8th International IFAC Symposium on
Dynamics and Control of Process Systems
Preprints Vol.3, June 6-8, 2007, Cancún, Mexico

ADAPTIVE MODEL PREDICTIVE CONTROL OF DISSOLVED OXYGEN IN A BIOREACTOR

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Abstract: Dissolved oxygen variation in a bioreactor is representative of a non-linear time varying system. In this work we propose a novel algorithm for Adaptive Model Predictive Control (AMPC) of dissolved oxygen in a bioreactor. The model is comprised of deterministic and stochastic components and is updated on-line by Recursive Least Squares method. The deterministic and stochastic components are then combined to form a state space model to formulate AMPC at each sampling instant. The proposed AMPC scheme is shown to achieve tight control of dissolved oxygen in *Escherichia coli* cultivation in the presence of disturbances.

Keywords: Adaptive Model Predictive Control, Recursive Least Squares, Dissolved Oxygen, Bioreactor Control, *Escherichia coli*

1. INTRODUCTION

Model predictive control (MPC) has emerged as a powerful tool for dynamic optimization and control. A key feature contributing to the success of MPC is that various process constraints can be incorporated directly into the on-line optimization performed at each time step (Lee and Ricker, 1994). Industrial advantages of using MPC for explicit handling of inequality constraints have been discussed by Richalet *et al* (1978).

Variation of dissolved oxygen (DO) concentration in a fermentation typically presents as a non linear time varying system. Precise control of DO permits effective experiment designs for the study of metabolic changes and the improvement of productivity in aerobic fermentations. DO is also an excellent tool for fault diagnosis and supervision of biotechnical processes. The time varying nature of DO in fermentation processes often leads to instability of conventional controllers with constant coefficients. Nonlinear adaptive control has been shown to improve control of DO (Goodwin *et al.*, 1982). Lee *et al* (1991) have reported adaptive control of DO, through a sophisticated model of DO electrode dynamics, incorporating the probe response lag. Hsiao *et al* (1992) have shown that simultaneous manipulation of agitation and aeration leads to reduction in non-linearity of the process, eliminating abrupt changes in process dynamics. Youssef and Dahhou (1996) have developed a complete control structure employing a nonlinear process model coupled with an adaptive estimator for on-line tracking of unavailable state and time-varying parameters. Diaz *et al* (1995) have reported an algorithm for the adaptive control of DO concentration in a bioreactor using a generalized predictive control strategy. The use of error modeling with auto-regressive moving average (ARMA) has been shown to improve the control performance and to reduce the control input variability of DO control in *Bacillus subtilis* fermentations for the production of recombinant β-galactosidase (Sargantanis and Karim, 1997).

Olivera *et al.*, (2004) proposed a DO controller based on a model of oxygen mass balance, which was more susceptible to errors in the oxygen transfer rate (OTR). An integral feedback controller with adaptive gain has been reported for DO control in yeast cultivations based on adaptive feeding of glycerol at oxygen limiting conditions (Olivera *et al.*, 2005). Adaptive feeding may present large transients when the organism exhibits diauxic growth characteristics. This could be a serious problem when the culture exhibits diauxic growth characteristics. *E.coli* utilizes glucose rapidly and then consumes acetate when glucose is limiting under aerobic conditions. The change in oxygen demand poses as a transient, which a conventional PID controller often fails to cope with. Such situations may not be desirable in practice where the controller may need frequent tuning and could lead to erratic behaviour of the process in the absence of operator intervention. Under such circumstances DO control based on adjusting physical variables such as stirrer speed and air flow rate should be favoured. The use of an adaptive controller manipulating these variables would be expected to nullify such transients.

In this work, we present a novel AMPC formulation based on a two-tier modelling scheme. The deterministic component of the model is parameterized using the output error (OE) structure. The parameters of the OE model are estimated online using the recursive OE (ROE) method. The stochastic component is identified by modelling the residuals generated by the ROE estimator as auto-regressive moving average (ARMA) processes. The deterministic and stochastic components are then combined to obtain a state-space model which is further used to formulate the AMPC problem at each sampling instant.

The paper is organized in six sections. In Section 2, we discuss the development of the model for AMPC. We present the AMPC formulation based on this model in Section 3. The results of the experimental implementation of AMPC on a bioreactor are presented in Section 5. Finally, we present the conclusions in Section 6.

2. MPC RELEVANT MODEL DEVELOPMENT

The primary concern in any MPC formulation is the quality of model prediction generated by the internal model. The quality of model predictions depends on (a) fidelity of the deterministic component of the model and (b) strategy used to model unmeasured disturbances and predict their effects on the future plant behavior. The quality of model predictions is linked with the model structure employed while identifying the MPC relevant model.

2.1 Models for the Deterministic and Stochastic Components

The most widely used finite impulse response (FIR) model in MPC formulations has output error (OE) structure. Since OE models are functions of past manipulated inputs alone, these models are ideally suited for long term predictions. The FIR model, however, is non-parsimonious in parameters and, therefore, not suitable for on-line parameter estimation. A better choice for on-line parameter estimation is the parameterized form of the OE model, which can be represented as follows

$$\delta\widehat{y}(t) = \frac{B(q^{-1})}{A(q^{-1})} q^{-t_d} \delta u(t) \quad (1)$$

$$\delta y(t) = \delta\widehat{y}(t) + v(t) \quad (2)$$

where $A(q^{-1})$ and $B(q^{-1})$ are polynomials in the shift operator q^{-1} and t_d represents time delay. In the context of a continuously operated system, $\delta y(t)$, $\delta\widehat{y}(t)$ and $\delta u(t)$ represent perturbation variables defined with respect to some steady state. In the context of time varying semi-batch systems, we can modify the OE model (1-2) by introducing perturbations in the neighborhood of time varying trajectories $\{y_s(t), u_s(t)\}$ as follows

$$\widehat{y}(t) - y_s(t) = \frac{B(q^{-1}, t)}{A(q^{-1}, t)} q^{-d} \left[u(t) - u_s(t)\right] \quad (3)$$

$$y(t) = \widehat{y}(t) + v(t) \quad (4)$$

This model can be rearranged as

$$\widehat{y}(t) = \frac{B(q^{-1}, t)}{A(q^{-1}, t)} q^{-d} u(t) + \frac{1}{A(q^{-1}, t)} \eta(t) \quad (5)$$

$$y(t) = \widehat{y}(t) + v(t) \quad (6)$$

where

$$\eta(t) = \left[A(q^{-1}, t) y_s(t) - B(q^{-1}, t) q^{-d} u_s(t)\right] \quad (7)$$

represents an unknown time varying bias term. Note that argument (t) has been added to each polynomial in (q^{-1}) to emphasize the fact that their coefficients are changing as a function of time. For the purpose of parameter estimation, the above model can be rearranged as follows

$$y(t) = \left[1 - A(q^{-1}, t)\right] \widehat{y}(t) + B(q^{-1}, t) u(t) + \eta(t) + v(t) \quad (8)$$

The time varying bias term $\{\eta(t)\}$ in the OE model given by equation (5) can also be viewed as a slowly drifting or non-stationary component of the unmeasured disturbance affecting the output.

To develop a model for the residual signal, $\{v(t)\}$, defined as

$$v(t) = y(t) - \left[1 - A(q^{-1},t)\right]\widehat{y}(t) - B(q^{-1},t)u(t) - \eta(t) \quad (9)$$

we assume that

- The parameterization of deterministic component is such that there is no correlation between the residual sequence $\{\widehat{v}(t)\}$ and the manipulated inputs sequence $\{u(t)\}$ and
- The non-stationary component of the unmeasured disturbances is captured through $\{\widehat{\eta}(t)\}$, and therefore sequence $\{\widehat{v}(t)\}$ represents a stationary stochastic process

Under these assumptions, we can model the variation of $\{\widehat{v}(t)\}$ as an ARMA process as follows

$$\widehat{v}(t) = \frac{C(q^{-1})}{D(q^{-1})}e(t) \quad (10)$$

where $\{e(t)\}$ is a white noise sequence and $C(q^{-1})$ and $D(q^{-1})$ are monic polynomials.

Thus, the final form of the proposed model for time varying processes can be expressed as follows

$$y(t) = \frac{B(q^{-1},t)}{A(q^{-1},t)}u(t) + \frac{1}{A(q^{-1},t)}\eta(t) + v(t)$$

$$v(t) = \frac{C(q^{-1},t)}{D(q^{-1},t)}e(t) \quad (11)$$

where $y(t)$ and $u(t)$ represent absolute values of the measurement and manipulated input. Also, when $d > 0$, the first d coefficients of $B(q^{-1},t)$ will be zero.

Model parameters of OE model are estimated on-line using a *recursive pseudo-linear regression* (RPLS) method called *recursive output error* (ROE) as follows (Ljung, 1999; Astrom and Wittenmark, 2001),

$$\widehat{\boldsymbol{\theta}}_d(t+1) = \widehat{\boldsymbol{\theta}}_d(t) + \mathbf{K}_d(t)\varepsilon(k+1) \quad (12)$$

$$\varepsilon(k+1) = y(t+1) - \boldsymbol{\varphi}_d(t+1)^T\widehat{\boldsymbol{\theta}}_d(t) \quad (13)$$

$$\boldsymbol{\varphi}_d(t) = [-\widehat{y}(t-1)..-\widehat{y}(t-n_a) \quad u(t-1)..u(t-n_b) \ 1]^T \quad (14)$$

$$\boldsymbol{\theta}_d(t) = [a_1(t) \ .. \ a_{na}(t) \ b_1(t) \ .. \ b_{nb}(t) \ \eta(t)] \quad (15)$$

where gain $\mathbf{K}_d(t)$ is computed as follows

$$\mathbf{K}_d(t) = \frac{\mathbf{P}_d(t-1)\boldsymbol{\varphi}(t+1)}{\lambda_d(t-1) + \boldsymbol{\varphi}_d(t+1)^T\mathbf{P}_d(t-1)\boldsymbol{\varphi}_d(t+1)} \quad (16)$$

$$\mathbf{P}_d(t) = \frac{\left[\mathbf{P}_d(t-1) - \mathbf{K}_d(t)\boldsymbol{\varphi}_d(t+1)^T\mathbf{P}_d(t-1)\right]}{\lambda_d(t-1)} \quad (17)$$

Here $\mathbf{P}_d(t-1)$ represents the covariance matrix of model parameters and $\lambda_d(t-1)$ is an exponential forgetting factor. To avoid loss of sensitivity and parameter blow up in a region where the covariance of the parameters becomes very small, the forgetting factor can be updated as suggested by Fortescue et al.(1981). The parameters of the ARMA model can be estimated using an extended recursive least square (ELS) algorithm, which also belongs to the family of recursive pseudo-linear regression (RPLR) methods (Astrom and Wittenmark, 2001). Convergence results for RPLS scheme for models with OE and ARMA structure have been discussed by Ljung(1999).

Since the deterministic component of the model has output error structure, the above formulation can be extended to an $r \times m$ multivariable system by developing r MISO models of the form (for $i = 1, ..., r$),

$$A^{(i)}(q^{-1},t)\widehat{\mathbf{y}}_i(t) = \sum_{j=1}^{m} B^{(ij)}(q^{-1},t)\mathbf{u}_j(t) + \boldsymbol{\eta}_i(t) \quad (18)$$

$$\mathbf{y}_i(t) = \widehat{\mathbf{y}}_i(t) + \mathbf{v}_i(t) \quad (19)$$

where $\mathbf{y} \in R^r$ represents the controlled variable vector, $\mathbf{u} \in R^m$ represents the manipulated variable vector, $\mathbf{v} \in R^r$ represents the residual vector for OE model, $\boldsymbol{\eta} \in R^r$ represents the bias vector. Here, $A^{(i)}(q^{-1},t)$ and $B^{(ij)}(q^{-1},t)$ represents polynomial functions of (q^{-1}) operating on i^{th} output and j^{th} input, respectively. The dynamics of the residual signals can be captured either through SISO models of the form

$$D^{(i)}(q^{-1},t)\mathbf{v}_i(t) = C^{(i)}(q^{-1},t)\mathbf{e}_i(t) \quad (20)$$

or through MISO models

$$D^{(i)}(q^{-1},t)\mathbf{v}_i(t) = \sum_{j=1}^{r} C^{(ij)}(q^{-1},t)\mathbf{e}_j(t) \quad (21)$$

where $\mathbf{e} \in R^r$ represents the vector of innovations. The resulting MIMO model can be expressed in the following generic form

$$\mathbf{A}(q^{-1},t)\widehat{\mathbf{y}}(t) = \mathbf{B}(q^{-1},t)\mathbf{u}(t) + \boldsymbol{\eta}(t) \quad (22)$$

$$\mathbf{y}(t) = \widehat{\mathbf{y}}(t) + \mathbf{v}(t) \quad (23)$$

$$\mathbf{D}(q^{-1},t)\mathbf{v}(t) = \mathbf{C}(q^{-1},t)\mathbf{e}(t) \quad (24)$$

where

$$\mathbf{A}(q^{-1},t) = \mathbf{I} + \mathbf{A}_1(t)q^{-1} + .. + \mathbf{A}_{n_a}(t)q^{-n_a} \quad (25)$$

$$\mathbf{B}(q^{-1},t) = \mathbf{B}_1(t)q^{-1} + .. + \mathbf{B}_{n_b}(t)q^{-n_b} \quad (26)$$

$$\mathbf{C}(q^{-1},t) = \mathbf{I} + \mathbf{C}_1(t)q^{-1} + .. + \mathbf{C}_{n_c}(t)q^{-n_c} \quad (27)$$

$$\mathbf{D}(q^{-1},t) = \mathbf{I} + \mathbf{D}_1(t)q^{-1} + .. + \mathbf{D}_{n_d}(t)q^{-n_d} \quad (28)$$

Here, $\mathbf{A}_i, \mathbf{B}_i, \mathbf{C}_i$ and $\mathbf{D}_i$ represent matrices of dimension $(r \times r)$, $(r \times m)$, $(r \times r)$ and $(r \times r)$ respectively.

3. ADAPTIVE PREDICTIVE CONTROL FORMULATION

3.1 MPC Relevant State Space Model

While developing an MPC scheme based on the above model, it is convenient to work with a state realization of the identified model (22-24). Defining state vector $\mathbf{x}^d(t)$ at time instant t as,

$$\mathbf{x}^d(t) = [\widehat{\mathbf{y}}(t)^T..\widehat{\mathbf{y}}(t-n_a+1)^T \quad \mathbf{u}(t-1)^T..\mathbf{u}(t-n_b+1)^T]^T \tag{29}$$

the deterministic process model in discrete state space form can be given by

$$\mathbf{x}_d(t) = \mathbf{\Phi}_d(t)\mathbf{x}_d(t-1) + \mathbf{\Gamma}_d(t)\mathbf{u}(t-1) + \mathbf{\Psi}_\eta\widehat{\boldsymbol{\eta}}(t) \tag{30}$$

$$\widehat{\mathbf{y}}(t) = \mathbf{H}_d\mathbf{x}_d(t) \tag{31}$$

where matrices $\mathbf{\Phi}_d(t), \mathbf{\Gamma}_d(t)\mathbf{u}(t-1), \mathbf{\Psi}_\eta$ and $\mathbf{H}_d$ are constructed as described in Camacho and Bourdons (1999). Similarly, defining the state vector $\mathbf{x}^s(t)$ as

$$\mathbf{x}^s(t) = [\mathbf{v}(t)^T..\mathbf{v}(t-n_d+1)^T \quad \mathbf{e}(t)^T..\mathbf{e}(t-n_c+1)^T]^T \tag{32}$$

a state realization for the stochastic model can be expressed as follows,

$$\mathbf{x}_s(t) = \mathbf{\Phi}_s(t)\mathbf{x}_s(t-1) + \mathbf{\Gamma}_s(t)\mathbf{w}(t-1) \tag{33}$$

$$\mathbf{v}(t) = \mathbf{H}_s\mathbf{x}_s(t) \tag{34}$$

where $\mathbf{w}(t-1) = \mathbf{e}(t)$. Note that the system matrices $(\mathbf{\Phi}, \mathbf{\Gamma})$ appearing in the state realizations constructed above differ due to structural differences between the OE and the ARMA models. Defining augmented state vector

$$\mathbf{x}(t) = \begin{bmatrix} \mathbf{x}_d(t) \\ \mathbf{x}_s(t) \end{bmatrix}$$

a combined state space model can be obtained at t^{th} sampling instant by augmenting the two state realizations as follows

$$\mathbf{x}(t) = \mathbf{\Phi}(t)\mathbf{x}(t-1) + \mathbf{\Gamma}(t)\mathbf{u}(t-1) \tag{35}$$

$$+\mathbf{\Psi}\widehat{\boldsymbol{\eta}}(t) + \mathbf{K}\mathbf{w}(t-1) \tag{36}$$

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) \tag{37}$$

where

$$\mathbf{\Phi}(t) = diag\left[\,\mathbf{\Phi}_d(t) \;\; \mathbf{\Phi}_s(t)\,\right]$$

$$\mathbf{H} = \left[\,\mathbf{H}_d \quad \mathbf{H}_s\,\right]$$

$$\mathbf{\Gamma}(t) = \begin{bmatrix} \mathbf{\Gamma}_d(t) \\ [\mathbf{0}] \end{bmatrix};$$

$$\mathbf{\Psi} = \begin{bmatrix} \mathbf{\Psi}_\eta \\ [\mathbf{0}] \end{bmatrix}; \mathbf{K} = \begin{bmatrix} [\mathbf{0}] \\ \mathbf{\Gamma}_s \end{bmatrix} \tag{38}$$

3.2 AMPC Formulation with Time-varying Control Objective

At each sampling instant, the linear time varying state space model given by equations (35-37) is used for predicting future behavior of the plant over a finite future time horizon of length p (*prediction horizon*) starting from current instant t. In order to carry out predictions based on the above model, it becomes necessary to introduce a model for the behavior of the bias term. Since $\boldsymbol{\eta}(t)$ is expected to capture slowly varying disturbances, we assume that the bias term remains constant over the prediction horizon, i.e.,

$$\widehat{\boldsymbol{\eta}}(t+j+1|t) = \widehat{\boldsymbol{\eta}}(t+j|t) \tag{39}$$

$$\widehat{\boldsymbol{\eta}}(t|t) = \widehat{\boldsymbol{\eta}}(t) \tag{40}$$

for $j = 0, 1, ...p-1$. It is further assumed that only q (*control horizon*) future manipulated input moves can be chosen freely with following input blocking constraints

$$\mathbf{u}(t+j|t) = \mathbf{u}(t|t) \quad j = 0, 1, ..c_1 - 1 \tag{41}$$

$$........ \tag{42}$$

$$\mathbf{u}(t+j|t) = \mathbf{u}(t+c_{q-1}|t) \quad j = c_{q-1}, ..p-1 \tag{43}$$

where c_j are selected such that $0 < c_1 < c_2 < .... < c_{q-1}$.

The adaptive MPC problem at the sampling instant t is formulated as a constrained optimization problem as follows,

$$\underset{\mathbf{U}_f(t)}{min} \left\{ \sum_{j=1}^{p-1} J_{e_f} + \sum_{j=1}^{c_{q-1}} J_{\mathbf{\Delta u}} \right\} \tag{44}$$

$$J_{e_f} = \mathbf{e}_f(t+j|t)^T\mathbf{W}_E\mathbf{e}_f(t+j|t)$$

$$J_{\mathbf{\Delta u}} = \mathbf{\Delta u}(t+j|t)^T\,\mathbf{W}_{\Delta U}\,\mathbf{\Delta u}(t+j|t)$$

subject to the following constraints,

$$\mathbf{e}_f(t+j|t) = \mathbf{y}_r(t+j|t) - \widehat{\mathbf{y}}(t+j|t)$$

$$\widehat{\mathbf{x}}(t+j|t) = \mathbf{\Phi}(t)\widehat{\mathbf{x}}(t+j-1|t) + \mathbf{\Gamma}(t)\mathbf{u}(t+j-1|t) + \mathbf{\Psi}\widehat{\boldsymbol{\eta}}(t)$$

$$\widehat{\mathbf{y}}(t+j|t) = \mathbf{H}\widehat{\mathbf{x}}(t+j|t)$$

$$\mathbf{\Delta u}(t+l|t) = \mathbf{u}(t+l|t) - \mathbf{u}(t+j-1|t)$$

$$\mathbf{u}^L \le \mathbf{u}(t+j|t) \le \mathbf{u}^H$$

$$\mathbf{\Delta u}^L \le \mathbf{\Delta u}_f(t+j|t) \le \mathbf{\Delta u}^H$$

$$j = 1, 1, 2, ...p$$

together with the input blocking constraints given by equations (41-43). Here $\mathbf{W}_E$ and $\mathbf{W}_{dU}$ represent error weighting matrix and input move weighting matrix, respectively.

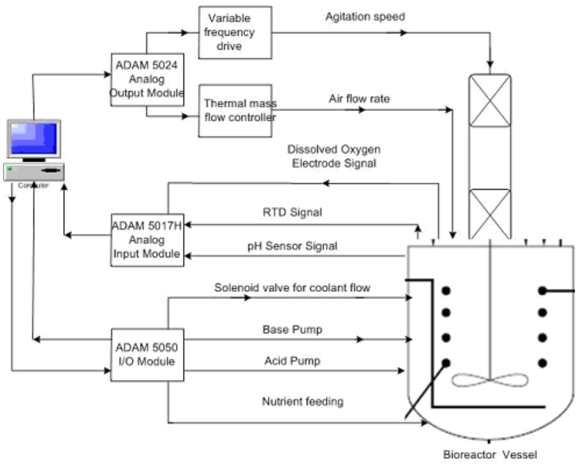

Fig. 1. Schematic of the experimental setup

4. MATERIALS AND METHODS

4.1 Control system hardware

The experiments were performed in a 10 litre stainless steel stirred tank bioreactor with a working volume of 7.5 litres. The pH of the fermentation medium was measured using an autoclavable gel-filled glass electrode (Phoenix Electrodes Inc., USA). Temperature was measured with a Pt-100 type 3-wired RTD. Both pH, and temperature were regulated by using stand alone on-off controllers. The air flow was regulated through a thermal mass flow controller (Sierra Instruments Inc, Monterey, CA, USA). Agitation rate was varied through a variable fequency drive (Model: Altivar 11, Schneider Electric Co., India). The air flow was distributed at the bottom of the bioreactor through a J tube sparger. Dissolved oxygen was monitored using an sterilizable polarographic electrode (Broadley James Corporation, USA). ADAM 5000 series data acqusition cards were used for interfacing the reactor to the PC. The Graphical User Interface to the ADAM 5000 series data acquisition modules was created through LabVIEW (National Instruments, Bangalore, USA).The control algorithm was developed in MATLAB and was invoked through the graphical programming environment of LabVIEW. A schematic of the setup is shown in Figure 1.

4.2 Microorganism and cultivation media

The experimental study was carried out with *Escherichia coli* strain BL21. The cultivation media was Luria-Bertani (LB) broth supplemented with 1.5% glucose at the start of fermentation. The fed-batch study was performed with 25% solution of glucose fed at a constant rate of 25 ml litre^{-1}hr^{-1}after glucose was completely consumed.

4.3 Analytical methods

The biomass concentration in the broth was estimated by measuring the absorbance at 600 nm in a spectrophotometer (Jasco, Japan). The cell weight was calculated using a standard equation,

$$\text{Cell dry weight (gl}^{-1}) = \text{A}_{600} \times 0.42$$

The glucose concentration in the broth was estimated by o-toluidine colorimetric method.

5. EXPERIMENTAL RESULTS

The control objective for AMPC was to maintain dissolved oxygen at 40% of saturation with air throughout the operation of the bio-reactor. The various parameters of the AMPC were taken as,

Prediction Horizon	30
Control Horizon	2
W_E	2
Weight on agitator speed	5
Weight on aeration rate	1
Constraints on agitator speed	150 to 1000 rpm
Constraints on aeration rate	2.75 to 10 lpm

Initially, the bioreactor was started in manual operation mode. The dissolved oxygen concentration in *E.coli* fermentation declined from the initial saturation levels as the cells accumulated. The oxygen demand of the culture went up as the cells entered the exponential growth phase. When the DO reached the value of 40% (around 72 min from the start), the agitation speed and air flow rate were perturbed using pseudo random binary sequence (PRBS) signals (switching time = 7 min) so as to provide sufficient excitation for initial model development. The agitation speed was perturbed between 330 and 370 rpm and aeration rate was perturbed between 2.75 and 4.75 lpm. This input perturbation was carried out for about 23 minutes (i.e. upto 95 min from the start). Model adaptation (recursive identification) was also initiated at the beginning of the perturbation period with AMPC in manual mode. A MISO model for DO concentration with agitator speed and aeration rate as inputs was recursively identified at every sampling instant using the scheme described in Section 2. The sampling time was chosen to be 30 seconds. The controller was started at the end of this perturbation period.

From Figure 2 it is evident that the DO was successfully controlled at the 40% set point for the complete batch. Glucose feed (25% w/v) addition at the rate of 25 ml litre^{-1}hr^{-1} was started during the 4th hour (vertical dashed line in Figure 2) when glucose in the broth was exhausted. The addition of glucose modifies *E.coli* metabolism patterns and acts as a disturbance to the system.

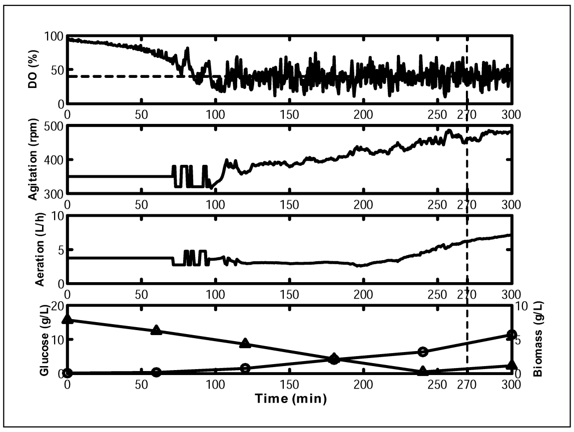

Fig. 2. Dissolved oxygen control in *Escherichia coli* cultivation using AMPC. The vertical line indicates the time at which glucose addition was initiated. (The dots indicate the biomass concentration and the filled triangles indicate the glucose concentration during fermentation)

The disturbance was effectively overcome by simultaneous adjustment of agitation speed and air flow rate to meet the enhanced oxygen demand.

6. CONCLUSIONS

The highly time-varying dynamics of DO in fermentation processes makes it a challenging task for control using conventional controllers. In the present work, it is proposed to use an adaptive model predictive control (AMPC) formulation based on a two-tier modelling scheme to address this challenge. The two tier modeling scheme involves on-line identification of the deterministic and stochastic components by two separate recursive pseudo-linear regression schemes. The deterministic component has output error structure and its parameters are updated by MISO recursive output error (ROE) type estimators. The residuals generated by the ROE estimators are modeled as ARMA processes to account for unmeasured disturbances. An interesting feature of the proposed modeling scheme is that it allows for separation of stationary and non-stationary components of the unmeasured disturbances. The deterministic and stochastic components of the model are combined to form a linear time varying state space model, which is further used to formulate the predictive control problem at each sampling instant. Analysis of the experimental results shows that the proposed AMPC algorithm enables successful DO control and disturbance rejection.

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