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Discrete system identification and self-tuning control of dissolved oxygen concentration in a stirred reactor

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Abstract−This work presents the applications of discrete-time system identification and generalized minimum variance (GMV) control of dissolved oxygen (DO) level in a batch bioreactor in which *Saccharomyces cerevisiae* is produced at aerobic condition. Air flow rate and mixing rate were varied to determine the maximum local liquid phase volumetric mass transfer coefficient (K_La). Maximum K_La value was determined at a mixing rate of 600 rpm and air flow rate of 3.4 $Lmin^{-1}$. For control purpose, manipulated variable was selected as air flow rate due to its effectiveness on the K_La. To examine the dynamic behavior of the bioreactor, various input signals were utilized as a forcing function and three different model orders were tested. A second0order controlled auto regressive moving average (CARMA) model was used as the process model in the control algorithm and in the system identification step. It is concluded that the ternary input is more suitable than the other input types used in this work for system identification. Recursive least squares method (RLS) was used to determine the model parameters. GMV control results were compared with the traditional PID control results by using performance criteria of IAE and ITAE for different types of DO set point trajectories. DO concentration in the batch bioreactor was controlled more successfully with an adaptive controller structure of GMV than the PID controller with fixed parameters.

Key words: Dissolved Oxygen (DO), Generalised Minimum Variance (GMV), Controlled Auto Regressive Moving Average (CARMA), Bioreactor Control, Discrete System Identification

INTRODUCTION

The need for self-tuning control essentially arises from the desire to control processes whose parameters are either unknown or slowly time-varying. Interest in this design method started with the self-tuning regulator (STR) originally developed by Aström and Wittenmark [1]. The control objective of this method is the minimization of the output's variance. The STR predicts the future output variance and then attempts to apply control action forcing the predicted variance to zero. Later it was extended to the generalized minimum variance (GMV) self tuning controller (STC) of Clarke and Gawthrop [2]. The STC is an adaptive algorithm based on the GMV cost function and a predictive form of the process model. This formulation leads to a very versatile adaptive that is easier to tune [3]. It has become very popular and is now widely applied in the process industries [4,5].

In recent years several linear self-tuners have been described. Minimum-variance self-tuning regulation of a bilinear model was first reported by Svoronos et al. [6] who used the simulation experiments to demonstrate the effectiveness of their work. Goodwin et al. [7] and Goodwin and Sin [8] described the minimum-variance controllers for the control of waste water treatment and pH neutralization and demonstrated the superiority of their methods through practical applications.

The effect of oxygen on the control of metabolic pathways by nutritional and environmental regulation is an important concern in bioprocesses. In addition, DO measurement and control is important to understand the fermentation and contributes crucially to the calculation of oxygen mass transfer coefficient. Overall volumetric mass transfer coefficient (K_La) is a commonly quantified variable and a critical parameter in bioprocesses because of the importance of oxygen as a metabolic substrate and its limited aqueous solubility. Its magnitude is process specific and can be determined experimentally by means of dynamic K_La method [9]. DO control can be accomplished by using various manipulated variables such as agitation speed [10], air and oxygen mole fraction in the inlet gas [11] or combination of them [12,13].

In this work, various types of optimal DO set point trajectory control of a batch bioreactor with GMV algorithm were examined. For this control method, CARMA model was used and its parameters were identified by applying RLS algorithm. Square wave, pseudo random binary sequence (PRBS) and random signals were given to the system as a forcing function in the open-loop condition for system identification. Also, a model validity test was performed for three different model orders in order to select the appropriate CARMA model describing the real system behavior. CARMA model and GMV controller parameters were calculated in the closed-loop by using RLS which is coded with MATLAB 6.5 and Visual Basic for theoretical and experimental control studies, respectively.

Effects of the air flow rate and agitation speed on the volumetric mass transfer coefficient were examined in order to select the manipulated variable for DO control. Air flow rate was chosen as the manipulated variable because it is more impressive on the volumetric mass transfer coefficient; consequently, its usage as a manipulated variable is suitable for DO control. GMV control results were compared for the basis of performance criteria (IAE and ITAE) with the PID control results to show the appropriateness of an adaptive

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control algorithm for DO control in the batch bioreactor. This comparison was performed both theoretically and experimentally. System identification results show that the second-order CARMA model and ternary input is suitable for studied bioreactor.

DYNAMIC SYSTEM MODELLING

1. Model Structure

Mathematical models of several types have been proposed with varying degrees. Difference equation models are the most important class of models, since they are the most widely implemented ones [14,15]. There are several reasons for their popularity:

i) difference equation models arise naturally from the physical laws of the system

ii) they have relatively few parameters and are numerically easy to handle

iii) the parameters of the model can be calculated using parameter estimation methods, which are not dependent on specialized input signals

iv) model may be easily implemented on a digital personal computer.

The linear difference equation form is

$$A(z^{-1})y(t)=B(z^{-1})u(t)+C(z^{-1})e(t) \quad (1)$$

Where, $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomials in the backward shift operator z^{-1}, y(t) is the system output, u(t) is the system input, e(t) is the noise. This model can be written as follows:

$$y(t)+a_1y(t-1)+\ldots+a_{na}y(t-na)=b_0u(t-1)+\ldots+b_{nb}u(t-nb)+e(t)+c_1e(t-1)+\ldots+c_{nc}(t-nc) \quad (2)$$

The main goal of identification is to accurately model the process under consideration. The desired model structure should approximate the process to a good degree and contain all the known relevant data and information about process operation.

2. Parameter Estimation by Using Recursive Least Squares Method

Sum of the squares of the differences between the parametric model and plant output data is minimized. This system identification method [15] uses the model given in Eq. (3).

$$y(t)=\varphi^T(t)\theta+e(t) \quad (3)$$

Where θ is the vector of the unknown parameters defined as

$$\theta^T=[-a_1, \ldots, -a_{na}, b_0, \ldots, b_{nb}, c_1, \ldots, c_{nc}] \quad (4)$$

In Eq. (3), $\varphi(t)$ is a regression vector partly consisting of measured input/output variables and is defined as

$$\varphi^T=[y(t-1), \ldots, y(t-na), u(t-1), \ldots u(t-nb), e(t-1), \ldots e(t-nc)] \quad (5)$$

Prediction error is described as the difference between the actual and predicted output:

$$\varepsilon(t+1)=y(t+1)-\varphi^T(t+1)\hat{\theta}(t) \quad (6)$$

For the recursive parameter identification, covariance matrix and parameter vector are calculated from Eqs. (7) and (8) respectively:

$$P(t+1)=P(t)-\frac{P(t)\varphi(t+1)\varphi^T(t+1)P(t)}{1+\varphi^T(t+1)P(t)\varphi(t+1)} \quad (7)$$

$$\hat{\theta}(t+1)=\hat{\theta}(t)+P(t+1)\varphi(t+1)\varepsilon(t+1) \quad (8)$$

3. Experimental Design for System Identification

Selection of experiments to be done plays a major role in the identification procedure. Various variables, e.g., input signals and sampling instants, have to be taken into account in the design procedure. A measure of the "goodness" of an experiment should be defined in order that experiments may be compared. As the parameter accuracy is dependent on both the estimation method and the experimental conditions, a sensible choice is a measure related to both of these factors. Exact choice of measure is not important so if numeric criteria are applicable, a good experiment will be judged to be good by all of them.

The choice of input signal is largely dependent on the disturbance affecting the plant. For a white noise disturbance it is usually sufficient to apply a PRBS input signal where the number of data points is finite; however, as the number of data points increases, a white noise input sequence may well be required.

Experiment design must be made as far as data preparation is concerned. For the identification procedures considered, the input/output data collected is assumed to be unbiased; thus its expectation must be zero. However, in practice it is usually the case that a certain amount of bias exists [15].

4. Generalized Minimum Variance Control

Conventional controller design procedures generate constant coefficient algorithms based upon a linear time-invariant assumption for the model under consideration. The philosophy of self-tuning control is that the coefficients within the control algorithms are considered to be time-dependent. More particularly, the strategy is to construct an algorithm that will automatically alter its parameter to meet a specific requirement or condition. This is managed by the addition of an adjustment mechanism which monitors the system and tunes the coefficients of the corresponding controller in order to maintain a desired performance. The success of this sort of control algorithm depends heavily on the model quality. It is therefore of the greatest importance to select model structure and to obtain a set of model parameters. Using this model, the GMV control system is applied to control the process variables.

The GMV was formed basically as a modification of the minimum variance (MV) technique. This controller is attained by minimizing the tracking criterion for a given linear input-output model:

$$J(u, t)=E\{(y_{t+k}-r_{t+k})^2\} \quad (9)$$

Where E is the expectation and k is the supposed delay. It is well known that the MV controller attempts to cancel explicitly the forward path zeros, some of which may lie outside the unit circle. Clarke and Gawthrop [2] devised the implicit GMV method as a generalization of the MV algorithm of Aström and Wittenmark [1] using control cost. The GMV cost function provides additional penalties in terms of the process output error and the control signal:

$$J(u, t)=E\{(y_{t+k}-r_{t+k})^2+\lambda u_t^2\} \quad (10)$$

Eq. (10) is the GMV control law [16] which employs a one-step-ahead optimal control strategy. While this scheme has the capability to generate an internal stabilizing control algorithm, the stability depends upon the value of λ chosen. The criterion is minimized at time t with respect to Δu_t. The logic for applying incremental inputs in the criterion is that Eq. (10) does not allow zero static error in the case of a non-zero constant reference unless the open-loop plant algorithm involves an integrator, which would permit y_t to stay at a constant value when the control input is zero.

GMV controller is attained by minimizing the cost function given in Eq. (10) [17]. This approach introduces a system pseudo-output defined by Eq. (11):

$$\Phi(t+k)=Py(t+k)+Qu(t)-Rr(t) \quad (11)$$

Where r(t) is the set point, and P, Q and R are the transfer functions in the backward shift operator z^{-1}. In this work, transfer functions in the generalized system output were selected as P=1, Q=λ R=1. λ is the control weighting and it is used as control tuning parameter. The role of the feed forward term is to shift the system open loop zeros from B to PB+QA. The cost function to be minimized is the variance of the pseudo-output.

$$J(u, t)=E\{\Phi^2(t+k)\} \quad (12)$$

Clearly, J is minimized by setting the predicted output equal to zero. The resulting control law is given in Eq. (13).

$$u_t=\frac{Hr_t-Gy_t-Ed}{F} \quad (13)$$

Where the polynomials are defined as F=BE+QC and H=CR.

The GMV algorithm produces a good set point following characteristics and is able to a certain extent to control non-minimum phase systems. If the supposed delay k is applied within the generalized system, then the feed-forward path gives the required route by which the control signal can suitably compensate the generalized output ϕ(t) as shown in Fig. 1.

With the simple choice of Q=λ, the characteristic polynomial is B+λA in which treating λ as a root-locus parameter shows that the potentially unstable roots due to B migrate towards the roots of A. Hence a stable open-loop system is also stable under predictive control with a correctly chosen λ. This GMV algorithm is implicit, i.e.,

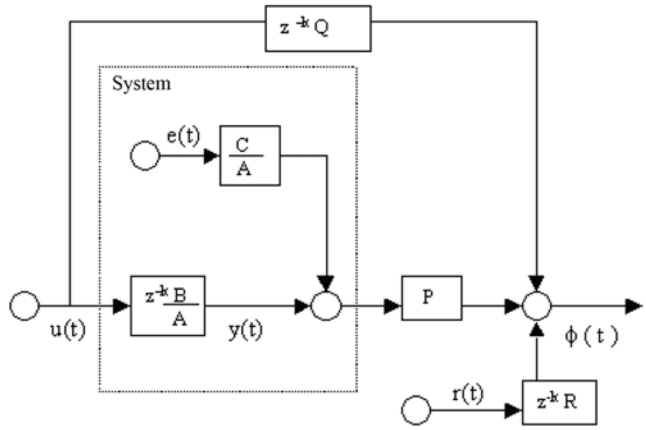

Fig. 1. Generalized system output.

the evaluated parameters are employed precisely in the control to be varied on-line without degrading the parameter estimates [18,19]. An additional modification to this design permits the control weighting to be on-line without influencing the parameter estimates. In the latter case, the control law is not completely implicit.

EXPERIMENTAL SYSTEM

A schematic diagram of the reactor system is shown in Fig. 2. The reactor is a 2 L jacketed glass vessel. Tap water is used as the coolant on the jacket. To heat the mixture in the reactor an electrical heater connected to a triac is used. Temperature measurements were made as on-line at each sampling period using J type thermocouples for the reactor, inlet and outlet of the coolant. A computer with A/D and D/A converters is employed for data acquisition and control of the experimental bioreactor. Air was continuously supplied to the reactor by a sparger after passing through a microbiological filter and an air rotameter. WTW Oxi 340 palografic DO

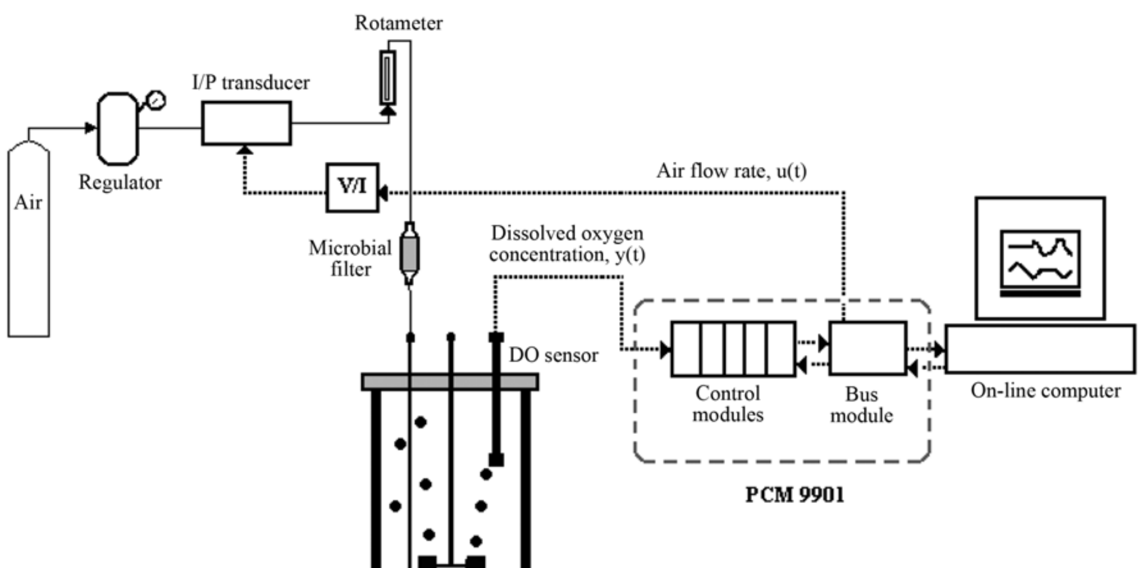

Fig. 2. Experimental system.

meter was placed in the reactor to measure dissolved oxygen concentration. Growth medium composion and preparation were explained in the previous work [20]. Optimal operating conditions are given in Table 2 for the experimental studies.

The reactor temperature during the bioreaction was maintained at 32 °C by using on-off control by manipulating flow rate of the cooling water passing through the jacket at 21 °C. pH of culture broth was maintained at 5. Foam formation was prevented by adding antifoam A. Samples taken from the bioreactor were analyzed by UV spectrophotometer and microorganism growth was observed.

MATLAB 6.5 and Visual Basic package were used in theoretical and experimental studies, respectively. System identification and control algorithms were coded in both languages. The reactor was modelled with black box models, and output data for simulation were obtained from these models.

RESULTS AND DISCUSSION

1. Determination of CARMA Model Order

Generally, it is possible to fit models of different order to the data obtained. When the “insufficient” or “wrong” model order is employed, serious errors can occur, or a redundancy of terms will be apparent. Thus a test is required to find the “correct” or “best” model order. As the model order increases, the sum of squares of the errors will decrease owing to a better fit being obtained. If the decrease is very slight between two models, the order of the second model being an increase on that of the first, then the use of a model of higher order does not significantly reduce the sum of squares.

Order selection of the model was achieved by using a cost function value, which is given as

$$V_n = \sum_{t=1}^{N} |\varepsilon(t)|^2 \tag{14}$$

Table 1. Cost function values for three different model orders

	Model order (n)	Mean	V_n (RLS)
$y(t)=\frac{b_0 z^{-1}}{a_0+a_1 z^{-1}}u(t)$	1	0.30	4.68×10^{-3}
$y(t)=\frac{b_0 z^{-1}+b_1 z^{-2}}{a_0+a_1 z^{-1}+a_2 z^{-2}}u(t)$	2	0.185	3.92×10^{-3}
$y(t)=\frac{b_0 z^{-1}+b_1 z^{-2}+b_2 z^{-3}}{a_0+a_1 z^{-1}+a_2 z^{-2}+a_3 z^{-3}}u(t)$	3	0.179	3.84×10^{-3}

Table 2. Optimal operating conditions used in the experimental studies

Parameter	Value
pH	5
Temperature	32 °C
Air flow rate	1.0 vvm
Agitation rate	600 rpm
Reactor volume	1.6 L
Cooling water flow rate	1.4 mL sec^{-1}
N_2 flow rate	0.5 $Lmin^{-1}$

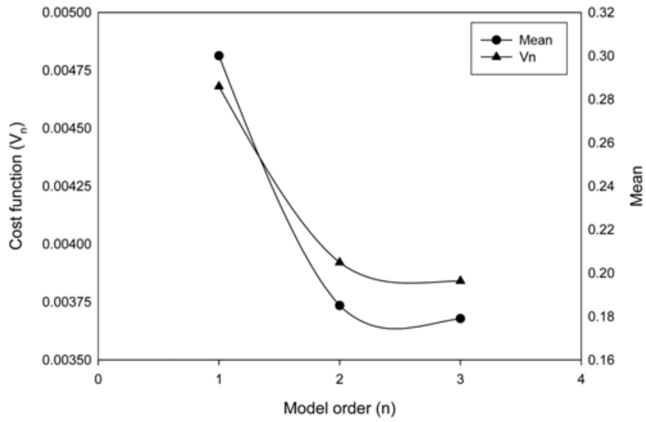

Fig. 3. Test for ‘correct’ model order.

Where n shows order of the model and N is number of data. First-, second- and third-order models were investigated for identification of the reactor. Table 1 shows that the model order of 3 does not decrease the V_n and mean values too much. In other words, a model order of 2 is suitable enough in order to identify the dynamic behavior of this bioreactor.

Fig. 3 shows V_n and mean values plotted against the model order (n) for RLS. It is obvious from the figure that slope changes greatly where n=2, indicating that a model order of 2 is the best choice. This result is consistent with the literature. Mohtadi suggested that the second order ARMAX model structure is the best for GMV control [21].

2. Determination of Volumetric Mass Transfer Coefficient

Due to the difficulties in predicting the volumetric mass transfer coefficients of oxygen by using correlations in the bioreactors, an experimental method called dynamic K_La technique based on the unsteady-state mass balance of oxygen was used. Optimum values of the agitation speed and the air flow rate providing maximum volumetric mass transfer coefficient were determined experimentally. Various agitation speeds and air flow rates were examined (Fig. 4). To determine the optimum value of agitation speed, air flow rate was kept at 0.5 $Lmin^{-1}$ during the experiments.

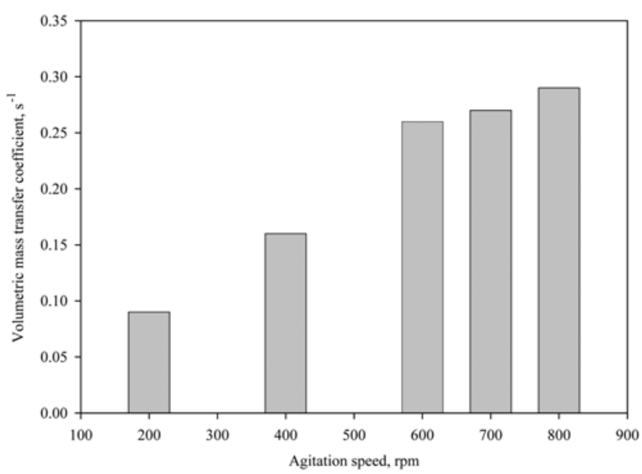

Fig. 4. Effect of the agitation speed on the volumetric mass transfer coefficient.

It can be seen from the figure that the K_La increases with the agitation speed, but agitation speed which is bigger than 600 rpm cannot increase the K_La considerably. These results suggest that the agitation speed of 600 rpm is the suitable value for this bioreactor. This value can be used as the optimum agitation speed value because of certain reasons such as excessive shear rate and power consumption at higher speeds. Especially in industrial practice, the growth medium is usually viscous and the agitation speed is limited by excessive power consumption. Therefore, the air flow rate may be more practical and economical in the DO control methods.

To investigate the effect of the air flow rate on K_La, various air flow rates were examined. To determine the optimum value of air flow rate, agitation speed was kept at 600 rpm during the experiments. From Fig. 5, optimum air flow rate was determined as 3.4 $Lmin^{-1}$.

Furthermore, if the value of the ordinates of Figs. 4 and 5 is investigated it can be seen that the air flow rate changes the K_La more than the agitation rate. Because of this, selection of air flow rate as the manipulated variable is suitable for DO control of this bioreactor.

3. The Choice of Input Signal for Identification of Reactor

To understand the dynamic behavior of the bioreactor, some experiments were carried out. When the process was at the steady-state, positive step changes were applied to the process input both during the non-growth and microorganism growth conditions. When the air flow rate was changed from 0.8 $Lmin^{-1}$ to 1.8 $Lmin^{-1}$, DO concentration increased from 0.77 mgL^{-1} to 2.27 mgL^{-1}, during the non-growth condition which means that the bioreactor filled with the growth medium does not contain any inoculated microorganism (Fig. 6). Similarly, when the air flow rate was changed from 0.5 $Lmin^{-1}$ to 3.4 $Lmin^{-1}$, DO level increased from 1 mgL^{-1} to 3 mgL^{-1} during the microorganism growth condition (Fig. 7). These figures show that the bioreactor has different dynamic behavior during the non-growth and microorganism growth conditions in the point of

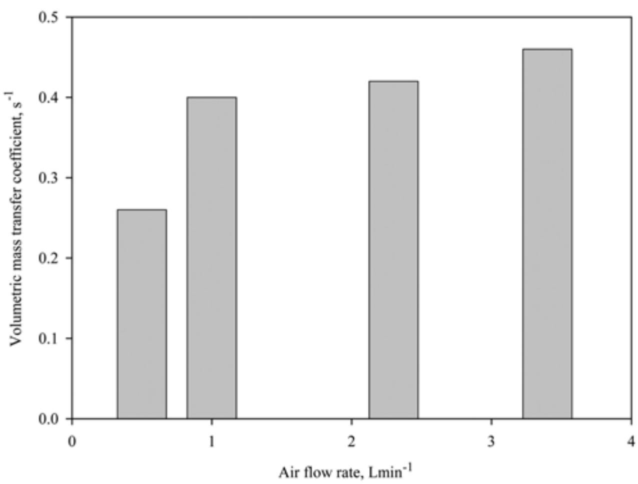

Fig. 5. Effect of the air flow rate on the volumetric mass transfer coefficient.

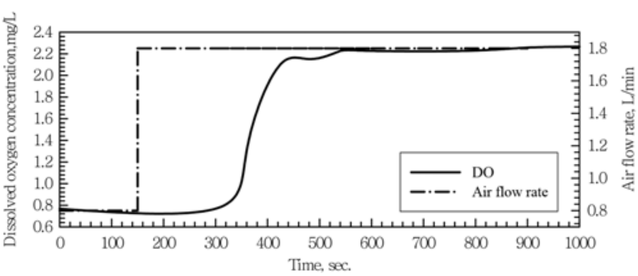

Fig. 6. Open loop response when positive step change in air flow rate from 0.8 $Lmin^{-1}$ to 1.8 $Lmin^{-1}$ during the non-growth condition in the bioreactor.

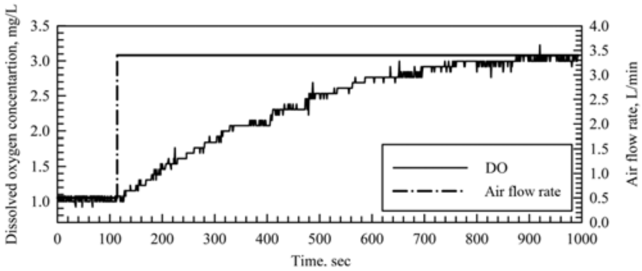

Fig. 7. Open loop response when positive step change in air flow rate from 0.5 $Lmin^{-1}$ to 3.4 $Lmin^{-1}$ during the microorganism growth in the bioreactor.

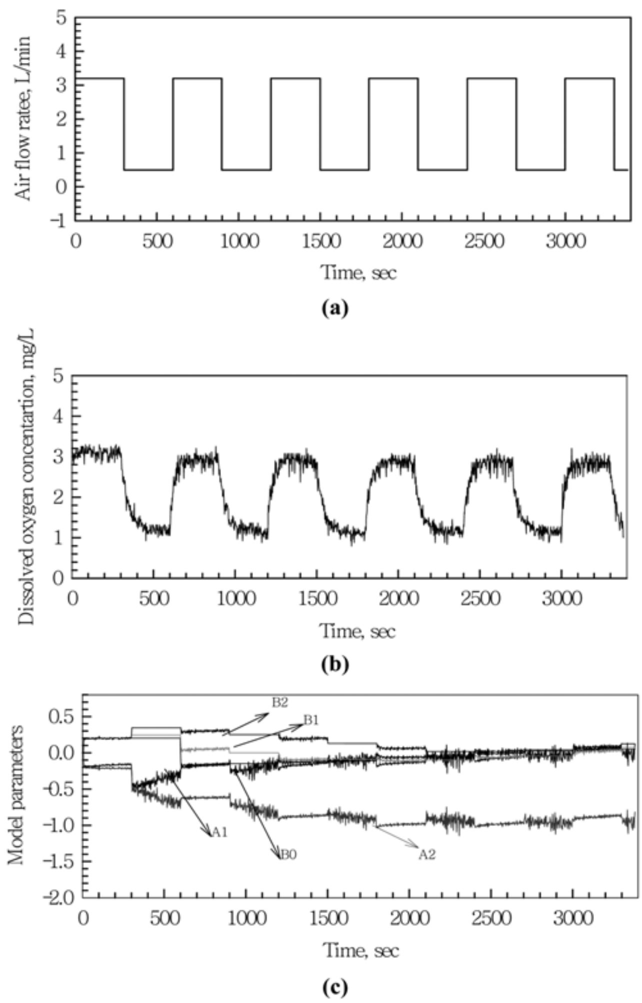

Fig. 8. The open loop system dynamic behaviour in the face of square wave excitation. (a) Manipulated variable, (b) Measured variable, (c) CARMA model parameters.

DO change. A more realistic "process reaction curve" of first-order with dead time model which was obtained from the microorganism growth condition (Fig. 7) can be used to calculate the PID controller parameters by using Cohen Coon Tuning Method [22].

The choice of input signal is largely important in system identification. In practice the square wave, PRBS and ternary signals are suitable for recursive estimation. Square wave signal is easy to generate and has a strictly limited amplitude range. This is useful since it is generally necessary to limit the amplitude excursion of a test signal to avoid taking a system outside its linear operating range. The frequency of the square wave needs to be selected such that the system dynamics are adequately excited [15]. The square wave period was selected approximately six times of time constant of the system. Alternatively, the square wave frequency should be approximately 0.16 times of the system bandwidth. These are rough guides aimed at ensuring that most of the square wave power is inside the system bandwidth. PRBS is another popular signal for system identification. PRBS offers an advantage of square waves in that they have only two amplitudes which do not exceed the bands of linearity of the system under test. The advantage of PRBS over a square wave is that it has a richer spectrum; the disadvantage is that PRBS is more difficult to implement.

The basic decisions in PRBS test signal design concerns the so-called clock frequency and the sequence length. The sequence length is not of great practical importance in recursive estimation. An indication of the relevance of this parameter, however, may be gained

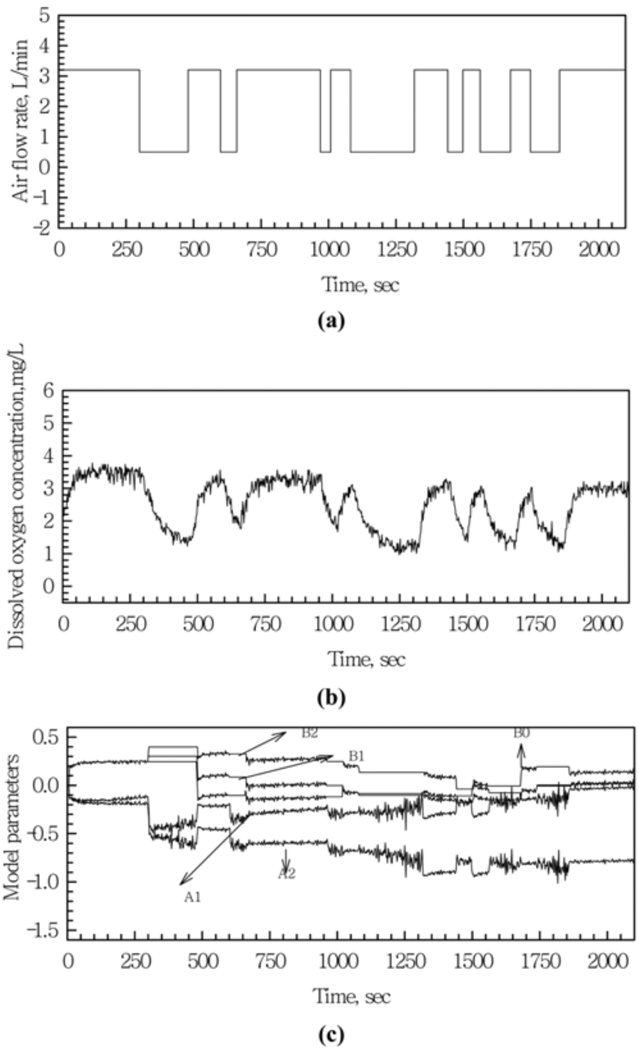

Fig. 9. The open loop system dynamic behaviour in the face of PRBS wave excitation. (a) Manipulated variable, (b) Measured variable, (c) CARMA model parameters.

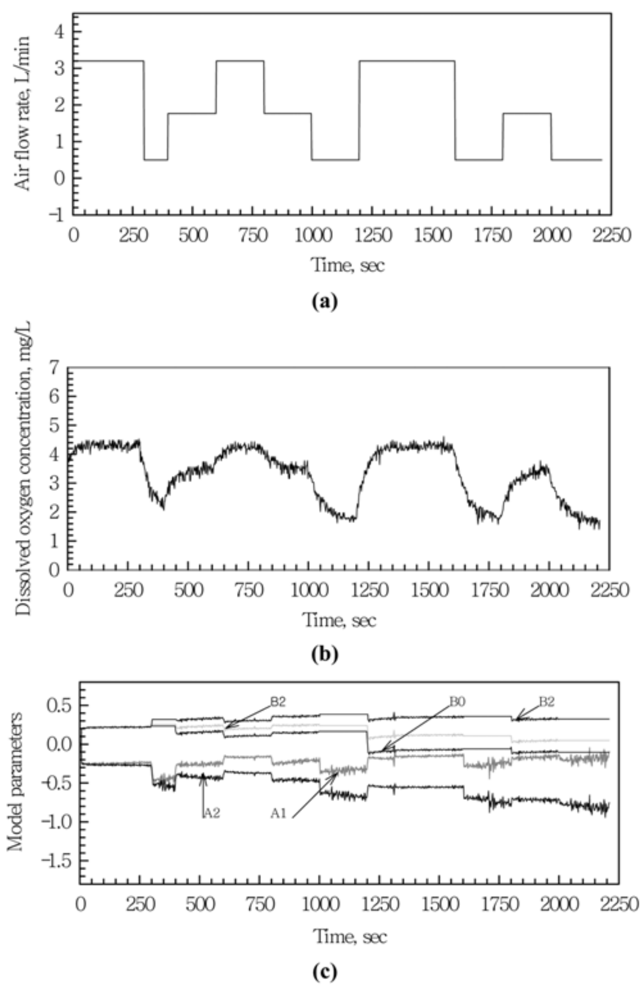

Fig. 10. The open loop system dynamic behaviour in the face of ternary wave excitation. (a) Manipulated variable, (b) Measured variable, (c) CARMA model parameters.

Table 3. CARMA model parameters obtained by using different types f input signal

Input type	a_1	a_2	b_0	b_1	b_2
Square wave input	−0.5637	−0.3898	0.0261	−0.0611	0.0941
Ternary input	−0.0960	−0.7510	−0.1030	0.0480	0.3250
PRBS input	−0.0220	−0.7840	0.1540	0.0420	0.0240

by noting that the sequence length gives the number of harmonic frequencies in the PRBS spectrum range from zero to the clock frequency. A choice of sequence length of 63 or greater is reasonable. In this study sequence length was chosen as 63.

Input and output data which were used for system identification studies are shown in Figs. 6, 7 and 8. To simulate the consumption of DO by microorganisms, nitrogen flow rate was kept at the 2 L·min^{-1} during the system identification studies which were carried out in a batch bioreactor filled with the growth medium (non-growth condition). Square wave, PRBS and ternary signals were applied as an input to the air flow rate to obtain the output which is DO. Second-order CARMA model parameters were evaluated off-line by using the RLS algorithm from the collected experimental data. Table 3 shows the obtained model parameters. For different type of input signals, model parameters were calculated with small differences but their signs were the same. Because of small fluctuations for the parameter values, a ternary wave is the suitable input for system identification for this process.

In the other dynamic work, during the microorganism growth at constant airflow rate, DO was not controlled (Fig. 11). Changes in

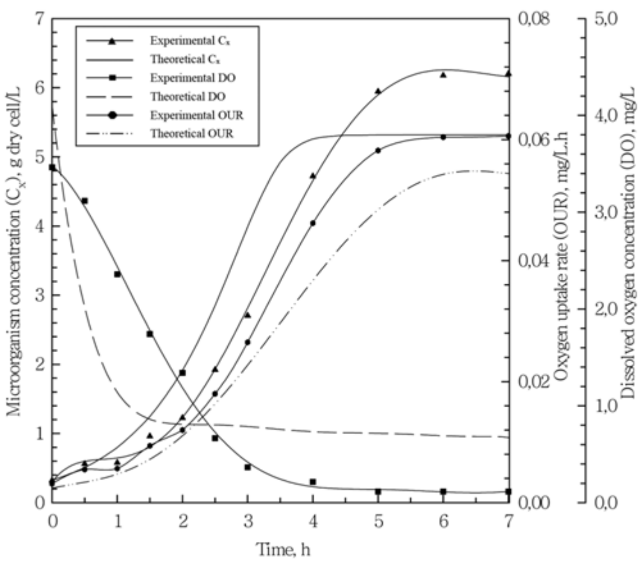

Fig. 11. Theoretical and experimental dynamic results during the microorganism growth.

Table 4. Performance criteria for different set point trajectories behaviour of PID and GMV controllers

PID			GMV		
Theoretical					
	IAE	ITAE		IAE	ITAE
Constant	5.10^2	$2.3.10^6$	Constant	161	$8.4.10^5$
Square wave	$9.8.10^2$	$3.7.10^6$	Square wave	1554	$2.9.10^6$
Random	1.017	$4.0.10^6$	Random	---	---
Experimental					
	IAE	ITAE		IAE	ITAE
Constant	$1.0.10^3$	$4.5.10^6$	Constant	$5.2.10^2$	$8.5.10^5$
Square wave	$1.8.10^3$	$7.8.10^6$	Square wave	$4.0.10^2$	$8.5.10^5$
Random	$1.7.10^3$	$6.8.10^6$	Random	---	---

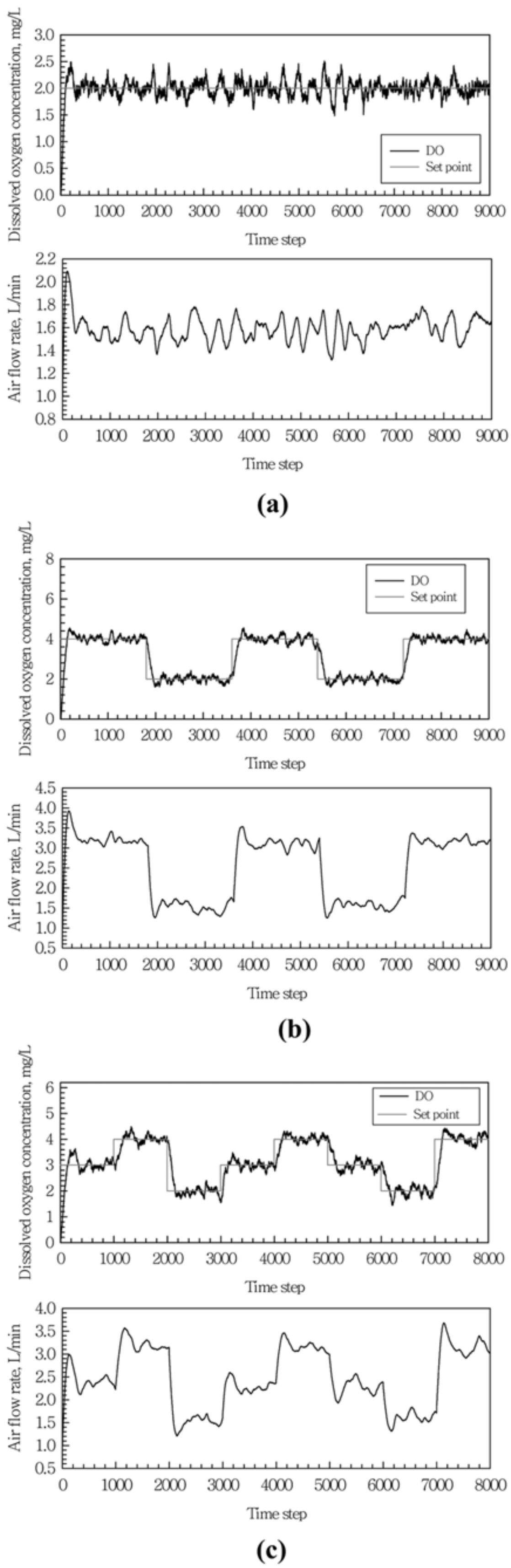

Fig. 12. Theoretical PID control results. (a) Constant set point profile, (b) Square wave set point profile, (c) Random set point profile.

the microorganism oxygen uptake rate (OUR), DO level and microorganism concentration with time were observed during the fermentation. As it is expected, while oxygen uptake rate increases during the fermentation, DO decreases. Therefore, DO must be controlled above its critical value to maintain aerobic growth conditions.

4. Control Results

PID and GMV controls were implemented theoretically and experimentally to track the DO concentration at different set point profiles. Controller performance was compared according to the performance criteria of IAE and ITAE. These results are given in Table 4. In the theoretical work a second-order CARMA model was used to simulate the dynamic system behavior. Theoretical control studies started with three different types of set profile trajection of PID (Fig. 12). PID controller parameters were fixed by Cohen Coon Method as K_C=4.4, τ_I=3.7 sec and τ_D=0.6 sec in both theoretical and experimental studies. Performance of PID controllers can be acceptable. Constant and square wave set point profiles tarjection were realized by using theoretical GMV control. Results are given in Fig. 13 and Fig. 14, respectively. GMV parameters used in both theoretical and experimental studies were R=1, Q=2/3, P=1. These figures show the variations of manipulated and controlled variables and calculated GMV tuning parameters versus time. When the bioreactor contained the growth medium, GMV controller provided good DO tracking with small fluctuations.

In the experimental control studies, similar set point trajectories were followed by PID and GMV control. Experimental PID control of DO was obtained with high oscillations around the set point, but smooth changes were observed in the manipulated variable (Fig. 15). For both controllers, performance criteria for the experimental cases were about two times bigger than those in the theoretical cases due to the high level of the noise for the real system. Satisfactory control was obtained by using GMV control because it had a good set point tarjection and load effect rejection, which is created by means of an increament in the nitrogen flow rate, with small changes for the manipulated variable (Fig. 16 and Fig. 17). Usually good control performance can be obtained with all the algorithms when the processes' dead time is small. However, it is known that it is more difficult to tune an adaptive controller when there is significant dead time. The PID controller cannot normally cope with dead time processes at all, and the GMV algorithm provides reasonable control in most cases.

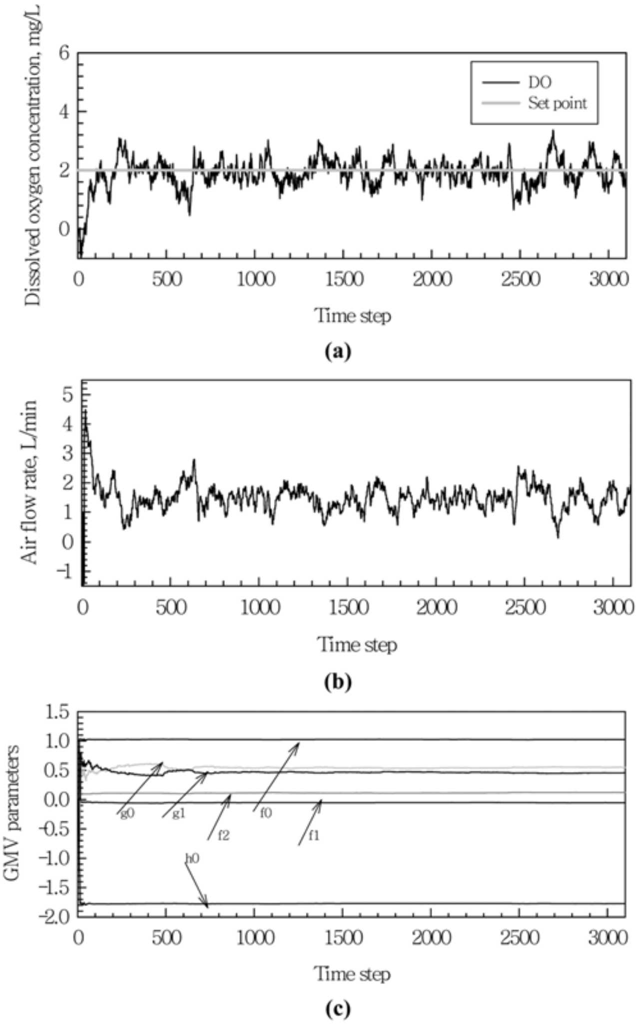

Fig. 13. The results of theoretical GMV control for constant set point. (a) Controlled variable, (b) Manipulated variable, (c) GMV controller parameters.

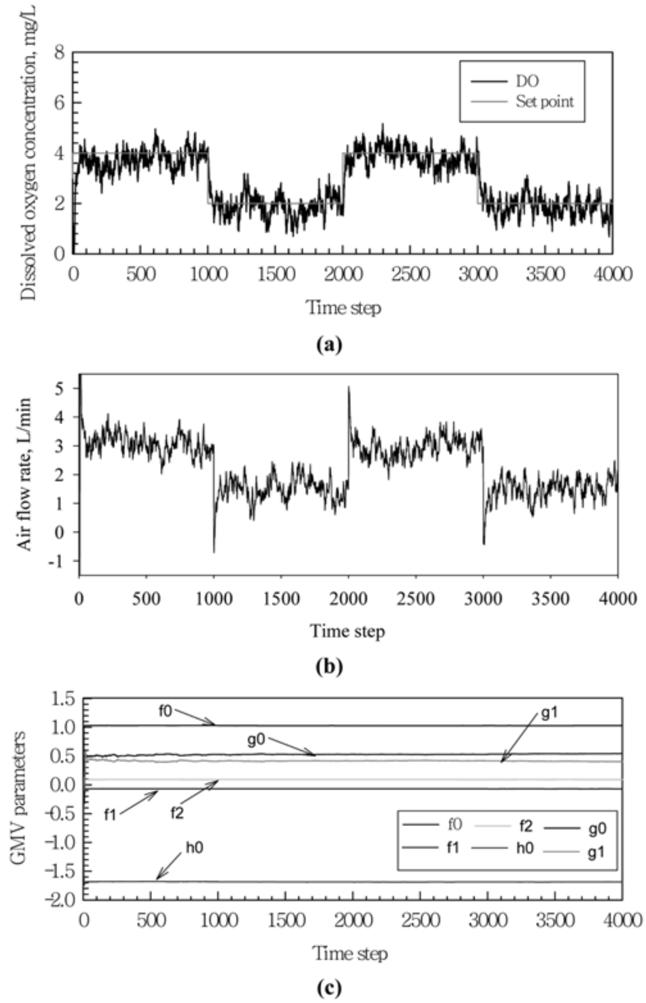

Fig. 14. The results of theoretical GMV control for square wave set point profile. (a) Controlled variable, (b) Manipulated variable, (c) GMV controller parameters.

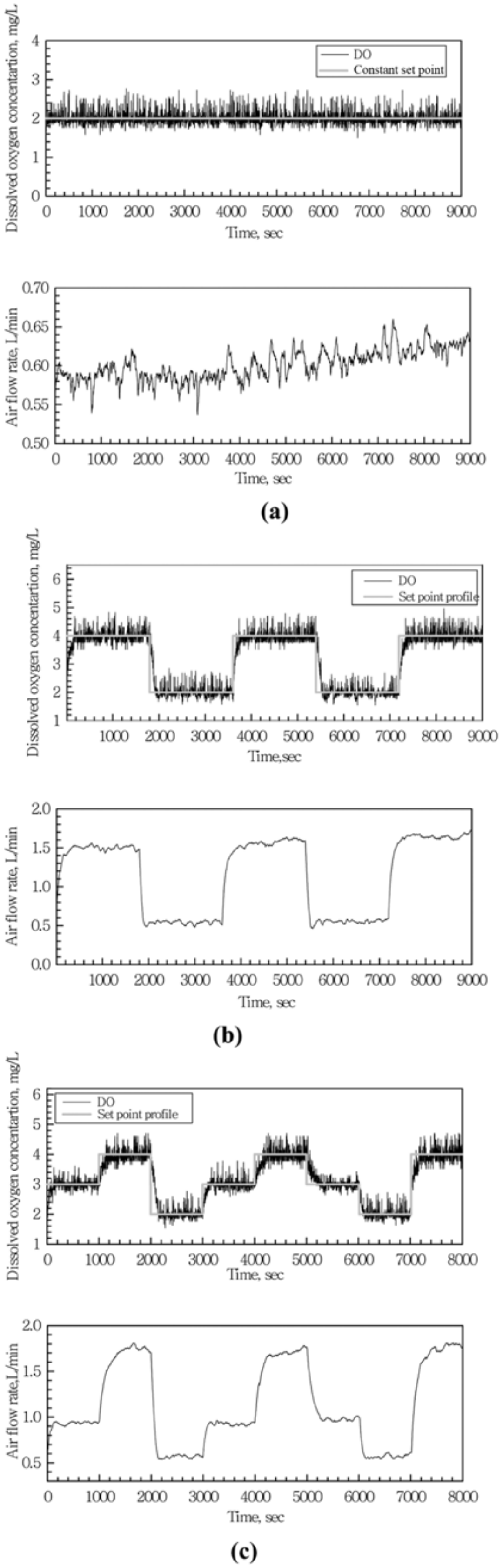

Fig. 15. The results of experimental PID control for growth medium without microorganism. (a) Constant set point trajectory, (b) Square wave set point profile, (c) Random set point profile.

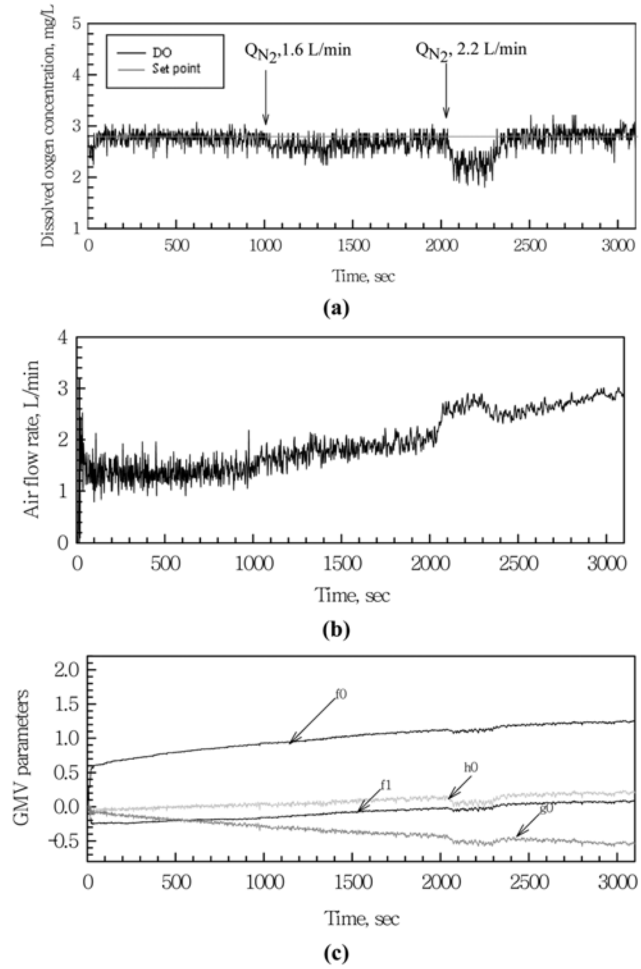

Fig. 16. The experimental results of GMV control of growth medium without microorganism for constant set point. (a) Controlled variable, (b) Manipulated variable, (c) GMV controller parameters.

CONCLUSION

Steady state conditions, dynamic behavior and DO concentration control in a batch bioreactor were investigated both experimentally and theoretically. A discrete-time black-box parametric model was developed. Optimum model order was determined and tested with experimental step response analysis. An adaptive self-tuning control algorithm, GMV, was implemented by using an on-line computer. The results of the GMV controller were compared with the traditional PID ones.

If model order and input type are chosen correctly, parameters which are estimated in RLS algorithm will converge rapidly to their true values. If the model is chosen incorrectly, large errors can be apparent in the parameter convergence. Therefore, a model order test can be done in order to select the preferred number of parameters.

Using appropriately-designed periodic ternary signals, the linear component of a system can be identified with errors from even-order nonlinear distortions eliminated, and errors from noise and odd-order nonlinear distortions minimized.

The majority of industrial design is based on the PID strategy. Practical experience with self-tuning has been growing rapidly over

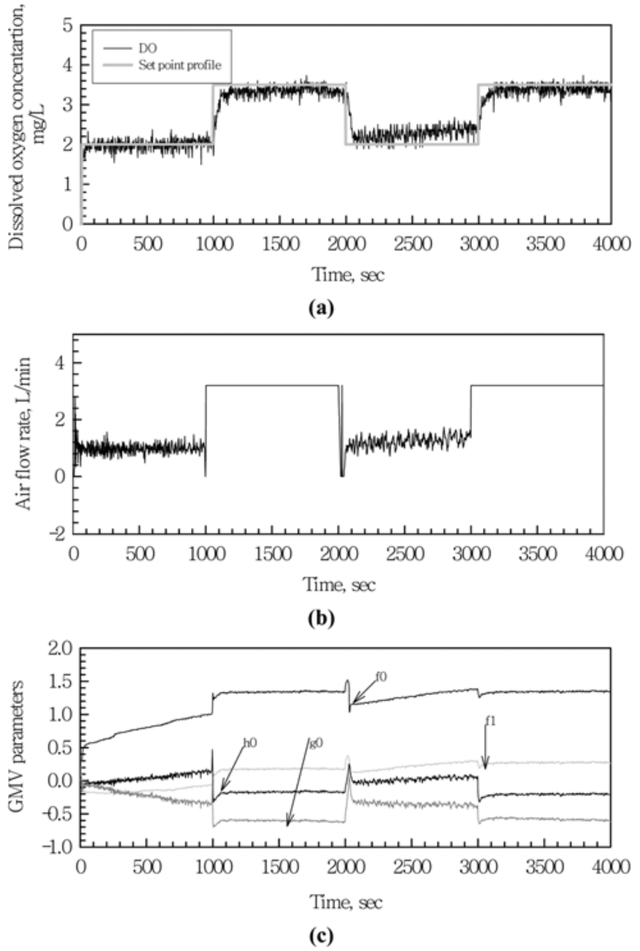

Fig. 17. The experimental results of GMV control of growth medium without microorganism for square wave set point profile. (a) Controlled variable, (b) Manipulated variable, (c) GMV controller parameters.

the last fifteen years. There are many cases in which self-tuning has been in routine operation in an industrial plant. Generally, the PID controller is considered as the standard algorithm; an alternative algorithm is selected only when the alternative provides better control performance. In addition, self-tuning methods can provide a considerable advantage over the conventional approaches [19].

The results obtained in this work can be implemented on all the systems which have time-varying dynamic characteristics. It is concluded that the GMV algorithm has a good set point trajectory and disturbance rejection futures in the case of accompliheshment of the system identification step.

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NOMENCLATURE

A : monic polynomial in the z-domain representing the poles of the discrete time system
B : polynomial in the z-domain representing the zeros of the discrete time system
C : monic polynomial in the z-domain representing the zeros of the process noise
e(t) : error
E : mathematical expectation
F : F polynomial in the GMV algorithm
F : G polynomial in the GMV algorithm
H : H polynomial in the GMV algorithm
J : objective function for the GMV algorithm
K_C : propotional gain of PID controller
K_La : volumetric oxygen transfer coefficient [s^{-1}]
ni : degrees of polynomials (i:a,b,c,p,q,r)
Q : weighting polynomial
P : polynomial in the z-domain representing the zeros of the discrete-time system
P(t) : covariance matrix
R : weighting polynomial acting on set point
r(t) : set point at time t
t : time (sec or h)
u(t) : input variable at time t
y(t) : output variable at time t
z^{-1} : forward and backward shift operators

Greek Letters

ε(t) : prediction error
τ_I : integral time constant of PID controller [min]
τ_D : derivative time constant of PID controller [min]
λ : control weighting
θ(t) : parameter vector
$\hat{\theta}$(t) : predicted parameter vector
φ(t) : data vector
ϕ(t+k) : best forecast of ϕ(t+k) established on data up to time t
Φ(t+k) : pseudo-output

Abbreviations

CARMA : controlled auto regressive moving average
DO : dissolved oxygen
MV : minimum variance
GMV: generalized minimum variance
PID : proportional-integral-derivative control
RLS : recursive least squares
STC : self tuning controller
STR : self tuning regulator

REFERENCES

1. K. J. Aström and B. Wittenmark, *Automatica*, **9**, 185 (1973).
2. D. W. Clarke and P. J. Gawthrop, *Proc. IEE*, **26**(6), 633 (1979).
3. D. R. Omstead, *Computer control of fermentation processes*, CRC Press, Florida (1990).
4. L. Shuler and F. Kargı, *Bioprocess engineering basic concepts*, Prentice Hall, New Jersey (1992).
5. K. R. Sales and S. A. Billings, *Int. J. Control* **51**(4), 753 (1990).
6. S. Svonoros, G. Stephanopoulos and R. Aris, *Int. J. Control*, **34**(4), 651 (1981).

7. G. C. Goodwin, B. McInnis and R. S. Long, *Optimal Control Applications and Methods*, **3**(4), 443 (1982).
8. G. C. Goodwin and K. S. Sin, *Adaptive filtering prediction and control*, Prentice-Hall, New Jersey (1984).
9. D. R. Omstead, *Computer control of fermentation processes*, CRC Press, Florida (1990).
10. T. A. Clarke, T. Hesketh and T. Seddon, *Biotechnol. Bioeng.*, **17**, 1507 (1985).
11. I. O. Sargantanis and M. N. Karim, *Biotechnol. Bioeng.*, **60**(1), 1 (1998).
12. S. C. Lee, Y. B. Hwang, H. N. Chang and Y. K. Chang, *Biotechnol. Bioeng.*, **37**, 597 (1991).
13. T. Suzuki, T. Yamane and S. Shimizu, *J. Ferm. Technol.*, **64**(4), 317 (1986).
14. D. Williams, P. Yousefpour and E. M. H. *Biotechnol. Bioeng.*, **28**, 631 (1986).
15. T. Soderström and P. Stoica, *System identification*, Prentice Hall Ltd., New York (1989).
16. P. E. Wellstead and M. B. Zarrop, *Self-tuning systems-control and signal processing*, John Wiley & Sons, New York (1991).
17. D. W. Clarke and P. J. Gawthrop, *Proc. IEEE*, **122**(9), 929 (1975).
18. A. R. Karagoz, H. Hapoğlu and M. Alpbaz, *Chem. Eng. Process.*, **39**, 253 (2000).
19. S. Ertunc, B. Akay, N. Bursali, H. Hapoglu and M. Alpbaz, *Food Bioprod. Process.*, **81**, 327 (2003).
20. S. Ertunc, B. Akay, H. Boyacioglu and H. Hapoglu, *Food Bioprod. Process*., **87**, 46 (2009).
21. C. Mohtadi, Industrial Digital Control Systems "Chapter 7. Adaptive Control": K. Warwick and D. Rees (Eds.), IEE Control Engineering Series 37, Institution of Engineering and Technology, London (1988).
22. G. Stephanopoulos, *Chemical process control*, Prentice Hall, New Jersey (1984).