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Mathematical Model and Advance Control for Activated Sludge Process in Sequencing Batch Reactor

Ahmmed S. Ibrehem[1]
Mohamed Azlan Hussain[1]
[1]*Department of Chemical Engineering, University of Malaysia, 50603, Kuala Lumpur, Malaysia*
E-mail : ahmadsaadi1@yahoo.com

This paper presents the results of a modeling and simulation study of an activated sludge process in a sequencing batch reactor (SBR), with emphasis on total nitrogen removal. This study focuses on the effect of dissolved oxygen (DO) and effluent chemical oxygen demand (COD). Neural-network based Predictive controller (MPC) is implemented to control the system for the DO set point and give better and acceptable results when compared with the conventional PID controller.

Keywords: Sequencing batch reactor, Mathematical model, Dynamic studies, Control system.

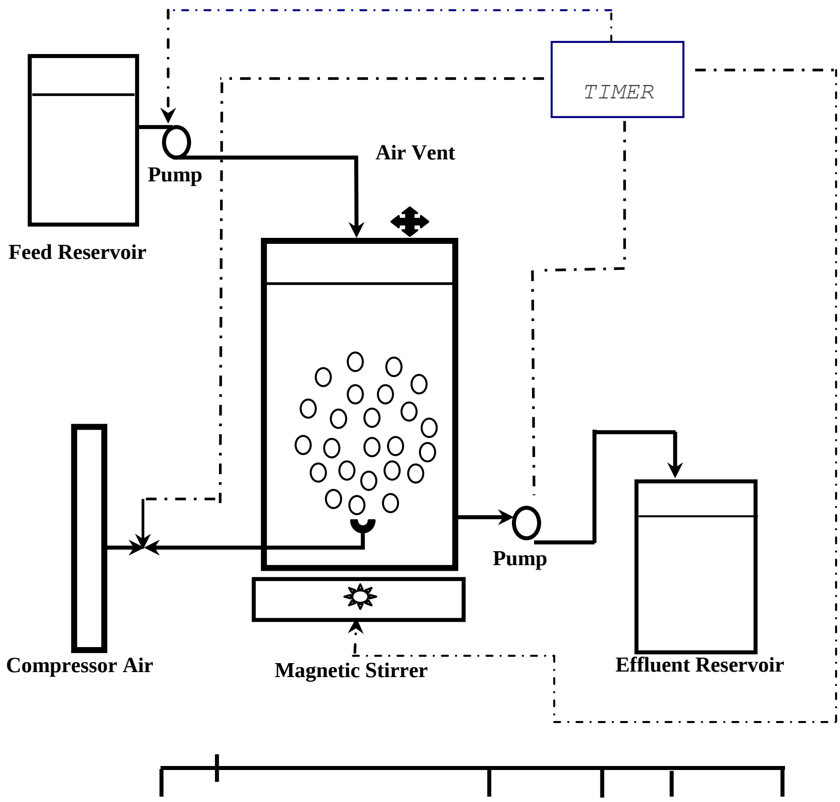
INTRODUCTION

Activated sludge wastewater treatment processes are normally difficult to be controlled and Dissolved Oxygen (DO) concentration regulation is regarded as the most important control parameter in activated sludge process due to economical reasons and to achieve optimum performance of the process. Too high a dissolved oxygen concentration will lead to unnecessary power consumption due to high aeration and affect the anoxic process. A DO concentration that is too low inhibits bacterial growth. Therefore, proper DO control can give an improved process performance and provide an economic incentive to minimize the excess oxygen consumption by supplying the necessary air to meet the time-varying oxygen demand. However, the principal difficulties in the control of the biological waste water process control are the variability of the kinetic parameters, time-varying influent wastewater conditions, non-linearity, time delay, sensor noise and the limited availability of on-line information; hence, adaptive and nonlinear controllers are the best choice for this type of biological process control. To overcome these problems, some successful conventional DO control schemes, such as proportional-only and PID control have been reported (Olsson, 1985). Several adaptive control strategies have been suggested recently for the control of DO concentration in the aeration basin (Holmberg et al., 1989; Carlsson, 1992; Lindberg and Carlsson, 1996; Lindberg, 1997; Yoo et al., 1999). Zhao et al. (1994) introduced a model-based predictive control strategy to reduce the effluent ammonia, nitrate and nitrite (SNOX) by adjusting the cycle length of a sequencing batch reactor (SBR) scheme. Using the same SBR process, Isaacs et al. (1995) formulated an adaptive control scheme by introducing an external carbon source, in order to achieve a similar end. Yoo and Lee (2003) compared several process identification methods for DO dynamics and compared the novel estimation methods for oxygen transfer rate and respiration rate and applied a supervisory control algorithm in the full-scale control of the system. However in recent years, model predictive control (MPC) technique introduced in the late 1990's have been increasingly applied for nonlinear process systems. Model predictive control refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of the plant. These predictive responses will then be utilized in the optimization routines to design the control moves of the controller to follow the set point trajectory for the system. However, the conventional MPC rely heavily on the precise model and since activated sludge processes may involve highly nonlinear models, the need for more reliable models is needed. Here, we propose the use of artificial neural networks to model the activated sludge process for use in the MPC scheme. Artificial neural networks ANN have recently been applied for activated sludge systems modeling and control (Capodaglio et al., 1991; Cote et al., 1995; Fu and Poch, 1995; Zhao et al., 1999; Olsson and Newell, 1999). ANNs are computing procedures used to model complex systems through a process of "learning" from examples, without a priori knowledge about the systems' structure or parameters. An interesting characteristic of ANN is that it can approximate any continuous function (Haykin, 1999). A process control system built with artificial neural network ANN models has been revealed as a reliable tool to optimize the operation performance in a dynamic complex water and wastewater treatment system (Zhang and Stephen, 1999; Hamoda et al., 1999; Cohen et al., 1997). Due to their impressive capability in dealing with severe non-linearity and uncertainty of a system, the application of neural network method for the design of controllers is flourishing (Hussain, 1999). This work proposes the application of MPC control study utilizes artificial neural networks to control the DO concentration in an SBR. The proper control strategy is developed after being preceded by simulation study of the dynamic behavior of the system. Simulation data from the mathematical model of a sequencing batch reactor was used to train and test various neural network topologies. The control method proposed utilizes feed forward neural networks in the indirect neural network control method. The MPC with the neural network model is then tested for set point tracking and load disturbances rejection tests.

EXPERIMNTAL METHOD

Sequencing batch reactor process

Activated sludge is an aerobic biological process in which wastewater is mixed with a suspension of microorganisms to assimilate pollutants and is then settled to separate the treated effluent. In the Sequencing Batch Reactor (SBR) system, all treatment steps takes place in a single reactor with different phases separated in time. The cycle in a typical SBR is divided into five discrete time period: Fill, React, Settle, Draw, and Idle period. The data used in this study were obtained from a bench-scale SBR (D. Orhon, 1986). Figure 1 shows this system and its operational description. This system was operated in a 6-hr cycle mode with as fill time of 0.5h, reaction time of 3h, settle time of 1h, draw time of 0.5h, and idle time of 1h.



Time(hr):	0	0.5		3.5	4.5	5	6
Stage :	Fill	React	Settle	Draw	Idle		
Air :	Off	On	Off	Off	Off		
Stirrer :	Off	On	Off	Off	On		

Figure 1. Schematic and Process Description of Sequencing Batch Reactor Operation

Mathematical model

The models used in the simulation studies are based on the Activated Sludge Model No. 1, or ASM1 (Henze et al., 1987). These models provide detail description of these processes Biochemical Oxygen Demand (BOD) removal, nitrification and denitrification. In the SBR, aerobic treatment, nitrification and denitrification are carried out in the same reactor. The dynamics of dissolved oxygen (S_o)in the reactor is described by the nonlinear differential equation (Olsson and Newel, 1999):

$$\frac{dS_o}{dt} = \frac{F}{V_f}(S_{o,f} - S_o) - \frac{1-Y_H}{Y_H} r_{H,G}^{aerobic} - \frac{4.57 - Y_A}{Y_A} r_{A,G} + k_L a(Q_{air}(t))(S_{o,sat} - S_o(t)) \quad (1)$$

where:

$$r_{A,G} = \mu_A \left(\frac{S_{NH}}{K_{NH} + S_{NH}} \right) \left(\frac{S_o}{K_{OA} + S_o} \right) X_{BA} \quad (2)$$

$$r_{H,G}^{aerobic} = \mu_H X_{BH} \left(\frac{S_s}{K_s + S_s} \right) \left(\frac{S_o}{K_{OH} + S_o} \right) \quad (3)$$

The function $k_L a(Q_{air}(t))$ describes the oxygen transfer and it is in general nonlinear and depends on aeration actuating system and sludge conditions. It is assumed linear (Olsson and Newell, 1999) and given by the following equation:

$$k_L a(Q_{air}(t)) = a\left(1 - e^{-\frac{qA(t)}{b}}\right) \quad (4)$$

Mass balance for slowly biodegradable substrate in the reactor:

$$\frac{dX_s}{dt} = \frac{F}{V_f}(X_{s,f} - X_s) + (1 - f_p)(r_{H,d} + r_{A,d}) - r_h \quad (5)$$

Mass balance for autotrophic biomass in the reactor:

$$\frac{dX_{BH}}{dt} = -\frac{F}{V} X_{BH} + r_{H,G} - r_{H,d} \quad (6)$$

Mass balance for heterophic biomass in the reactor:

$$\frac{dX_{BA}}{dt} = -\frac{F}{V} X_{BA} + r_{A,G} - r_{A,d} \quad (7)$$

Mass balance for particulate material in the reactor:

$$\frac{dX_P}{dt} = -\frac{F}{V} X_P + f_P(r_{H,d} + r_{A,d}) \quad (8)$$

Mass balance for nitrate and nitrite in the reactor:

$$\frac{dS_{NO}}{dt} = \frac{F}{V_f}(S_{No,f} - S_{No}) - \frac{1-Y_H}{2.86Y_H} r_{H,G}^{anoxic} + \frac{1}{Y_A} r_{A,G} \quad (9)$$

Mass balance for ammonium in the reactor:

$$\frac{dS_{NH}}{dt} = \frac{F}{V_f}(S_{NH,f} - S_{NH}) - (i_{XB} \frac{1}{Y_A}) r_{A,G} + r_{NH} - i_{XB} r_{H,G} \quad (10)$$

Mass balance for soluble organic in the reactor:

$$\frac{dS_{ND}}{dt} = \frac{F}{V_f}(S_{ND,f} - S_{ND}) + r_h(\frac{X_{ND}}{X_S}) - r_{NH} \quad (11)$$

The system characteristics, kinetic and stoichiometric parameter, influent characteristics and SBR initial conditions employed for the process is shown in Tables 1 and 2.

Table 1. System characteristics, kinetic and stoichiometric parameters used in SBR model (Lau et al., 1984; Dold and Marais, 1986; Henze, et al., 1987)

No	Parameter		Value	Units
1	Heterophic yield coefficient:	Y_H	0.67	Dimensionless
2	Heterotrophic growth rate:	μ_H	6	h^{-1}
3	Heterotrophic decay rate:	b_H	0.62	h^{-1}
4	Substrate half saturation:	K_S	20	mgCOD/l
5	Oxygen half saturation:	K_{OH}	0.2	mgO_2/l
6	Nitrate half saturation:	K_{NO}	0.5	mgN/l
7	Fraction of denitrifiers:	η_g	0.8	Dimensionless
8	Fraction of hydrolysis:	η_h	0.4	Dimensionless
9	Yield coefficient for nitrifiers:	Y_A	0.24	mgCOD/mgN
10	Growth rate for nitrifiers:	μ_A	0.8	h^{-1}
11	Ammonia half saturation:	K_{NH}	0.3	mgN/l
12	Oxygen half saturation:	K_{OA}	0.4	mgO_2/l
13	Decay rate for nitrifiers:	b_A	0.15	h^{-1}
14	Biomass nitrogen factor:	i_{xb}	0.086	$mgN(mgCOD)^{-}$
15	Particulate nitrogen factor:	i_{xp}	0.06	$mgN(mgCOD)^{-1}$
16	Saturated oxygen concentration:	S_{Osat}	10	mg/l
17	$K_L a$ value at infinite airflow rate:	a	166	h^{-1}
18	$K_L a$ exponent coefficient:	b	16	m^3/min
19	Reactor volume:	V_t	12,400	l
20	Initial volume:	V_o	2400	l
21	Fill time:	t_f	0.5	h
22	Aerobic reaction time:	t_r	3	h
23	volumetric flow rate:	F	20000	h^{-1}
24	Hydrolysis maximum rate:	K_X	0.03	h^{-1}
25	Ammonification rate:	k_a	0.08	$mg(m^{-3}.\ h^{-1})$
26	Endogenous biomass fraction:	f_P	0.08	Dimensionless

Table 2. Influent characteristics and initial conditions on sequencing batch reactor. (Lau *et al.*, 1984; Dold and Marais, 1986; Henze, *et al.*, 1987).

No	Parameter		Influent	Initial condition	Unit
1	Active Heterotrophic Biomass:	XbH	0.001	2240	mgCOD/l
2	Active Autotrophic Biomass:	XbA	0.001	560	mgCOD/l
3	Slowly Biodegradable Substrate:	Xs	175	20	mgCOD/l
4	Readily Biodegradable Substrate:	Ss	125	12	mgCOD/l
5	Nitrate and Nitrite Nitrogen:	SNo	1	0.01	mgN/l
6	Ammonium nitrogen:	SNH	30	0.6	mgN/l
7	Soluble Biodegradable Organic Nitrogen:	SND	5	0.4	mgN/l
8	Particulate Biodegradable organic Nitrogen:	XND	5	3	mgN/l
9	Oxygen Uptake Rate:	OUR	0	250	mg/l.h
10	Dissolved Oxygen concentration:	DO	6.8	0	mg/l
10	Dissolved Oxygen concentration:	Q_{air}	66	25	mg/l

The chemical oxygen demand (COD) and ammonium nitrogen (NH_4-N) increased during the fill period and rapidly decreased to the steady state values of 4.75 mg/l and 8.35mg/l, respectively. It is seen that the reaction rates of the processes mainly depend upon the DO concentration. Also, during the aeration off time (fill-period), the COD and ammonium nitrogen concentration are high as seen in Figure (2).

Figure (3) shows the dynamic simulations of the activated sludge process for active heterotrophic biomass, active autotrophic biomass and soluble biodegradable organic nitrogen in SBR. Biodegradable organic nitrogen consists of soluble organics nitrogen SND and particulate biodegradable organic nitrogen, XND. Ammonia nitrogen is readily available for incorporation into new cellular constituents, or for oxidation to NO_2 and NO_3 in nitrification. Further conversion of soluble organic nitrogen to ammonia is also, accomplished through an ammonification process mediated by similar heterotrophic activities.

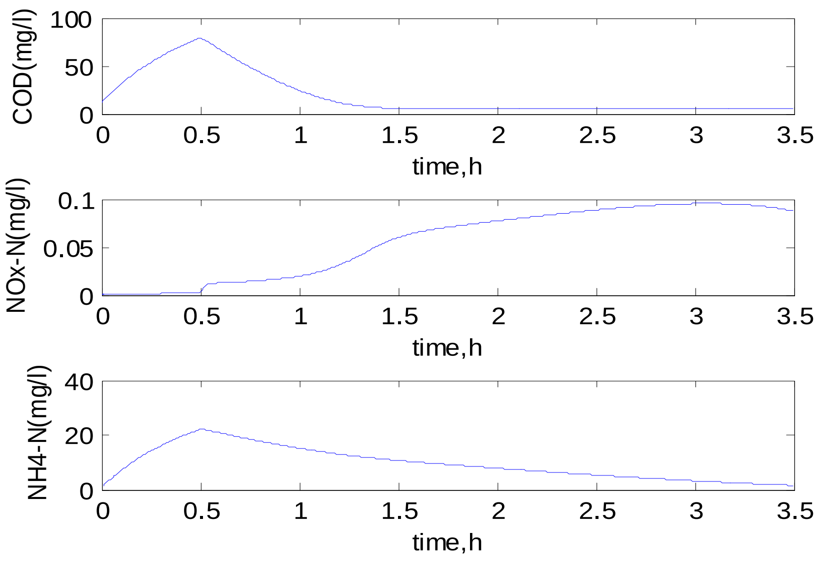


Figure 2. Dynamic Simulation of Activated Sludge Process for SBR

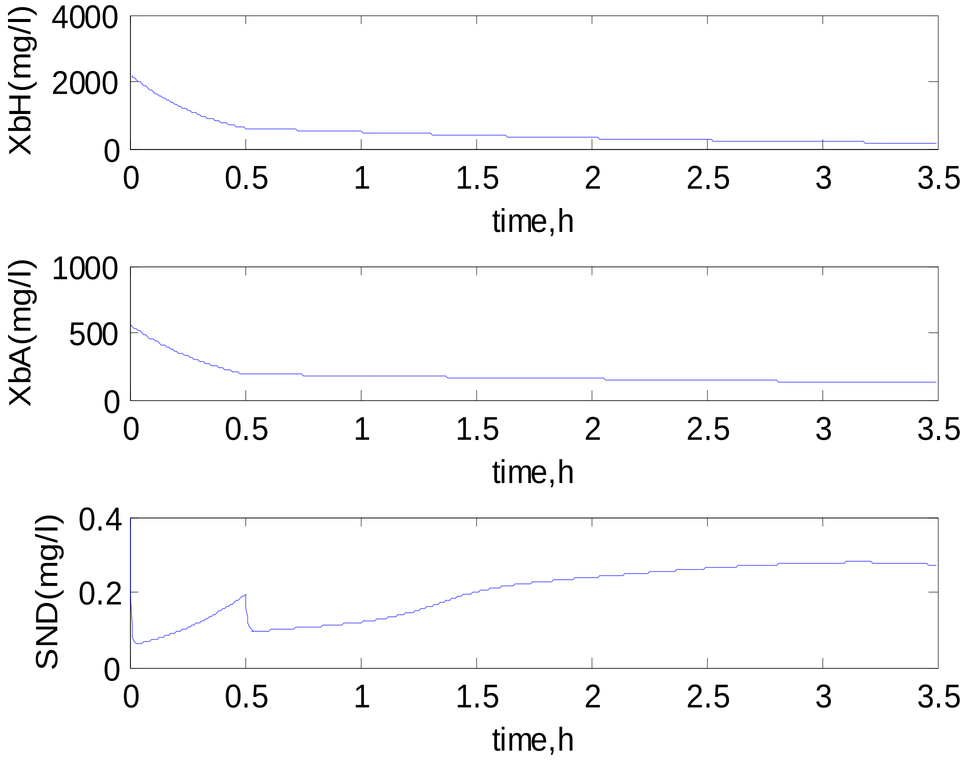


Figure 3. Dynamic Simulation for Heterotrophic Biomass, Autotrophic Biomass, and Soluble Biodegradable Organic Nitrogen in Neural Network.

Control study

The neural net-based model predictive control method implemented in this work can be seen in Figure (4).

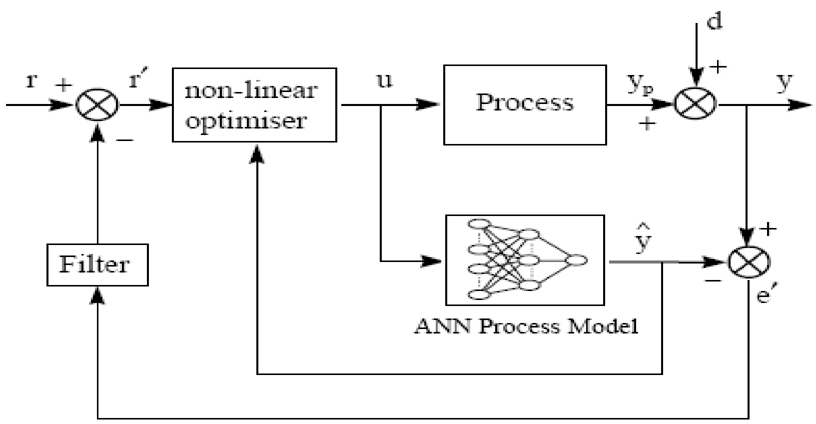


Figure 4. The Neural Network Predictive controller implementation

The formulate of the objective function of thre MPC is given as (ahammed s et al.,)

$$J = \sum_{i=P1}^{i=P2} (\tilde{y}(t+i) - r(t+i))^2 + \lambda \sum_{i=1}^{i=C} (u(t+i-1) - u(t+i-2))^2 \quad \text{min } u(t) \qquad (12)$$

Where

$$u(t+i) = u(t+C-1), \quad i >= C \tag{13}$$

$$u_{\min} \le u(t) \le u_{\max} \tag{14}$$

J is the cost function to be minimized, P1 to P2 define the prediction horizon, C is the control horizon, $\tilde{y}$ (t + i) is the predicted process output for time t + i, u(t) is the vector of manipulated variable values of length C and λ is a weighting coefficient, *t* represent the iteration time. In common with linear MPC, corrections should be made to the model output to account for process/model mismatch and unmeasured disturbances (Ahmmed s et.al,), and this can be done with an additive disturbance, e (t) as

$$\tilde{y}(t+i) = \hat{y}(t) + e^{'}(t) \tag{15}$$

Where $\hat{y}(t+i)$ is the i-step ahead ANN model prediction. A simple approach, which was adopted here, is to use the process/model mismatch to estimate this disturbance.

$$e^{'}(t) = y(t) - \hat{y}(t) \tag{16}$$

Introduction the modified set point, $r^{'}(t)$

$$r^{'}(t+i) = r(t+i) - e^{'}(t) \tag{17}$$

In this study y (t) represents the DO which is the controlled variable and the manipulated variable u(t) represents air flow rate. The optimization problem outlined by equation (12) is solved using the sequential quadratic algorithm.

RESULTS AND DISCUSSION

The simulation results for the training neural net work are shown in Figures (5) and (6) give us very good performance and ability for ANN model that makes error less than 1 $\times 10^{-3}$.Also, the behavior of training was high performance without digressive behavior when step change happened at time 0.5 hr from0 to 6×10^{-3}. The closed loop control implementation of the PID controller and Neural-network based Predictive controller for controlling the DO in SBR system is shown Figures (7) and (8) respectively. The behavior of PID controller was not stable, digressive and manipulated variable was unstable compare to MPC. The performance of the controller is investigated by considering the set point tracking disturbance rejection characteristics of the controller. The disturbances introduced are changes in the initial volumetric flow rate as shown in Figure (9) give us good idea about high ability of MPC. The integral absolute errors (IAE) of the process responses are shown in Table (3). From these results it can be inferred that the behavior of the PID controller is shown in Figure (7) is characterized with aggressive control action with oscillations before achieving the set point. The neural-network based predictive controller gives smooth set point tracking without any oscillations in both cases as shown in Figures (8), (9), (10) and (11) compare to PID controller.

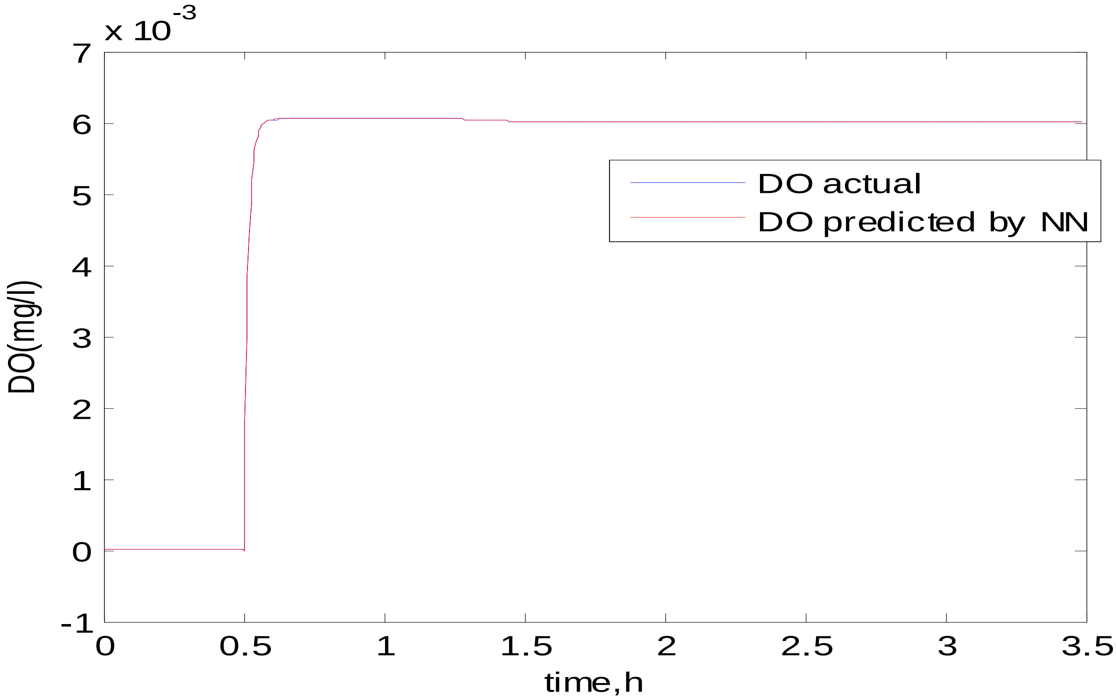


Figure 5. Training Result for Neural Net Work

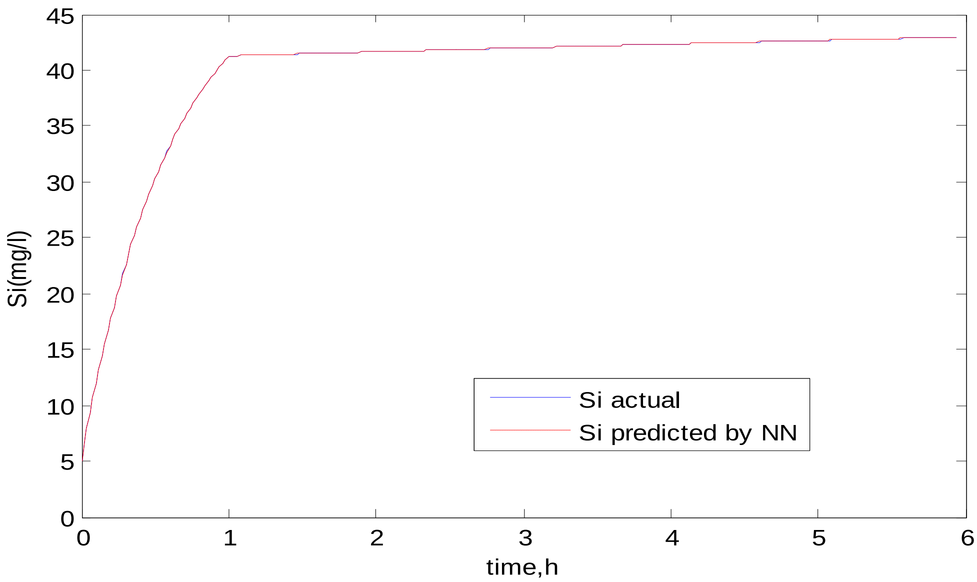


Figure 6. Training Result for Neural Network for Mass Nitrogen per Mass COD

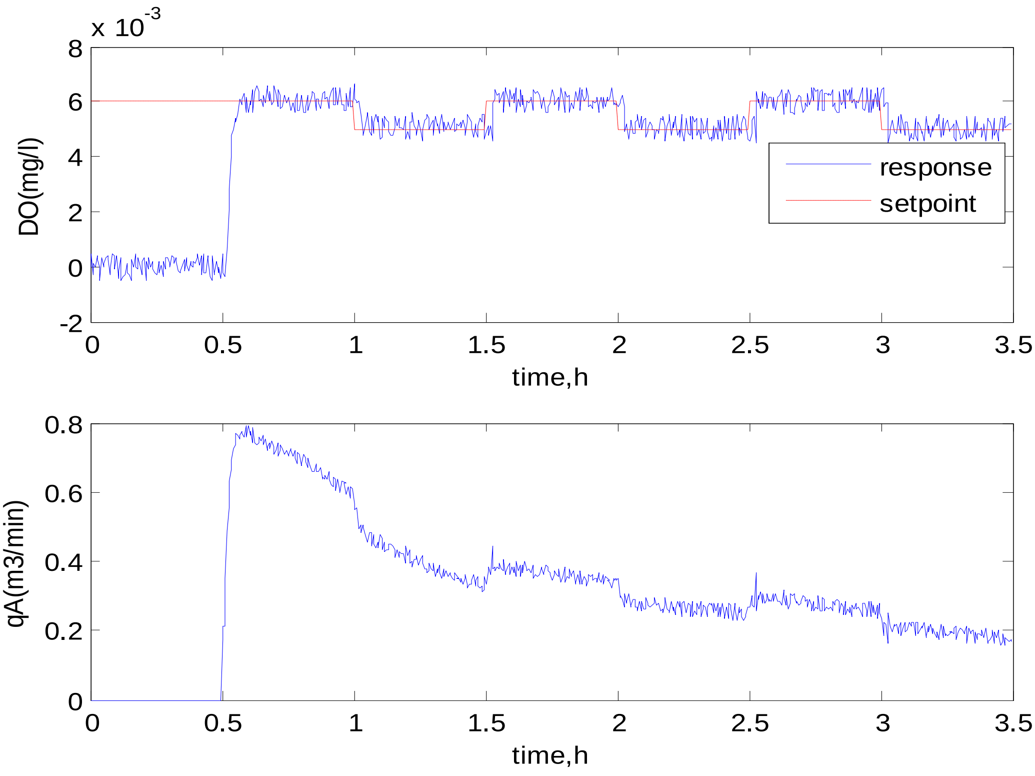


Figure 7. Process and Controller Performance of PID Controller for Tracking Set Point Changes with Measurement Noise

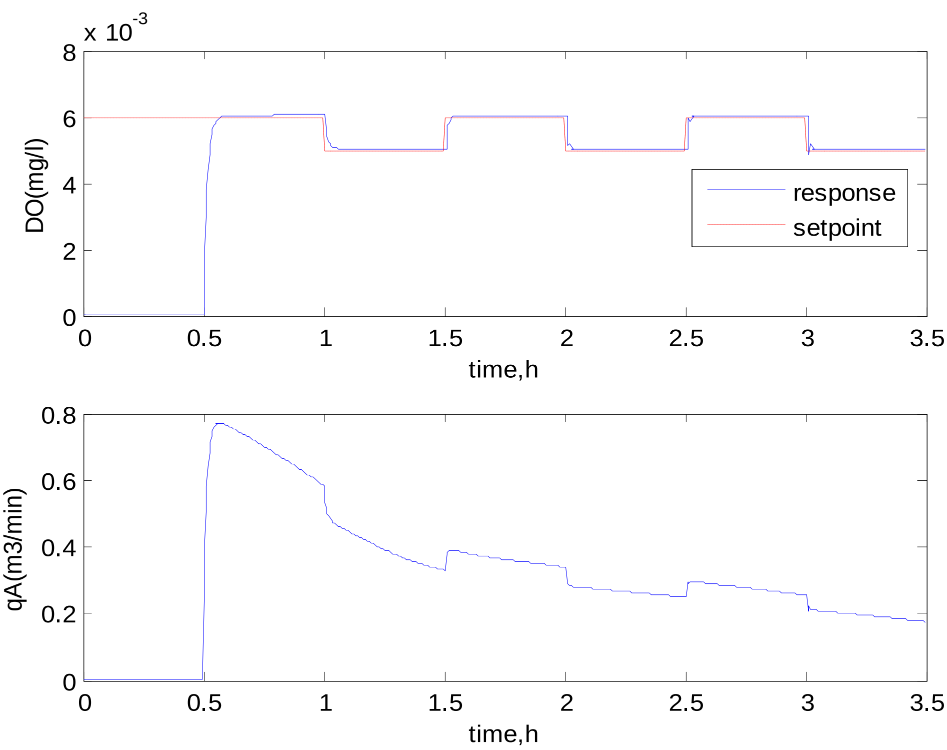


Figure 8. Response for Set Point Tracking Studies - MPC controller.

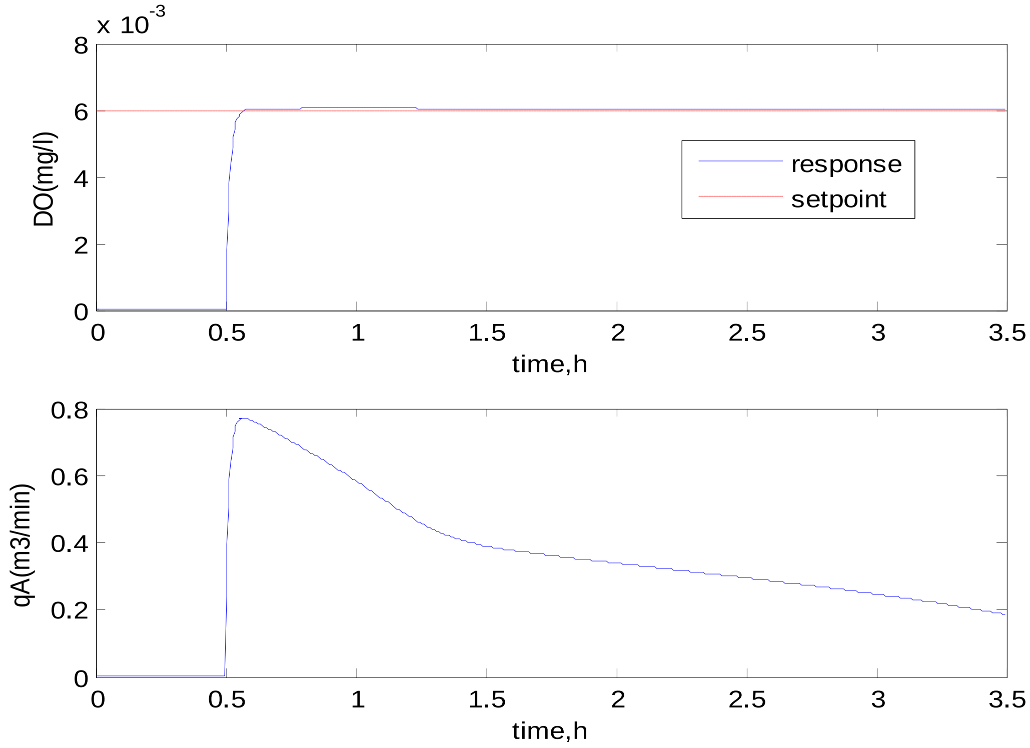


Figure 9. Response for Disturbance by Soluble Biodegradable Organic Nitrogen Study - Mpc Controller

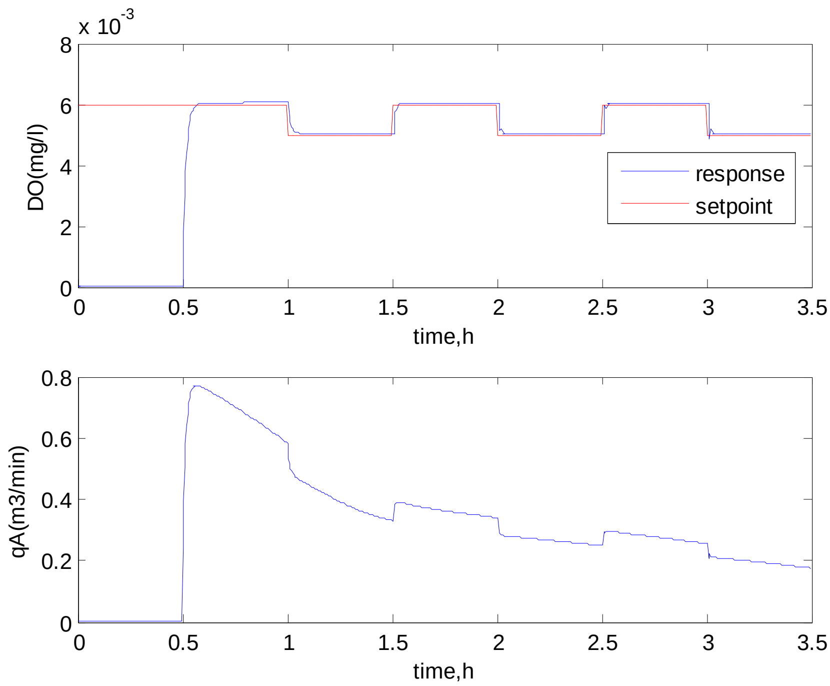


Figure 10. Process and Controller Performance of MPC Controller for Tracking Set Point Changes with Measurement Disturbance by Ammonium

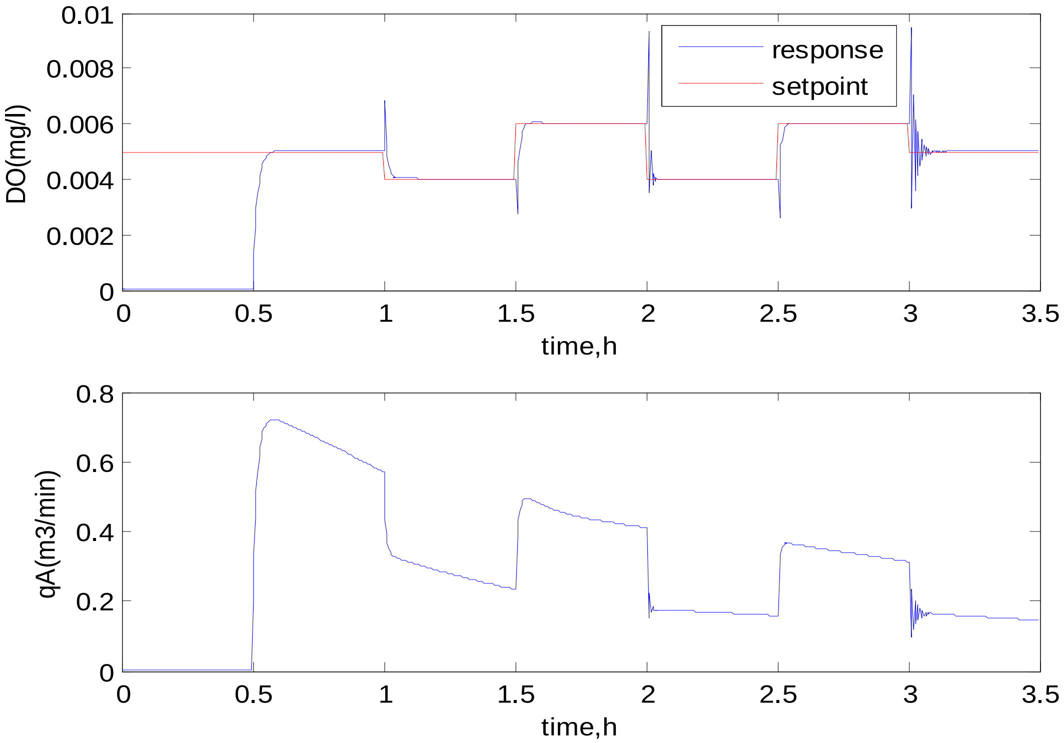


Figure 11: Process and Controller Performance of PID Controller for Tracking Set Point Changes with Measurement Noise

Table 3. Integral Absolute Error

No	Studies	IAE for PID	IAE for MPC
1	Set point tracking condition	0.0649	4.621-005
2	Noises rejection study	0.1975	0.0153

CONCLUSIONS

We have studied the effect of DO concentration to reduce the effluent of COD and nitrogen in a sequencing batch reactor, and also, shown how DO concentration reacts to the air flow rate changes. The effect of the air flow rate profile on DO concentration is clearly observed. Simulation results suggest that the air flow rate could be an efficient control variable for an efficient process control system. This paper also presents the application of Neural-network based Predictive controller implemented to control the system and compared with the conventional PID controller, giving good, acceptable results.

Nomenclature

a — K_La value at infinite airflow rate (l/d)
b — K_La exponent coefficient (m^3/min)
f_P — Fraction of biomass leading to particulate products (dimensionless)
Y_A — Yield for autotrophic biomass (g. N oxidized)$^{-1}$
Y_H — Yield for heterotrophic biomass (g. COD oxidized)$^{-1}$
K_{NH} — Ammonia half-saturation coefficient for autotrophic biomass (g. NH_3-N m^{-3})
k_a — Ammonification rate (m^3 COD (g. day)$^{-1}$)
b_A — Decay coefficient for autotrophic biomass
b_H — Decay coefficient for heterotrophic biomass (day^{-1})
K_S — Half-saturation coefficient for heterotrophic biomass (g. COD m^{-3})
K_X — Half-saturation coefficient for hydrolysis of slowly biodegradable substrate (g. COD (g. cell COD)$^{-1}$)
i_{XB} — Mass of nitrogen per mass of COD in biomass (g. N (g. COD)$^{-1}$)
i_{XP} — Mass of nitrogen per mass of COD in products from biomass (g. N (g. COD)$^{-1}$)
k_h — Maximum specific hydrolysis rate (g. COD (g. cell COD)$^{-1}$)
K_{NO} — Nitrate half-saturation coefficient for denitrifying heterotrophic biomass (g. NO_3-N m^{-3})
$K_{O,A}$ — Oxygen half-saturation coefficient for autotrophic biomass (g. O_2 m^{-3})
K_{OH} — Oxygen half-saturation coefficient for heterotrophic biomass (g. O_2 m^{-3})
$S_{O,sat}$ — Saturated oxygen concentration (mg/l)

Greek symbols

η_g — Correction factor for μ_H under anoxic conditions (dimensionless)
η_h — Correction factor for hydrolysis under anoxic conditions (dimensionless)
μ_H — Maximum specific growth rate for heterotrophic biomass (day^{-1})
μ_A — Maximum specific growth rate for autotrophic biomass (day^{-1})

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