics for robust optimised control of the biological wastewater treatment was proposed in (Brdys and Zhang, 1999, 2001). In this paper we shall consider a design of the lower level controller that allows tracking the robustly optimised dissolved oxygen concentration (DOC) trajectory prescribed by the higher control level. The DO control design was considered in (e.g., Haarsma and Keesman, 1995; Olsson and Newell, 1999; Lindberg and Carlsson, 1996; Holmberg et al., 1989 and Brdys and Konarczak, 2001). A model predictive control based on linearised model of the DO dynamics was first considered by Haarsma and Keesman (1995). Model reference adaptive control and nonlinear predictive control was investigated by Brdys and Konarczak (2001) for the nitrogen and phosphorus removal showing an excellent performance of the predictive controllers. A superior performance of nonlinear predictive controller over the linear one was demonstrated. However, necessity of solving a nonliner optimisation task during the controller operation limits its performance under large and fast changes of disturbances or reference set-point trajectories (Brdys and Konarczak, 2001). In the paper, in order to increase a computational efficiency of the nonlinear predictive controller a fuzzy model of the nonlinear dynamics is produced based on its local linearisations by blending the linear local models using Takagi - Sugeno fuzzy technology. The fuzzy predictive control strategy proposed by Hadjili et al. (1998) and also developed independently by the authors is then applied to obtain a nonlinear fuzzy predictive controller. The controller performance is tested and validated on physical data sets showing substantial savings in computing time with negligible loss on its performance.

2. PROBLEM FORMULATION

A structure of considered wastewater treatment plant is illustrated in Fig. 1.

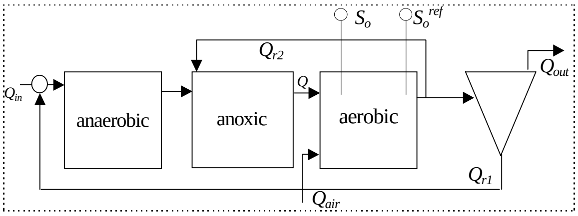

Fig. 1. A structure of a wastewater treatment plant.

The recycled flow $Q_{r2}(t)$ and the returned from the settler, activated sludge flow Q_{r1} are prescribed by the higher control levels (Brdys and Zhang, 2001). The aeration flow Q_{air}(t) is used as the control input to the reactor in order to track a prescribed by the mid control level trajectory of the dissolved oxygen $S_{o,ref}$(t). A dynamics of S_o is described by the nonlinear differential equation (Olsson and Newell, 1999):

$$\frac{dS_o(t)}{dt} = -\frac{Q_{out}(t)}{V(t)} S_o(t) + k_{La}(Q_{air}(t))(S_{o,sat} - S_o(t)) - \frac{S_o(t)}{K_o + S_o(t)} R_r(t) \tag{1}$$

where V=0.475m^3, $S_{o,sat}$=9.23gm^{-3},K_o=0.3gm^{-3} denote volume of aeration tank, DO saturation concentration and Monod constant determining the DO limit, respectively; Q_{out}(t)=0.06m^{3}h^{-1}.

The function $k_{La}(Q_{air})$ describes the oxygen transfer and it is in general nonlinear and depends on the aeration actuating system and sludge conditions. It is assumed linear in the paper (Olsson and Newell, 1999) and

$$k_{la}(Q_{air}) = \alpha Q_{air} + \beta \tag{2}$$

where the constants α, β are equal to 3.34m^{-3} and 3.54h^{-1}, respectively.

The third term in (1) denotes the respiration rate in the reactor. Although the respiration rate may rapidly change responding to fast changes of the influence or returned sludge flows the quantity R_r(t) changes much slower than S_o (t) (Brdys and Konarczak, 2001). There are another twelve nonlinear differential equations in the ASM1 model and eighteen in the ASM2d model needed to determine R_r(t), knowing the control input Q_{air}(t), inflow Q_{in}(t) and sophisticated information concerning parameters of the wastewater inflow to the plant. It means that the state-space model of the dissolved oxygen concentration is described by very high order nonlinear dynamics. Moreover, with phosphorus reactions taken into account the ASM2d model (Henze, et al., 1999) needs to be used that involves more than sixty parameters. Most of these parameters cannot be identified (they are not identifiable). Hence, the control problem is also under heavy uncertainty and adaptive or robust control technology is needed in order to handle the uncertainty. Regardless on obvious difficulties in developing good dynamic performance control algorithm, a dimension of the resulting controller would be not tractable for an efficient implementation as the S_o dynamics is fast. The uncertainty as it follows from (1) has an impact on S_o only through R_r. Clearly, S_o influences R_r. This cause-effect loop can be broken by considering R_r(t) as an external signal. Indeed, assuming R_r(t) is the disturbance input the overall dynamic model reduces to (1) and becomes the SISO nonlinear model. The control design problem becomes vastly simplified. A fundamental prerequisite to be successful in the controller design that is based entirely on (1) is an ability to obtain on-line good enough estimates of R_r(t) over required periods. Lindberg and. Carlsson (1996) have developed Kalman filter for estimation the respiration rate (the third term in (1)) together with parameters of the exponentially nonlinear function $k_{La}(Q_{air})$. The estimates were used to feed their nonlinear controller designed based on a feedback linearisation. As there exist practically active constraints on the magnitude and rate of change of Q_{air} the paper applies model predictive control technology (Maciejowski, 2001) for the DO controller design. Hence, a predictor of R_r is needed. As the problem has at least two-time scale structure, that is R_r changes much slower than S_o, Brdys and Konarczak (2001) have shown that (1) can be used to design the predictor suitable for the model predictive controller (MPC) design. Namely, discretising in time (1), the respiration value at t=kT, where T denotes the DO sampling rate, can be obtained in terms of the measured values of S_o at the time instants kT and $(k+1)T$ and the control input applied at the k-th time step as:

$$R_r(k) = -\frac{S_o(k+1) - S_o(k)}{T} \cdot \frac{K_o + S_o(k)}{S_o(k)} - \left(\frac{Q_{out}(k)}{V(k)} S_o(k) + k_{La}(Q_{air}(k))(S_{o,sat} - S_o(k)) \right) \cdot \frac{K_o + S_o(k)}{S_o(k)} \tag{3}$$

As R_r(t) changes slowly this value is taken as the prediction $\hat{R}_{r,[k+1,k+1+H_p]}(k)$ of $R_r(k)$ over the horizon $[k+1,k+1+H_p]$ in the model based optimisation problem that is solved by the MPC at $(k+1)T$. If clean measurements of R_r(t) are available the formula (3) is used to interpolate the values between the measurement time instants. The control input $Q_{air}(k)$ is a set-point to the reactor actuator that is to an aeration system and therefore the following constraints must be satisfied:

$$Q_{air}(kT) \le Q_{air}^{\max} \quad \text{and}$$
$$\left|Q_{air}((k+1)T) - Q_{air}(kT))\right| \le \Delta Q_{air}^{\max} \qquad (4)$$

where $Q_{air}^{\max} = 3$ m^{3}h^{-1} and $\Delta Q_{air}^{\max} = 0.3$ m^{3}h^{-1}.

The DO concentration can be measured on-line and the measurement error is small so that it is neglected. As the second and third terms in (1) are nonlinear the optimisation problem to be solved by MPC at $(k+1)T$ is also nonlinear. The computing time needed to find the optimal sequence of inputs over a control horizon will limit ability of the controller response to fast and large changes of the disturbances or DO set-point. Next section proposes a method for increasing the controller computational efficiency.

3. FUZZY MODEL PREDICTIVE CONTROLLER (FMPC)

3.1 Takagi-Sugeno model of DO dynamics.

The nonlinear DO dynamics described by (1) is linearised at three steady-state operating points $\{(Q_{air,lini}; S_{0,lini})\}_{i=1}^{3}$ corresponding to R_r(t)=40gm^{-3}h^{-1} and Q_{out}(t)=0.06m^{3}h^{-1}: (1;3.7747), (2;5.4214), (3;6.354). The three linear models obtained in this manner are combined into one fuzzy model of Takagi-Sugeno type (Passino and Yurkovich, 1998) giving a nonliner approximation of (1) over the control input range. Standard triangular membership functions are used that are illustrated in Fig. 2.

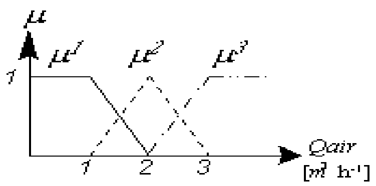

Fig. 2. Membership functions for the fuzzy predictive controller.

Fig. 3. compares responses of the fuzzy model and plant excited by a ramp input $Q_{air} = 3$ m^{3}h^{-1} showing very good approximation accuracy. The piecewise linear approximation was found by applying a method of trial and error. First, two linear models were used leading to significant errors outside the regions close to the approximation points. Next five model were tried offering a bit better overall approximation. However, the computing time with this approximation is noticeably greater than with the three models. Hence, the three model based approximation was finally chosen as a good compromise between the solution suboptimality and computational efficiency

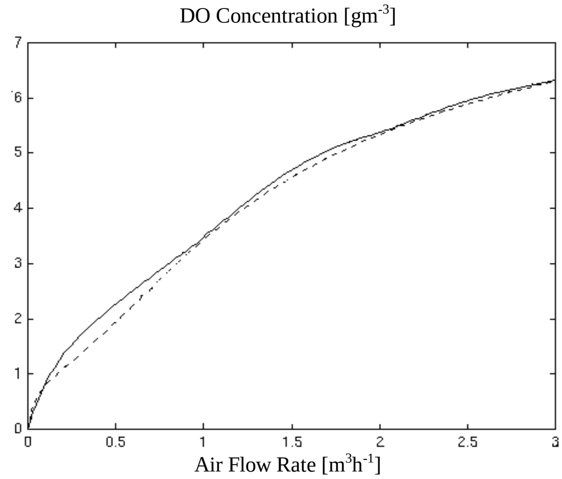

Fig. 3. Responses of the plant (discontinuous) and fuzzy approximation (continuous).

3.2 The fuzzy controller

The MPC controller is designed for each of the local linear models. The three controllers are run separately in parallel taking measurements from the plant and producing at time instants *(k+1)T* the control inputs $Q_{air}^{i}(k+1)$, i=1,2,3. The local linear-quadratic MPC's outputs are blended as:

$$\hat{Q}_{air}(k+1) = \sum_{i=1}^{3} \mu^{i}(\hat{Q}_{air}(k)) Q_{air}^{i}(k+1) \qquad (5)$$

to produce the overall controller output that is applied to the plant at the time instant *(k+1)T.*

The linear- quadratic constrained optimisations carried out in parallel by the local controllers is much faster than the nonlinear optimisation to be performed by nonlinear MPC.

4. SIMULATION RESULTS

Performance of the controller was investigated by computer simulation using real data records.

The following parameters were used in the controller implementation: prediction horizon H_P=8 and moving horizon H_M=3. Hence, the control inputs were allowed to change their values during three time steps out of eight steps of the output prediction horizon at each time instant when the controller generates future actions. Three linear models were proved to be sufficient to approximate the real nonlinear plant. The simulations were performed using Matlab-Simulink software and the Model Predictive Control and Optimisation toolboxes. The sampling period was T=1h. . Initially, the actuator constraints were dropped.

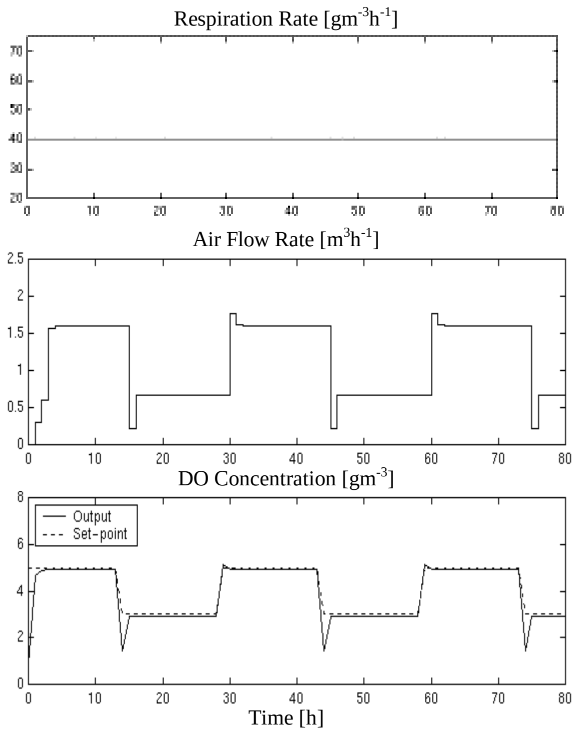

Fig. 4. Tracking a train pulse under constant disturbance and no actuator constraints.

The controller managed to achieve desired DO concentration under constant disturbance $R_r(t)=40gm^{-3}h^{-1}$ as it is illustrated in Fig. 4.

An impact of the actuator constraints is shown in Fig.5.

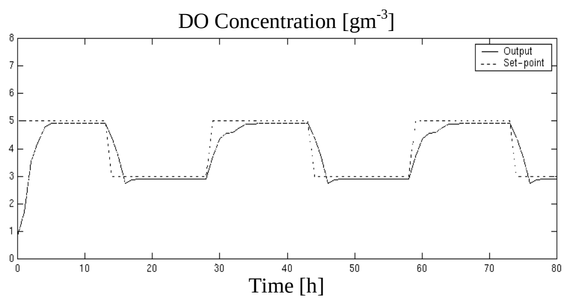

Fig. 5. Tracking a train pulse under constant disturbance and the actuator constraints.

The comparison between three MPC controllers each of them based on one linear model out of the three models used to design the fuzzy controller is illustrated in Fig. 6.

Each linear-quadratic MPC controller operates well only within the set-point range corresponding to the linearisation point. The fuzzy controller shows good tracking performance over the whole range.

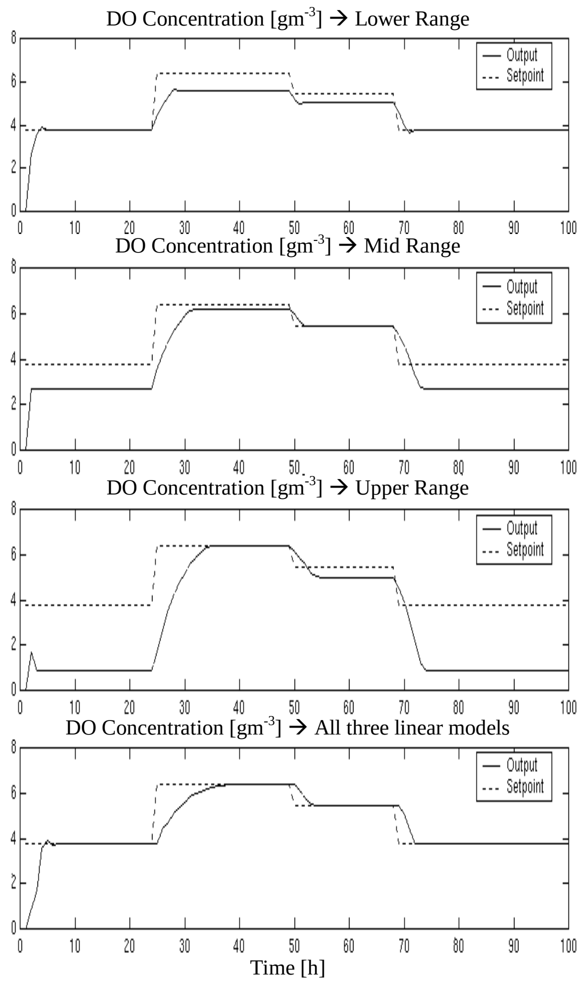

Fig. 6. A comparison of tracking performance of linear MPC´s and the fuzzy controller.

Next an impact of rate of change of $R_r(t)$ was investigated. It was assumed that $R_r(t)=r+A\sin(t/6)$, where r=40 and A=0 and 20.

Fig. 7. illustrates the results showing on decreasing tracking performance when the rate of change increases. An increase of the sampling rate with the allowed limits would improve the situation. This is illustrated in Fig. 8.

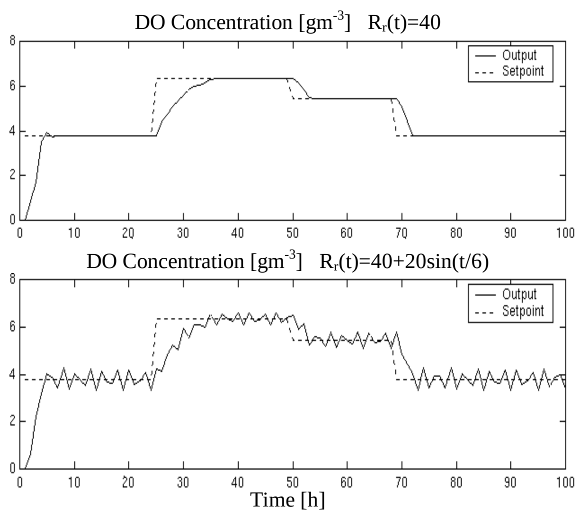

Fig. 7. Influence of the $R_r(t)$ rate of change.

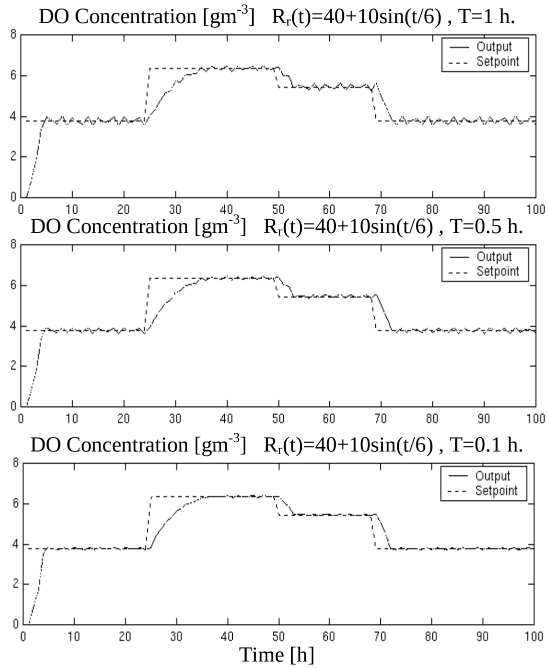

Fig. 8. Influence of the sampling rate on the controller tracking performance.

5. CONCLUSIONS

The paper has proposed and validated by simulation a fuzzy model predictive controller for the dissolved oxygen concentration tracking in an activated sludge process. The controller maintains good performance achieving by previously proposed predictive controller that was based on an original nonlinear dynamics of the plant. On the other hand it is much more computationally efficient, hence is able to respond in time to fast changes of disturbances and large changes of the set-points. The fuzzy controller uses linear models that locally approximate the plant dynamics. On-line design of such models in a closed loop is currently under a research. Also different strategies for fuzzy blending of the local controller outputs are currently investigated.

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