Bioprocess Biosyst Eng (2006) 28: 251–265
DOI 10.1007/s00449-005-0031-2

ORIGINAL PAPER

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The study of neural network-based controller for controlling dissolved oxygen concentration in a sequencing batch reactor

Received: 30 September 2005 / Accepted: 8 October 2005 / Published online: 17 December 2005

Abstract The design and development of the neural network (NN)-based controller performance for the activated sludge process in sequencing batch reactor (SBR) is presented in this paper. Here we give a comparative study of various neural network (NN)-based controllers such as the direct inverse control, internal model control (IMC) and hybrid NN control strategies to maintain the dissolved oxygen (DO) level of an activated sludge system by manipulating the air flow rate. The NN inverse model-based controller with the model-based scheme represents the controller, which relies solely upon the simple NN inverse model. In the IMC, both the forward and inverse models are used directly as elements within the feedback loop. The hybrid NN control consists of a basic NN controller in parallel with a proportional integral (PI) controller. Various simulation tests involving multiple set-point changes, disturbances rejection and noise effects were performed to review the performances of these various controllers. From the results it can be seen that hybrid controller gives the best results in tracking set-point changes under disturbances and noise effects.

Keywords Sequencing batch reactor · Dissolved oxygen · Direct inverse neural network control · Internal model control · Hybrid neural network control

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Introduction

Dissolved oxygen (DO) concentration is regarded as the most important control parameter in activated sludge process because of economic reasons and process performance. Too high a DO 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 improved process performance and provide 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 biological 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 non-linear controller is the better choice for such biological process control. Due to their impressive capability in dealing with severe non-linearity and uncertainty of a system, the application of neural network (NN) method for the design of such controllers is promising [1].

To overcome these problems previously, various successful conventional DO control schemes, such as proportional-only and PID control have been applied [2]. Several adaptive control strategies have been suggested recently for the control of DO concentration in the aeration basin [3–6]. Ref. [7] introduced a model-based predictive control strategy to reduce the effluent ammonia, nitrate and nitrite (SNO_X) by adjusting the cycle length of a sequencing batch reactor (SBR) scheme. Using the same SBR process [8] formulated an adaptive control scheme by introducing an external carbon source, in order to achieve a similar end. Ref. [9] applied a closed loop identification and control method to a full-scale coke wastewater treatment plant. Ref. [10] 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 wastewater treatment plant.

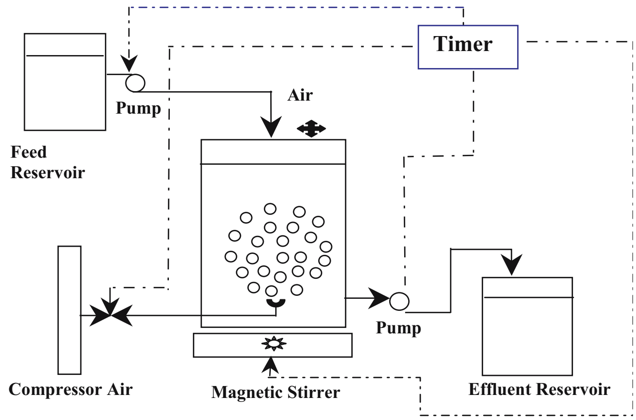
Artificial neural networks (ANN) have also been applied recently for activated sludge systems modeling and control [11–14]. ANN are computing procedures used to model complex systems through a process of "learning" from examples, without a priori knowledge about the systems' structure or parameters. An interesting characteristic of ANN is that they can approximate any continuous function [15]. A process control system built with ANN models has been revealed as a reliable tool to optimize the operation performance in a dynamic complex water and wastewater treatment system [16–18].

This paper proposes an application of ANN to control DO concentration in a SBR. Simulation data from the mathematical model of a SBR was used to train and test various NN topologies. The models were chosen in an effort to identify the one that best represented the system. The training cycle was repeated with all the sets of input/output pair patterns in data set, and the iteration was continued until the error function was minimized. The proposed control method utilizes feed forward NN model in various control configurations namely the direct inverse method, internal model control (IMC) and the hybrid scheme. The performance of these proposed strategies is then demonstrated through simulation studies involving multiple set-point tracking study and disturbance rejection under multiple set-point tracking and noise effect.

Model development

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 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 periods: fill, react, settle, draw, and idle period. The system used in this study is based on a bench-scale SBR [19]. Figure 1 shows this system and its operational description. This system was operated in a 6-hour cycle mode with a fill time of 0.5 h, reaction time of 3 h, settle time of 1 h, draw time of 0.5 h, and idle time of 1 h.



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	

Fig. 1 Schematic and process description of sequencing batch reactor operation

Mathematical model

These models provide a detailed description of biochemical oxygen demand (BOD) removal, nitrification, and denitrification. In the SBR, aerobic treatment, nitrification and denitrification are carried out in the same reactor. The models used in the simulation studies are based on the Activated Sludge Model No1, or ASM1 [20, 21] as below

Mass balance for the readily biodegradable substrate:

$$\frac{dS_s}{dt} = \frac{F}{V}(S_{s,f} - S_s) - \frac{1}{Y_H} r_{H,G} + r_h. \quad (1)$$

Mass balance for the slowly biodegradable substrate:

$$\frac{dX_s}{dt} = \frac{F}{V}(X_{s,f} - X_s) + (1 - f_p)(r_{H,d} + r_{A,d}) - r_h. \quad (2)$$

Mass balance for the nitrate and nitrite:

$$\frac{dS_{NO}}{dt} = \frac{F}{V}(S_{NO,f} - S_{NO}) + \frac{1}{Y_A} r_{A,G} - \frac{1 - Y_H}{2.86 Y_H} r_{H,G}^{anoxic}. \quad (3)$$

Mass balance for the ammonium:

$$\frac{dS_{NH}}{dt} = \frac{F}{V}(S_{NH,f} - S_{NH}) - \left(i_{XB} + \frac{1}{Y_A}\right) r_{A,G} + r_{NH} - i_{XB} r_{H,G}. \quad (4)$$

Mass balance for the soluble organic nitrogen:

$$\frac{dS_{ND}}{dt} = \frac{F}{V}(S_{ND,f} - S_{ND}) + r_h\left(\frac{X_{ND}}{X_s}\right) - r_{NH}. \quad (5)$$

Mass balance for particulate organic nitrogen in the reactor

$$\frac{dX_{ND}}{dt} = \frac{F}{V}(X_{ND,f} - X_{ND}) + (i_{XB} - f_p i_{XP})(r_{H,d} + r_{A,d}) - r_h\left(\frac{X_{ND}}{X_s}\right), \quad (6)$$

where

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

$$r_{\mathrm{H,G}} = r_{\mathrm{H,G}}^{\mathrm{aerobic}} + r_{\mathrm{H,G}}^{\mathrm{anoxic}},$$

$$r_{\mathrm{H,G}}^{\mathrm{aerobic}} = \mu_{\mathrm{H}} X_{\mathrm{BH}} \left(\frac{S_{\mathrm{s}}}{K_{\mathrm{s}} + S_{\mathrm{s}}}\right)\left(\frac{S_{\mathrm{o}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right),$$

$$r_{\mathrm{H,G}}^{\mathrm{anoxic}} = \mu_{\mathrm{H}} X_{\mathrm{BH}} \left(\frac{S_{\mathrm{s}}}{K_{\mathrm{s}} + S_{\mathrm{s}}}\right)\eta_{\mathrm{g}}\left(\frac{K_{\mathrm{OH}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right)\left(\frac{S_{\mathrm{NO}}}{K_{\mathrm{NO}} + S_{\mathrm{NO}}}\right),$$

$$r_{\mathrm{NH}} = k_{\mathrm{a}} S_{\mathrm{ND}} X_{\mathrm{BH}} \times \left[\left(\frac{S_{\mathrm{o}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right) + \eta_{\mathrm{g}}\left(\frac{K_{\mathrm{OH}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right)\left(\frac{S_{\mathrm{NO}}}{K_{\mathrm{NO}} + S_{\mathrm{NO}}}\right)\right],$$

$$r_{\mathrm{h}} = k_{\mathrm{h}} \frac{X_{\mathrm{s}}/X_{\mathrm{BH}}}{K_X + (X_{\mathrm{s}}/X_{\mathrm{BH}})} X_{\mathrm{BH}} \times \left[\left(\frac{S_{\mathrm{o}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right) + \eta_{\mathrm{h}}\left(\frac{K_{\mathrm{OH}}}{K_{\mathrm{OH}} + S_{\mathrm{o}}}\right)\left(\frac{S_{\mathrm{NO}}}{K_{\mathrm{NO}} + S_{\mathrm{NO}}}\right)\right].$$

The dynamics of DO (S_{o}) in the reactor is described by the non-linear differential equation [14]:

$$\frac{\mathrm{d}S_{\mathrm{o}}}{\mathrm{d}t} = \frac{F}{V_{\mathrm{f}}}(S_{\mathrm{o,f}} - S_{\mathrm{o}}) - \frac{1 - Y_{\mathrm{H}}}{Y_{\mathrm{H}}} r_{\mathrm{H,G}}^{\mathrm{aerobic}} - \frac{4.57 - Y_{\mathrm{A}}}{Y_{\mathrm{A}}} r_{\mathrm{A,G}} + k_{\mathrm{L}} a(Q_{\mathrm{air}}(t))(S_{\mathrm{o,sat}} - S_{\mathrm{o}}(t)). \tag{7}$$

The function $k_{\mathrm{L}}\,a(Q_{\mathrm{air}}\,(t))$ describes the oxygen transfer and depends on the aeration actuating system and sludge conditions. It is assumed to be linear [14]; given by the following equation:

$$k_{\mathrm{L}} a(Q_{\mathrm{air}}(t)) = a\left(1 - e^{-\frac{qA(t)}{b}}\right). \tag{8}$$

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

Control variable selection

The biological nitrification, denitrification, and phosphorus removal processes are strongly dependent on the concentration of DO in the aerobic reactor. In particular, while the nitrification and phosphorus removal processes are aided by higher concentrations, for the denitrification process an opposite influence is found. It is therefore clear that the strategy in the choice of the DO set point, which considers the actual dynamics of the above processes, can help in assuring suitable conditions for their correct development.

It is well known that control of DO within the aerobic reactor is important not only because it affects the behavior of organic nutrients such as nitrogen and phosphorus but also characteristics of flocs and sludge sedimentation. Ref. [24] observed that DO profiles in channeled-type aerators could give indications of the rate of carbonaceous substrate removal, nitrification as well as sludge sedimentation characteristics. Another important incentive for controlling the DO concentration is that if it is possible to control the DO set points along the channeled-type aerobic reactor, a significant amount of air and hence energy could be saved, rather than maintaining a constant airflow rate throughout the reactor. The airflow rate introduced into the aerobic reactor can often be independently adjusted by manip-

Table 1 System characteristics, kinetic, and stoichiometric parameters used in SBR model [19, 22, 23]

No	Parameter	Value	Units
1	Heterotrophic yield coefficient: Y_{H}	0.67	Dimensionless
2	Heterotrophic growth rate: μ_{H}	0.25	h^{-1}
3	Heterotrophic decay rate: b_{H}	0.0258	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}	0.0333	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}	0.0063	h^{-1}
14	Biomass nitrogen factor: i_{xb}	0.086	mgN (mg COD)$^{-}$
15	Particulate nitrogen factor: i_{xp}	0.060	mgN (mg COD)$^{-1}$
16	Saturated oxygen concentration: S_{Osat}	10	mg/l
17	$K_{\mathrm{L}}\ a$ value at infinite airflow rate: a	166	h^{-1}
18	$K_{\mathrm{L}}\ a$ exponent coefficient: b	16	m^3/min
19	Reactor volume: V_t	12,400	l
20	Initial volume: V_{o}	2,400	l
21	Fill time: t_{f}	0.5	h
22	Aerobic reaction time: t_{r}	3	h
23	Volumetric flow rate: F	20,000	1/h
24	Hydrolysis maximum rate: K_X	0.0013	h^{-1}
25	Ammonification rate: k_{a}	0.0033	mg (m^{-3} h^{-1})
26	Endogenous biomass fraction: f_{P}	0.080	Dimensionless

Table 2 Influent characteristics and initial conditions on sequencing batch reactor [19, 22, 23]

No	Parameter	Influent	Initial condition	Unit
1	Active heterotrophic biomass: X_{bH}	0.001	2240	mgCOD/l
2	Active autotrophic biomass: X_{bA}	0.001	560	mgCOD/l
3	Slowly biodegradable substrate: X_s	175	20	mgCOD/l
4	Readily biodegradable substrate: S_s	125	12	mgCOD/l
5	Nitrate and nitrite nitrogen: S_{NO}	1	0.01	mgN/l
6	Ammonium nitrogen: S_{NH}	30	0.6	mgN/l
7	Soluble biodegradable organic nitrogen: S_{ND}	5	0.4	mgN/l
8	Particulate biodegradable organic nitrogen: X_{ND}	5	3	mgN/l
9	Oxygen uptake rate: OUR	0	250	mg/l h
10	DO concentration: DO	6.8	0	mg/l
11	Airflow rate : q_A	0.65	0	m^3/h

ulating the airflow. Nevertheless, this control strategy alone cannot guarantee good removal of nutrients such as ammonia due to the highly interacting nature of the biological nitrogen removal activated sludge process. One way to circumvent this problem is to design a ''supervisory'' controller to adjust the DO set points of the DO profile controller such that outlet COD, S_{NH_4} and S_{NO_3} are controlled.

As mentioned above, since DO concentration is the main factor affecting the aerobic reactor (react period), its regulation is important. In this study, we used DO as a controlled variable by regulating the airflow rate. The performance of the controller was evaluated by observing the process responses through set-point tracking for the nominal value of DO at 0.004, 0.005, and 0.006 mg/l and disturbance rejection studies. The set point value is chosen as a compromise among the various values that would be more suitable in different operational conditions.

Design of neural networks model

Before the NN-based controllers can be applied, the procedure for obtaining the NN models, i.e., the forward and inverse models used in these strategies will have to be performed together with the method of training the controller. These steps will be discussed in the next few sections.

Forward modeling

The procedure of training a NN to represent the dynamics of the system is referred to as forward modeling. Forward modeling in this case refers to training the NN model to predict the plant output of DO concentration at the next instant of time($t+1$), i.e., $DO_{(t+1)}$. The architecture of forward NN model can be seen in Fig. 2.

The input to the network consists of present and one past value of the X_s ,S_s, S_{NOx-N}, $NH_4 - N$,S_{ND},DO variables. The desired network output is the $DO_{(t+1)}$ value. Those input and output values are fed into the network in the moving window approach.

From these training exercises, the NN architecture that has been produced is a 14-node input layer, 28-node hidden layer, and 1 output layer system. The activation function applied for the nodes is the sigmoidal function in both the hidden and output layer. The NN is trained by switching between the two training sets, generated by the open loop studies as mentioned in the previous section. Further, another set of data is generated to act as the validation data. The network is considered trained when it satisfies the performance criteria with an RMSE of less then 0.001 in all the three cases. The forward modeling results in the first training data and second training data are shown in Figs. 3 and 4, respectively.

The validation results for the forward model can be seen in Fig. 5. The results show that the NN model has been properly trained to predict the forward dynamics of the system. The final forward model obtained represents the model to be utilized in the IMC method later.

The integral absolute error (IAE) for the training and validation for forward model are listed in Table 3.

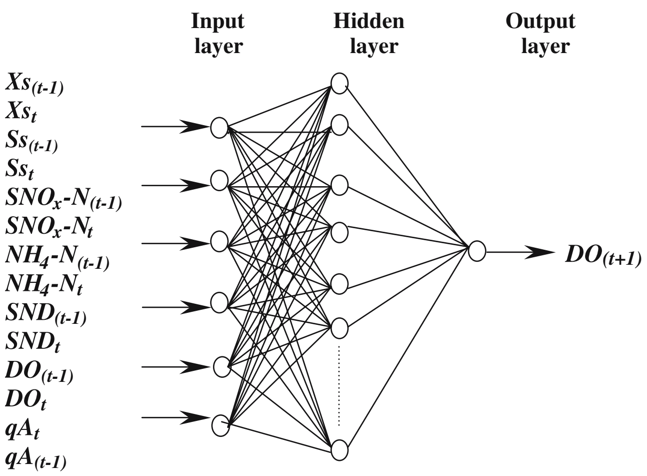


Fig. 2 The forward model architecture for sequencing batch reactor

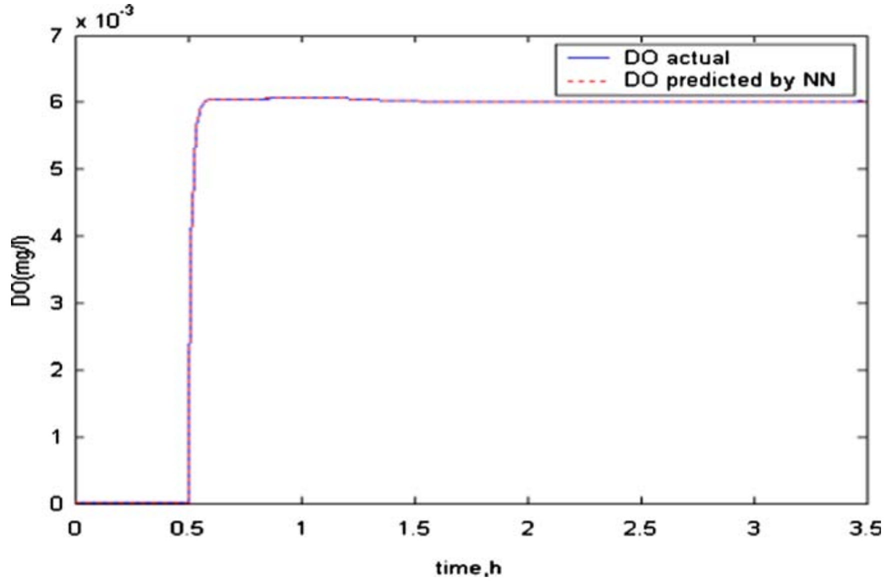


Fig. 3 Forward modeling of DO with first training data

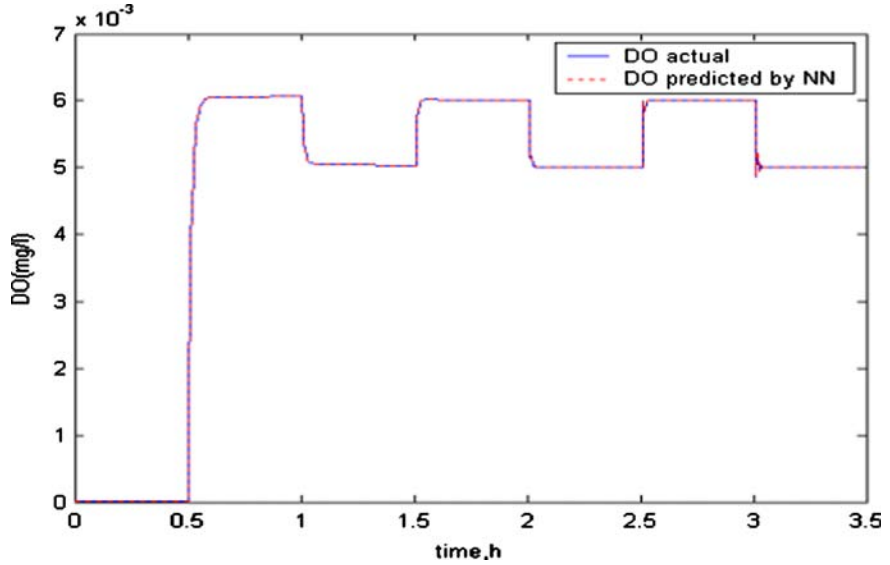


Fig. 4 Forward modeling of DO with second training data

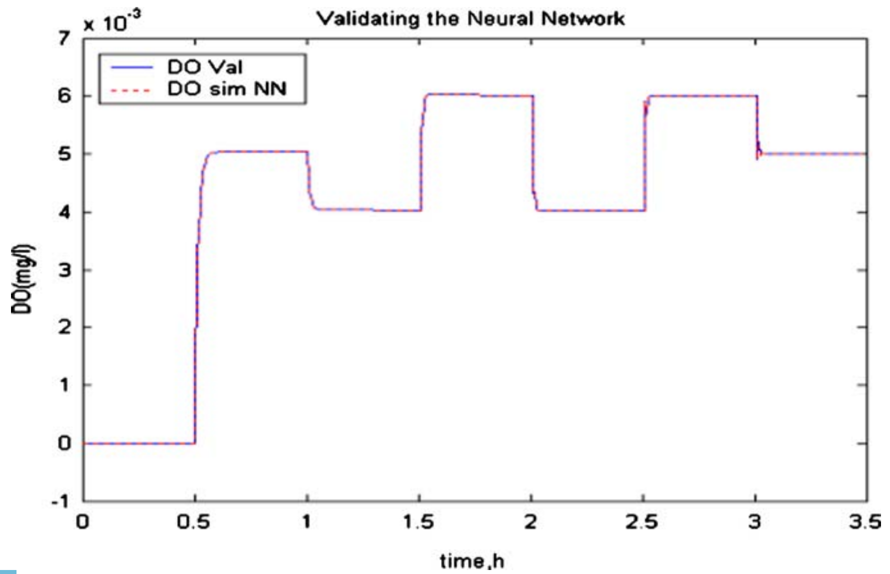


Fig. 5 Forward model of DO for validating data

Inverse modeling

Inverse modeling refers to the training of the NN in predicting the input to the plant given past data of the inputs and outputs together with the desired output. The inverse model is used directly as the controller within the feedback loop. Similar to the forward modeling methodology two training data sets were used, which were switched from one to the other during training to improve the identification process. Similar to the forward modeling, the two layered feed-forward network that has 14 input nodes, 24 hidden nodes, and 1 output node is used. The architecture of the inverse model can be seen in Fig. 6.

During training the network is fed with the required future value,$DO_{(t+1)}$, together with the present and past input and outputs similar to the forward model inputs to predict the current input or control action, $qA_{(t)}$ as seen in Fig. 6. The network architecture obtained for the inverse model is a 14 input, 24 hidden, and 1 output node systems. Figures 7 and 8 show the inverse using first and second training data.

Figure 9 shows the performance of the inverse model using the validation data. The results show that the NN has been adequately trained, with only slight offsets at certain values in order to predict the inverse dynamics of the system and hence ready to be used as a controller in the direct inverse model-based control strategy for the SBR system. The IAE for the training and validation studies are listed in Table 4.

Table 3 IAE for the training and validation for forward model

Training record	Training data 1	Training data 2	Validation data
Num of Epochs	1,000	1,000	–
IAE	5.8145e-020	2.9886e-022	5.9491e-026

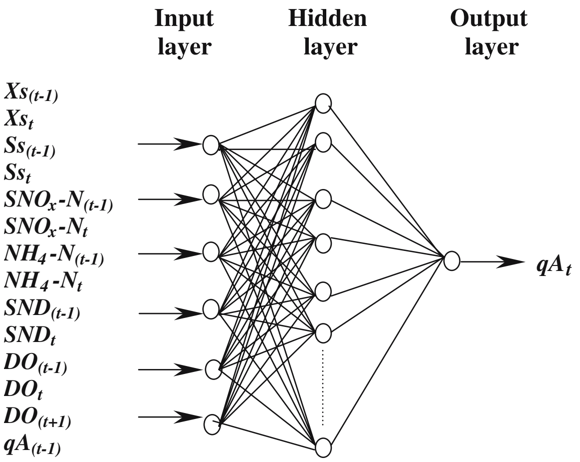


Fig. 6 The inverse model architecture for sequencing batch reactor

Neural network controller scheme

In this section, the performances of the various NN-based controllers are discussed. The performances of the controllers are investigated with studies under nominal operating condition for multiple set-point tracking under loading disturbance and noise. The disturbances considered in this study were generated through the changes in growth rate for nitrifiers (μ_A), which represent the internal disturbance. The variation in disturbance was generated by changing the growth rate of nitrifiers (from nominal value of 0.80/day). The varying values of the set point and disturbances are given in Table 5. The sampling time interval of 0.01 h is chosen in all these simulations.

Direct inverse neural network controller

In this strategy the basic direct inverse neural network (DINN) model is used as the controller for the process and utilized directly as an element within the feedback loop.

From Fig. 10, it can be seen that the inverse model acts as the controller and provides the current control action with respect to certain current and past values of the process variables. In this case, the NN model is trained to predict the required manipulated variable, i.e., airflow rate (q_A) and to bring the process to the set point, i.e., DO.

Figure 11 shows the process and controller response using this strategy for a multiple set-point tracking study under nominal operating condition.

It can be seen that aggressive control actions are observed during $t=0.5$ h until $t=3.5$ h. The performance of this controller is generally acceptable because the controller is successful to bring the process to follow the given set-point changes. But in the period around at $t=1$, 1.5, 2, 2.5, and 3 h, respectively, the controller over acts and caused the process response to deviate from the set point.

Figure 12 shows the process and controller response of this NN controller under disturbance and set-point changes simultaneously. The disturbance considered in this study was generated by changing the maximum specific growth rate for autotrophic biomass μ_A (nominal value of 0.8/day) by decreasing and increasing it by 25% from the nominal value as shown in Table 5.

From Fig. 12, we can see that the controller performs reasonably when responding to deviation but, it becomes sluggish when responding to large deviations in the process response and the controller does not reject the disturbance completely as noticed in the range $t=2$–2.05, $t=2.5$–2.55, and $t=3$–3.05 h, respectively. Generally, it can be concluded that the disturbances slightly affected the system under NN controller strategy with simultaneously set-point changes.

Figure 13 represents the controller's performance subject to the condition in which the measurement of the

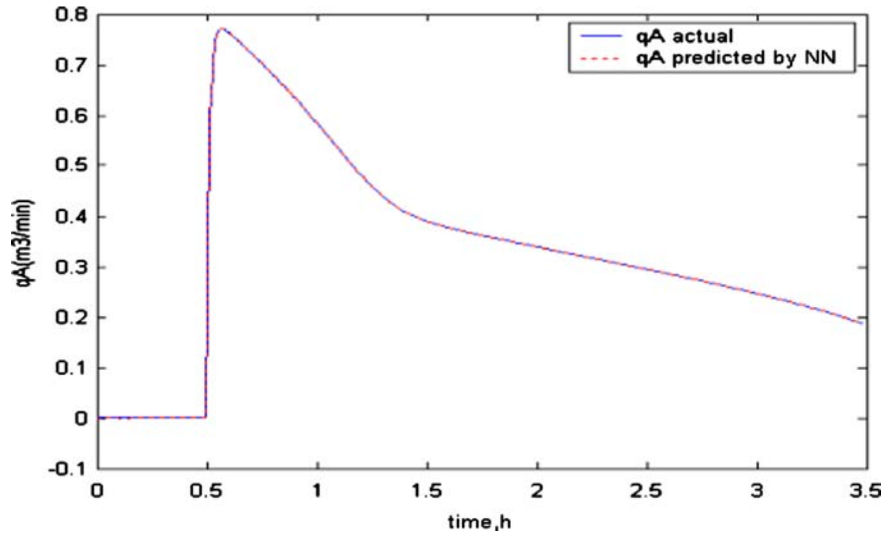


Fig. 7 Inverse modeling of airflow rate for first training data

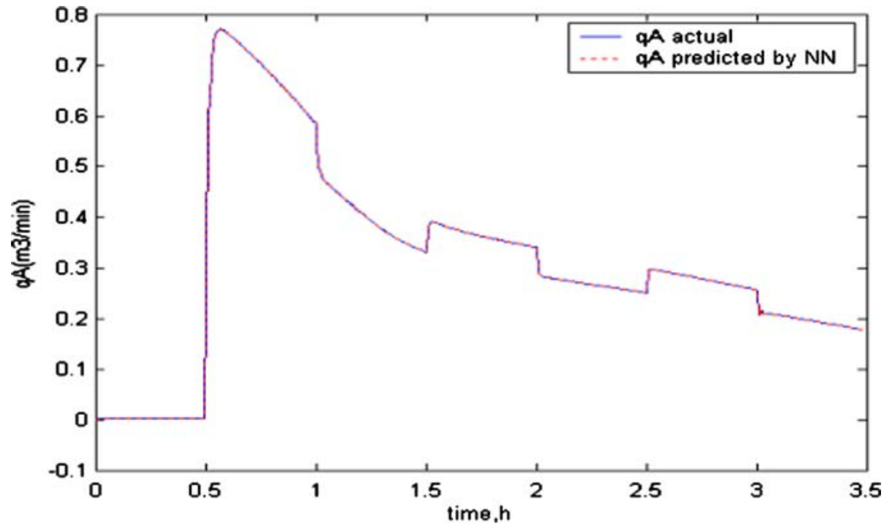


Fig. 8 Inverse modeling of airflow rate for second training data

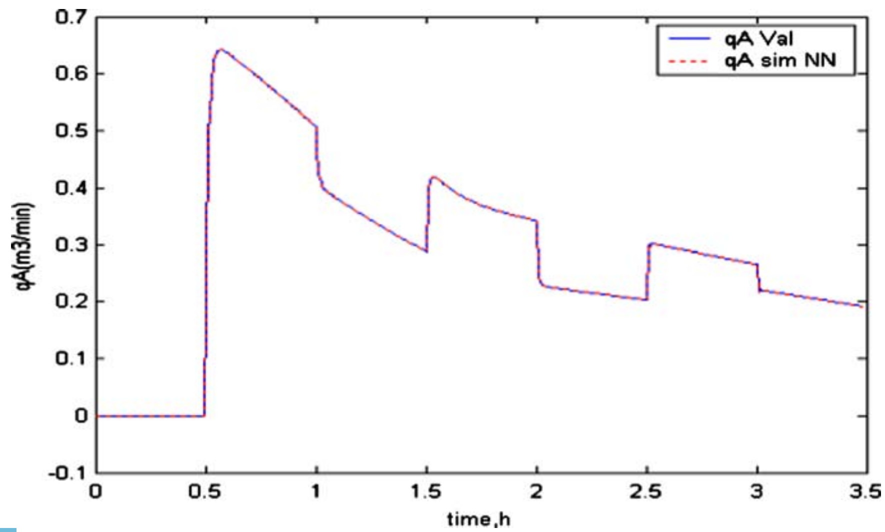


Fig. 9 Inverse model of DO for validating data

Table 4 IAE for the training and validation for inverse model

Training record	Training data 1	Training data 2	Validation data
Num of Epochs	1,000	1,000	–
IAE	3.0193e-015	2.5986e-016	4.8335e-016

Table 5 Operating values of process variables, disturbances and set-point change used in the controller performance in the controller investigation

No	Periods (h)	Set-point (DO)	Disturbances (μ_A)
1	0.5–1.0h	0.005	1.00
2	1.0–1.5	0.004	0.60
3	1.5–2.0	0.006	1.00
4	2.0–2.5	0.004	0.60
5	2.5–3.0	0.006	1.00
6	3.0–3.5	0.005	0.60

controlled variable is corrupted by 10% noises. From this figure, it can be seen that, although the changes in set point can be tracked and the disturbances can be rejected, the controller action is affected by the noises as significant fluctuations.

It can be also noticed in the above-mentioned figure, in spite of disturbance and noisy measurement to the process, the controller is also capable of following the time varying characteristic of the process response and able to track the set-point changes. However, the disadvantage exhibited by this controller is that the adaptation action works slowly so that the rise time or settling time of the process response is long and these capabilities do not cover a wide control range. In view of the disadvantages observed above, other types of NN controller, such as the IMC and hybrid neural network (HNN) will be utilized to improve its performance especially for handling disturbances, noisy measurement, and delay problems.

Internal model control scheme

In the IMC strategy, both the forward and inverse models are used directly as elements within the feedback loop. The network inverse model is utilized in the control strategy, acting as the controller, has to learn

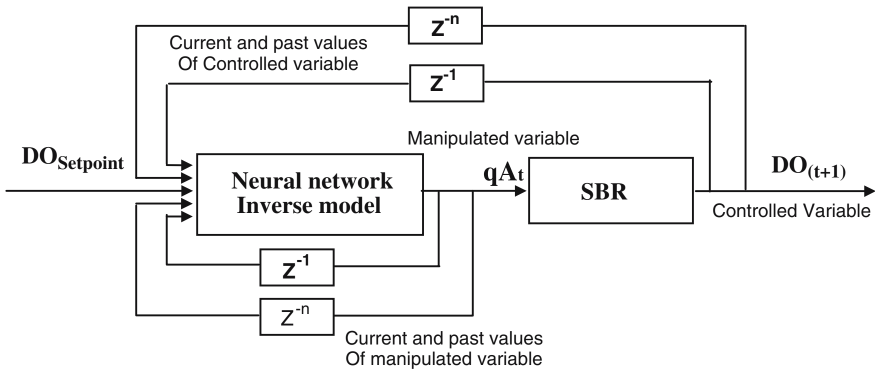


Fig. 10 Block diagrams for NN inverse-based model control strategy

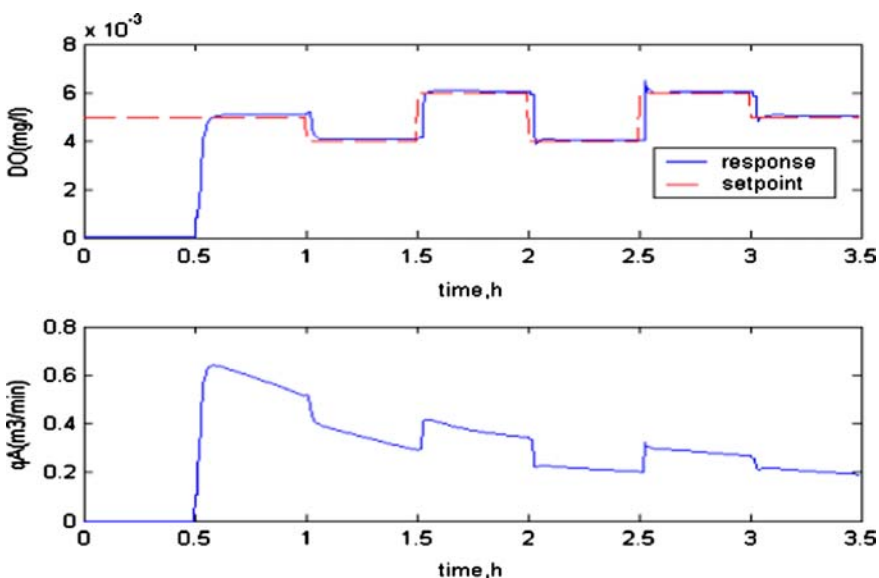


Fig. 11 Process and controller response of basic NN controller with nominal operating condition for multiple set-point tracking study

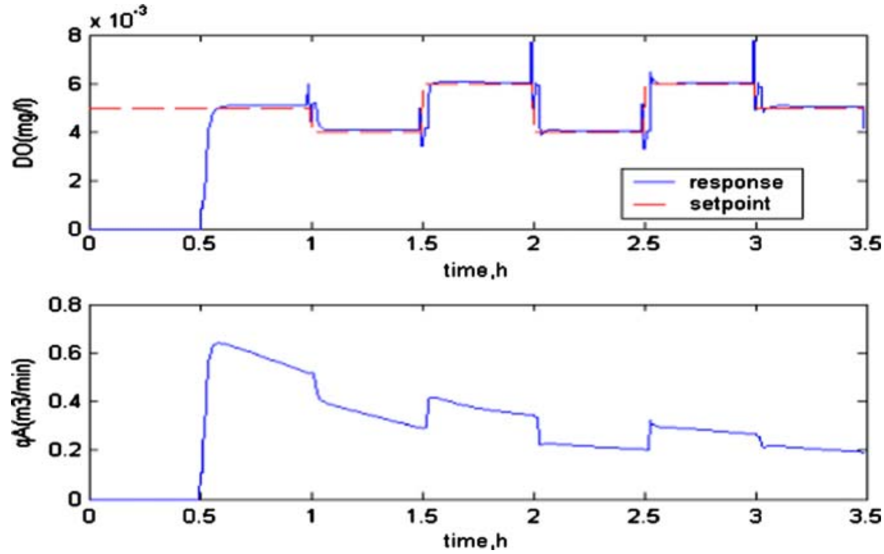


Fig. 12 Process and controller response of basic NN controller for multiple set-points tracking in dealing with disturbance rejection study

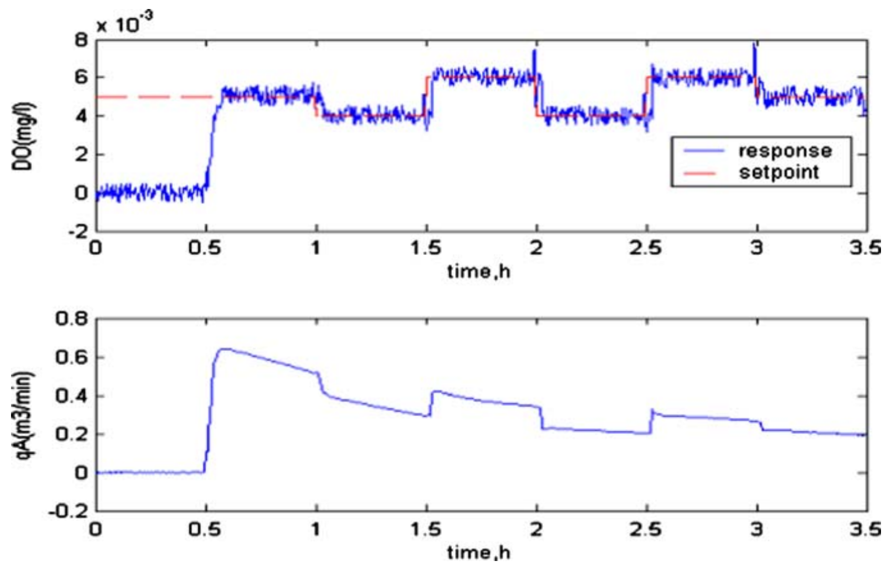


Fig. 13 Process and controller response of basic NN controller for multiple set-points tracking in dealing with disturbance rejection study and measurement noise

to supply at its output, the appropriate control parameter, qA_t for the desired targets, DO_{Sp} at its input. The NN forward model is applied in parallel to compare with the process model and the error between the plant output and the neural net forward model is subtracted from the set point before being feedback into the inverse model. The schematic of the IMC is illustrated in Fig. 14.

Figure 15 shows the result of the simulation with the IMC in dealing with the tracking of the set-point changes under nominal operating condition. It can be seen that quite sluggish control actions are observed from $t=0.5$ h until $t=3.5$ h. However, the performance of this controller is generally acceptable because the controller is able to keep the process at its set point with only small offsets and oscillations.

Figure 16 shows the process and controller response in dealing with disturbances. The disturbance considered in this study was generated by changing the maximum specific growth rate for autotrophic biomass μ_A with nominal value of 0.8 (1/day) by decreasing and increasing it by 25% from the nominal value.

From the figure, it can be seen that the controller performs quite reasonably in rejecting the disturbances. However, sluggish control actions occur to some extent in range $t=2$–2.05, $t=2.5$–2.55, and $t=3$–3.05 h, respectively. Generally, it can be concluded that the disturbances affected the system under IMC more than the basic NN inverse model controller.

Figure 17 represents the process and controller performance for multiple set-point tracking study in which the measurement of the controlled variable is corrupted

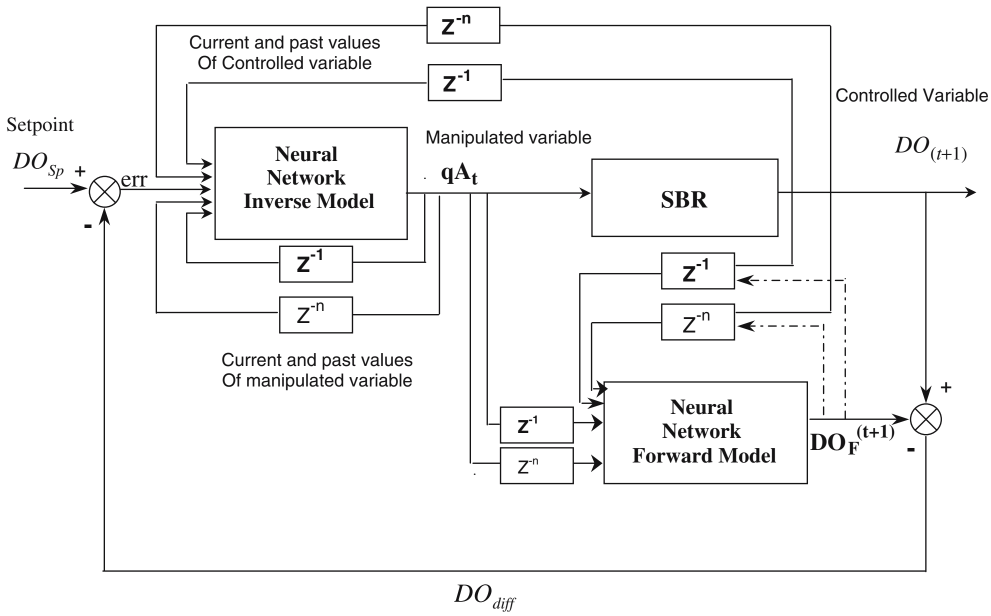


Fig. 14 Block diagrams for IMC system of NN controller

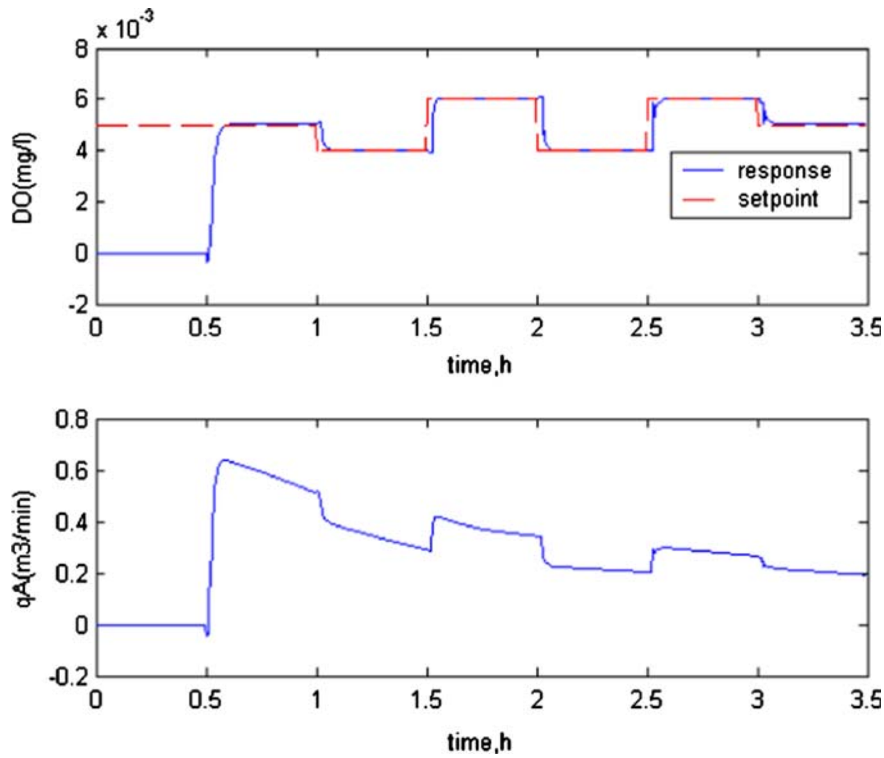


Fig. 15 Process and controller response of IMC for nominal operating condition

by 10% noises. From this figure, it can be seen that the controller can prevent its control action from fluctuation due to the noises.

Hybrid neural network controller scheme

This study focuses on the development of a hybrid NN technique as a controller of activated sludge process in a SBR. The hybrid scheme consists of a basic NN controller in parallel with a proportional integral (PI) controller. The schematic of the hybrid controller is illustrated in Fig. 18.

The actual control action in this control system is the combination of the two controllers. Here, the role of the PI controller is to compensate for the possible sluggish control action resulting from the basic NN controller. The control law for the PI controller can be expressed as:

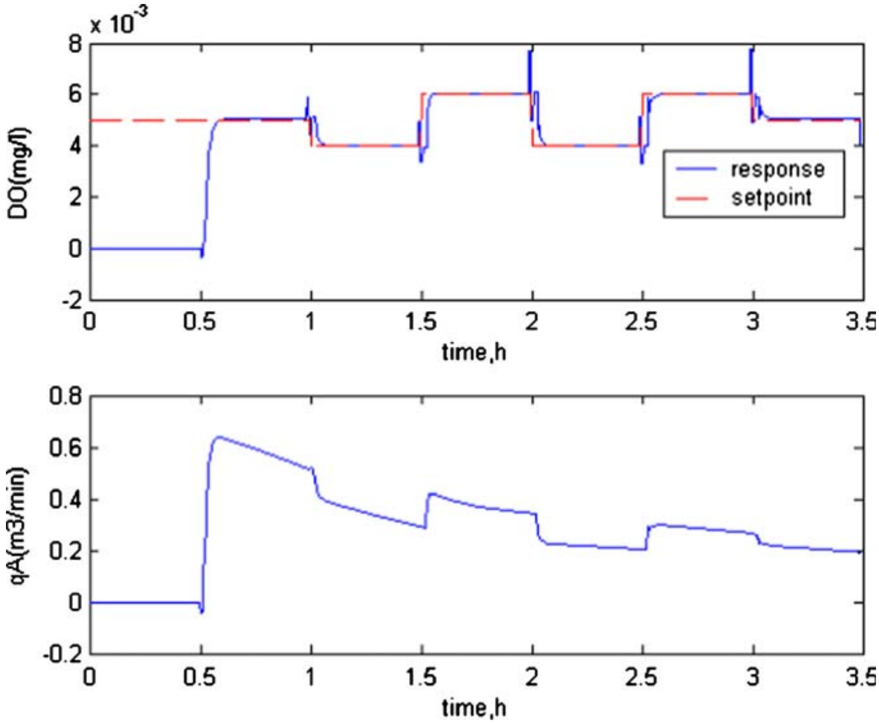


Fig. 16 Process and controller response of IMC for multiple set-points tracking with disturbance rejection study

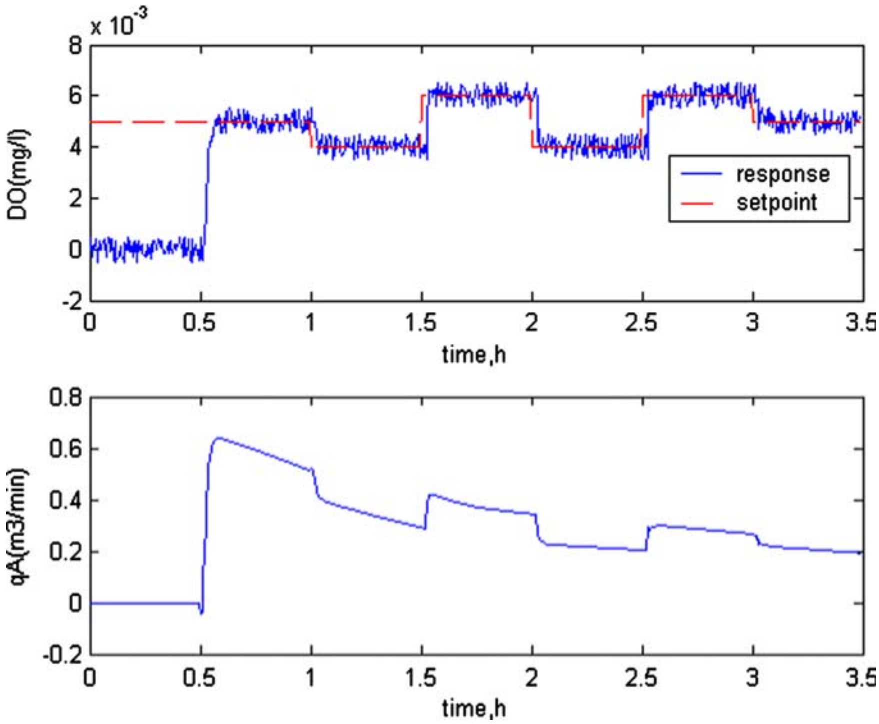


Fig. 17 Process and controller response of IMC for multiple set-point tracking study with measurement noise

$$u(t) = k_\mathrm{c}\left(e(t) + \frac{1}{k_\mathrm{I}}\int_0^t e(t)\mathrm{d}t\right) + u_\mathrm{s}, \tag{9}$$

where u_s is the value of the output signal when $e(t) = 0$. In digital control implementation, the formula is given in discrete form and expressed as follows:

$$\Delta u_t = k_\mathrm{c}\left(e_t + \frac{\Delta t}{k_I}\sum_{i=1}^{t} e_i\right), \tag{10}$$

where

$$u_{t+1} = u_t + \Delta u_t, \tag{11}$$

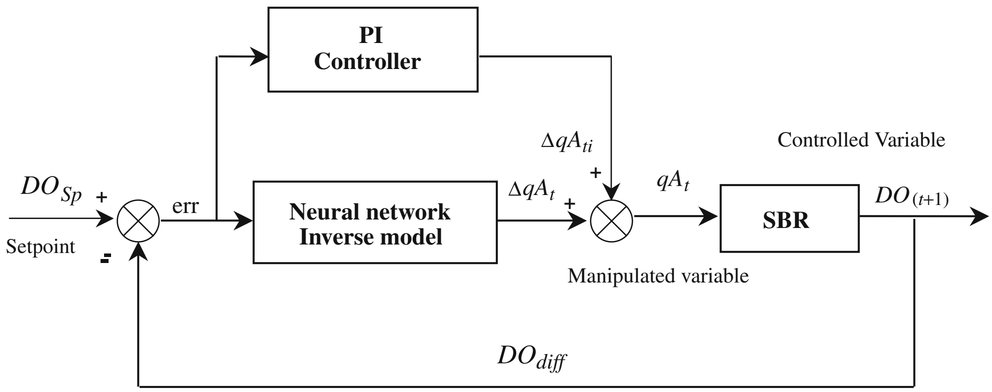


Fig. 18 Block diagrams for hybrid control system of NN controller combination with PI controller

$$e_t = y_{sp} - y_t, \tag{12}$$

where subscripts t and $t-1$ denote the sampling time; t stands for the current time sampling and $t-1$ stands for the sampling at the previous time.

By considering airflow rate (qA) as the control output and DO as the controlled variable, the control law can be written as:

$$\Delta qA_{t+1} = k_c\left(e_t - e_{t-1} + \frac{\Delta t}{k_I} e_t\right), \tag{13}$$

$$qA_{t+1} = qA_t + \Delta qA_{t+1}, \tag{14}$$

$$e_t = (\mathrm{DO}_{sp} - \mathrm{DO}_t), \tag{15}$$

where k_c and k_I are proportional and integral constants, respectively. In the implementation, the values of k_c and k_I, above were scheduled according to linear segments based on variable airflow rate.

The control law of this hybrid controller is formulated as follows:

$$qA_{(t+1)} = qA_t + \Delta qA^{PI}_{(t+1)} + \Delta qA^{NN}_{(t+1)}, \tag{16}$$

where $\Delta qA^{PI}_{(t+1)}$ is the output of PI controller and $\Delta qA^{NN}_{(t+1)}$ is the output of the basic NN controller.

Figure 19 shows the result of the controller performed for the hybrid NN controller. The figure shows the performance of the controller response in dealing with the tracking of the set-point changes under nominal operating condition. It can be seen that control actions smooth are observed during $t = 0.5$ h until $t = 3.5$ h.

Figure 19 shows that the controller performs successfully where the controlled variable can be maintained at its set-point changes without overshoot and significant offset. The controller is able to bring the process to follow the given set-point changes and it is successful in rejecting the disturbances to the process. From Fig. 19, it can be concluded that considerable improvement is achieved by HNN control scheme over the basic NN scheme.

The study of set-point change-tracking performance of HNN controller for disturbance rejection is shown in Fig. 20. The figure shows that the performance of the controller is excellent and the set-point changes can be tracked. Although in the HNN controller some overshoot occurs it is still lesser than in the basic NN

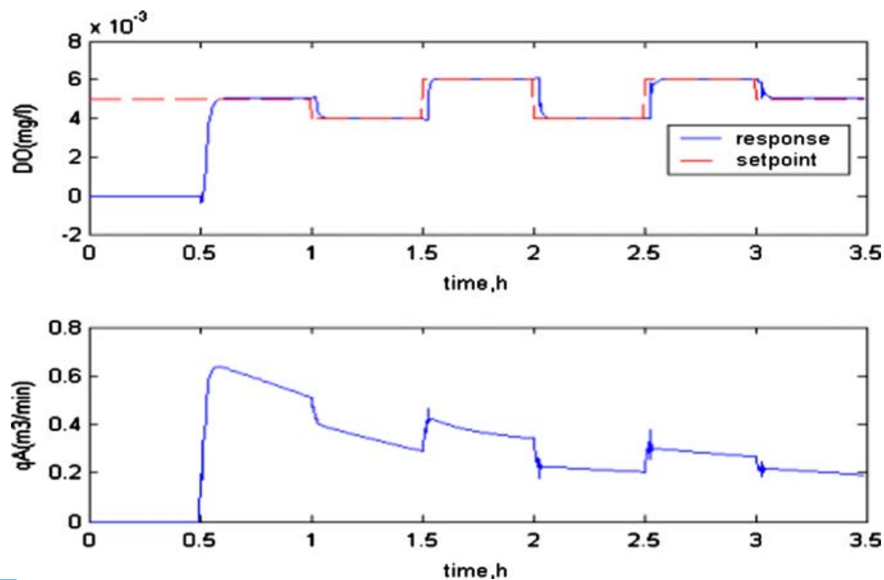


Fig. 19 Process and controller response of set-point tracking performance for HNN controller with nominal operating condition

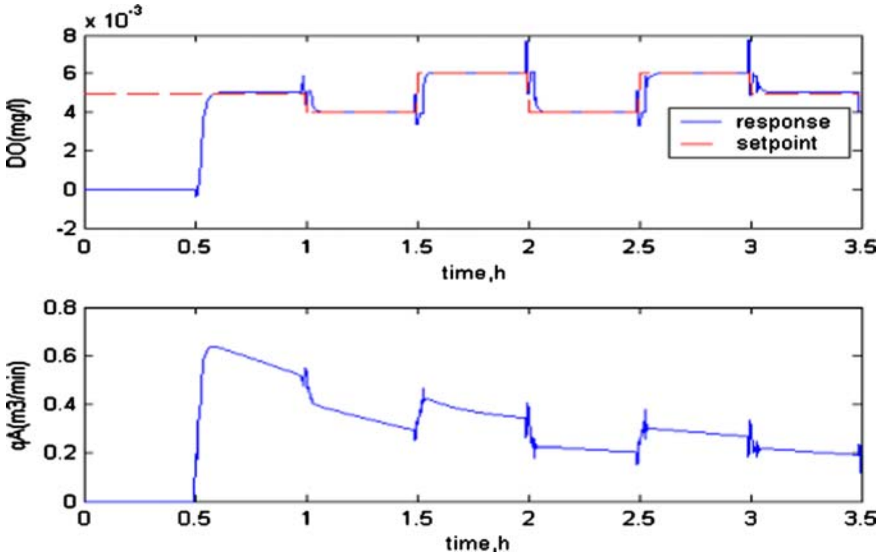


Fig. 20 Process and controller response of set-point tracking performance for HNN controller with disturbance rejection study

controller and in the IMC method. The HNN controller results give relatively fast response so that the rise time can be attained shortly. It can also be seen that considerable improvement in reducing the offsets is achieved by this control scheme over the basic NN controller.

The performance of HNN controller in dealing with the condition as corrupted by 10% noises in the process can be seen in Fig. 21.

From the above-mentioned figure, it can be seen that the controller exhibits satisfactory performance. The controller is not affected by the noises and can ensure reasonable set-point change-tracking study with quite smooth control action.

The ability of the HNN controllers in dealing with the condition where internal disturbance with 10% measurement noises occurs simultaneously can be seen in Fig. 22.

The performance of this hybrid controller is again better than that of the basic NN controller. From all the results above, it can be concluded that significant improvement is achieved by utilizing this control scheme, especially in terms of control precision. The incorporation of the PI controller in this hybrid control scheme ensures the suppression of oscillation as it works around the process set point. As can be seen in Table 6, the average integral absolute errors resulting from this controller are smaller compared with basic NN controllers and the IMC.

Conclusion and summary of work

In this work, NN-based controller for DO concentration in a SBR have been studied. The SBR system is a highly non-linear system with a need to control the oxygen intake accurately. The controller performance to control the DO was evaluated through set point and disturbance rejection studies. In order to use DO profile as the

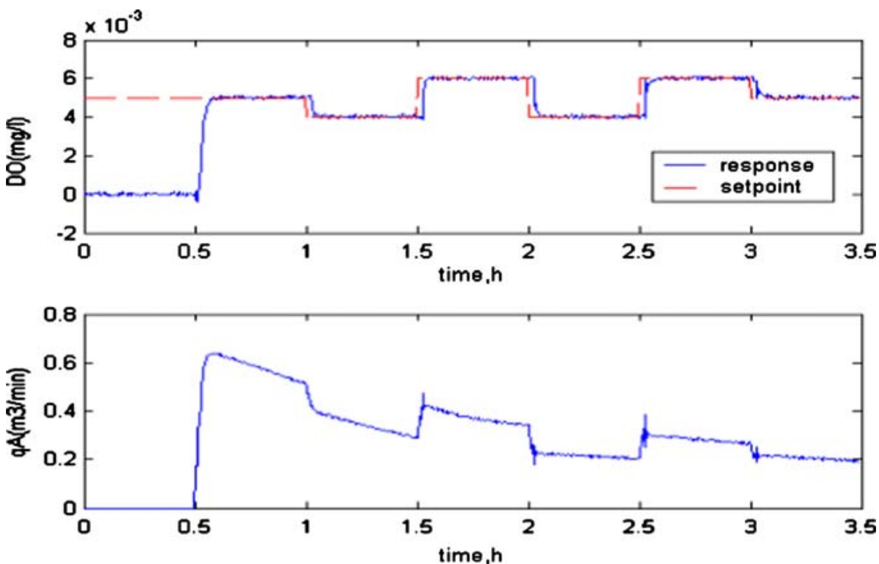


Fig. 21 Process and controller response of set-point tracking performance for HNN controller with measurement noise

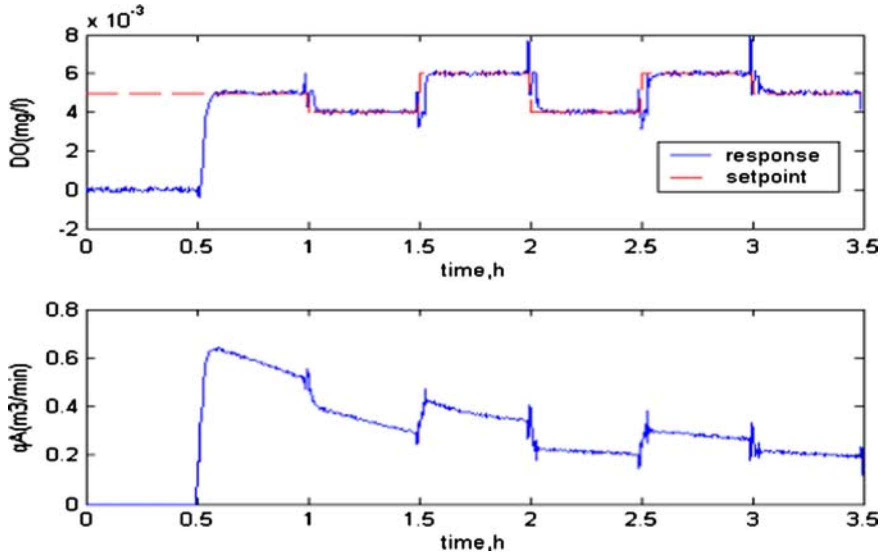


Fig. 22 Process and controller response of set-point tracking performance for HNN controller with disturbance rejection study and measurement noise

Table 6 The comparison of IAE for controller response under BNN, IMC, and HNN controller for multiple set-point tracking study

Multiple set-point tracking study	IAE		
	Basic NN controller	IMC	HNN controller
Nominal condition	1.6813e-007	2.4393e-008	4.0180e-010
Disturbance rejection	2.2802e-005	1.2074e-006	2.1030e-007
Noise measurement	1.0633e-006	2.2599e-007	4.2064e-008
Disturbance rejection and noise measurement	1.3002e-005	1.0822e-006	1.0868e-007

control variable, a more complex ASM1 [20] model was simulated. Simulation with different oxygen profiles showed that the DO level could be effectively as a control variable to optimize the processes, i.e., to achieve the desired COD and nitrogen reduction at the end of react period.

The controller was evaluated through process and controller response of the DINN controller, IMC, and HNN controller for nominal operating condition and disturbance rejection study. In the evaluation and performance of the DINN controller for constant and multiple set-point tracking study, it can be concluded that the controller was fairly acceptable in controlling the DO concentration but with some offsets persisting. In the case of disturbance and noisy measurement to the process, the controller can prevent the process from fluctuating and in turn, a slightly smoother process can be achieved. However, the disadvantage exhibited by this controller is that the adaptation action works slowly so that the rise time or settling time of the process response is long.

The controller performance of IMC for constant and multiple set-point tracking under disturbances rejection and process corrupted by noise simultaneously has also been studied. The process can still be maintained around its set point and only small oscillations and offset are observed in the process response. The controller is capable of following the time-varying characteristic of the process and seems capable of dealing with the process non-linearity as indicated by its ability in linear set-point study. However, these capabilities do not cover a wide control range.

In the study of constant and multiple set-point tracking performance using the HNN controller under disturbances, it can be concluded that the performance of the controller is excellent. Although in the HNN controller some overshoot occurs but however, compared to the DINN and IMC schemes, the performance of the HNN controller is much better. The HNN controller also results in fast response with rise time and offsets being minimal in the process response. The performance of HNN controller in dealing with disturbances and process corrupted by noise simultaneously shows very satisfactory performance. The controller is slightly affected by the noises and can ensure reasonable set-point change-tracking study with smooth control action. Based on these results, the HNN controller scheme is recommended for controlling DO concentration in SBR.

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