A coupled pH and level control in pH process by data-driven based, input-output linearization

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ABSTRACT

A pH process is one of the essential units used in many industries for preparing substance to be under proper conditions before sending to consequent units. A highly nonlinear of pH characteristics, process disturbances, process condition, and interaction between control pairs create difficulty in developing a high-quality physical model for a controller development. In this work, a data-driven based control is presented to handle a coupled control of the pH and liquid level in the pH reactor. A real-time, estimation of the process data is implemented to provide robustness in empirical modeling. This developed model is used in a formulation of a discrete-time, input/output (I/O) linearizing controller. The proposed control method has a simple model structure and controller equations that are suitable for a control application. The proposed control method is embedded in myRIO, and its performance is evaluated and compared with the PI controller through the servo test with a bench-scale pH reactor in real-time. The experimental results showed that the proposed control method provides faster response and less overshoot in the outputs than the PI controller.

***Keywords**: Data-driven based modeling, pH control, real-time embedded control, input-output linearizing controller, multivariable control*

1 INTRODUCTION

A pH adjustment is one of the operations essentially required in many industries. For instance, pH of the effluent stream from wastewater treatment plant must be maintained within environmental limits [1], the product selectivity in an anaerobic acidosis strongly depends on the reactor pH [2], and a hydrogen gas can be recovered from a microbial fermentation of organic substrates at high concentrations, if the pH of the process is in a proper condition [3]. There are many advanced control techniques based on physical model had been proposed to handle pH control problems [4] – [7]. An adaptive nonlinear output feedback control strategy was experimentally evaluated to account for unmeasured buffering changes [4]. It was developed by combining an input-output linearizing controller, an open-loop nonlinear state observer, and a recursive least square parameter estimator with an assumption that reaction invariants are available. An adaptive nonlinear control based on fuzzy logic systems was also addressed, — the fuzzy logic system was employed as a parametric approximator of the model [5]. The method does not require composition measurement. An ANFIS (adaptive-network-based fuzzy inference system) was used to identify linear and nonlinear parameters of the adaptive model [6]. A multi-model IMC (internal model control) algorithm was implemented using several different linear models over the operating range [7]. The control techniques [4] – [7] require the physical model. However, it is difficult to develop a high-quality physical model due to a degradation of the physical model quality caused by a highly nonlinear of pH characteristics, unmeasured process disturbances, process condition and interaction between control pairs [8].

There are some studies of the control technique that do not require the physical model [9] – [13]. An 'intelligent' PID controllers (iPIDs) that tuning parameters automatically change based on statistical process information was proposed [9]. The statistical information is then used to produce an ultra-local model that is updated in real time. A data-driven model-free adaptive control (MFAC) approach is used to control a class of multi-input multi-output nonlinear discrete-time system. A feature of this approach is that the controller depends only on the measured input and output process data [10]. The methods [9] – [10] are a simulation study, not focused on a pH process. Chen and colleagues [11] presented a study simulation of a combined method of fuzzy control, and sliding mode control applied to a pH neutralization process. The sliding mode reduces the input numbers of the fuzzy controller. It makes the combined method simpler, and it could reduce a computational load of the controller calculation. A neural network PID controller was also evaluated with the pH process simulation [12]. The control system includes two parts: a neural network identifier and a signal neuron PID controller. The VRFT (virtual reference feedback tuning) method translates the model reference control problem into an identification problem [13]. The experimental results showed a high oscillation in the setpoint tracking test if the sampling frequency is low.

In this work, a data-driven based control is presented to handle a coupled control of the pH and liquid level in the pH reactor. A real-time, estimation of the process data is implemented to provide robustness in empirical modeling. This developed model is used in a formulation of a discrete-time, input/output (I/O) linearizing controller. The proposed control method is suitable for a real-time control application because it has a simple in both model structure and controller equations. The control algorithm is embedded in myRIO, and its performance is evaluated and compared with the PI controller through the servo test with a bench-scale pH reactor in real-time.

2 PROCESS DESCRIPTION OF THE pH REACTOR

A schematic of the pH reactor is illustrated in Fig. 1. The process is composed of a continuous stirred tank reactor, which is a glass vessel of 19 cm in diameter and 50 cm in height. The pH and liquid level in the reactor are regulated by sodium hydroxide (NaOH) and feed flows, respectively. Peristaltic pumps are used to adjust the flow rate of both streams. The reactor pH is measured by a pH sensor installed at the outlet stream, while the liquid level is measured by an ultrasonic sensor installed at the top of the reactor. Measuring data from pH and ultrasonic sensors are used by a developed input-output linearizing controller embedded in NI myRIO-1900 (the National Instrument). The NI myRIO then transmits electrical currents to the NaOH and feed pumps for adjusting the pH and level to the desired setpoints.

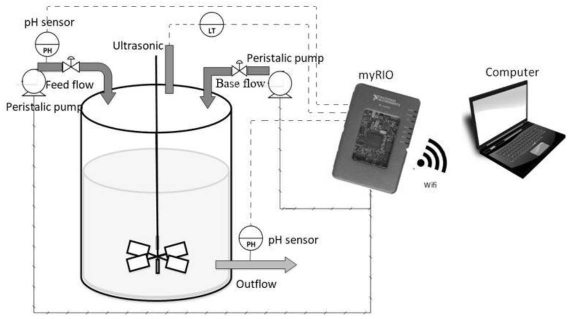

Fig. 1 *Schematic of the pH Reactor*

3 DATA-DRIVEN MODELING FOR DISCRETE-TIME pH PROCESS

In this section, details of the data-driven modeling of the pH process are discussed. The control objective is to handle the liquid level and pH of the reactor (y_1=pH, y_2=h) by adjusting the flows of sodium hydroxide ($u_1=F_B$) and the feed flow ($u_2=F_W$) respectively. The following descriptions are used for developing the data-driven based model.

Consider the following discrete-time system:

$$y_i(k+1)=f_{y,i}(y_i(k),...,y_i(k-n_y),u_i(k),...,u_i(k-n_u)) \\ +f_{\phi,i}(\phi_i(k),...,\phi_i(k-n_\phi),t) \quad i=1,2 \tag{1}$$

where y_i is the i^{th} controlled output, u_i is the i^{th} input, $f_{y,i}$ is a nonlinear function of the i^{th} output, $f_{\phi,i}$ is a function of error between observed and predicted values of the i^{th} controlled output, ϕ_i is an error between observed and predicted values of the i^{th} controlled output, and n_y, n_u, and n_ϕ are the lags of output, input and error variables, respectively. The relation between input and output differences is represented by

$$\Delta y(k+1)=j_y(k)\Delta u(k) \tag{2}$$

where $j_y(k)$ is a matrix of gains between input-output pairs. The matrix $j_y(k)$ is updated in every time interval by regressing a dataset of input and output with eq (3). The equation of the matrix of gain can be expressed by

$$j_y(k)_{1\times1}=([\Delta u]^T_{n_u\times1}[\Delta u]_{n_u\times1})^{-1}([\Delta u]^T_{n_u\times1}[\Delta y]_{n_y\times1}) \quad (3)$$

Approximations of the controlled outputs inevitably have an error between the observed output and predicted output ($\phi(k)$) which is

$$\phi(k)=y_{observed}-y_{predicted} \quad (4)$$

The vector of error ($[\Delta\phi]_{n\times1}$) during the observed time is expressed by

$$[\Delta\phi]_{n\times1}=[\Delta t]_{n\times1}\, j_\phi(k)_{1\times1} \quad (5)$$

where $j_\phi(k)$ is an error gain. An equation of an error gain can be written in a form eq (6)

$$[j_\phi(k)]_{1\times1}=\left([\Delta t]^T_{n\times1}[\Delta t]_{n\times1}\right)^{-1}\left([\Delta t]^T_{n\times1}[\Delta\phi]_{n\times1}\right) \quad (6)$$

We can predict the error between observed output and predicted output by

$$\tilde{\phi}(k+1)=j_\phi(k)\Delta t+\phi(k) \quad (7)$$

where $\tilde{\phi}(k+1)$ is a predicted error, and Δt is a step time. In this work, Δt is equal to one second. Therefore, an equation of the predicted output ($\tilde{y}$) can be written as

$$\tilde{y}(k+1)=y(k)+j_y(k)\Delta u(k)+j_\phi(k)\Delta t+\phi(k) \quad (8)$$

4 CONTROL SYSTEM DESIGN

The empirical model that is obtained from a data-driven technique and the input-output linearizing controller is used to develop the control strategy. The input-output linearizing controller in discrete time formulation is presented by

$$\beta_i\frac{\tilde{y}_i(k+1)-y_i(k)}{\Delta t}+y_i(k)=v_i(k) \quad (9)$$

where β_i is a tuning parameter of the input-output controller, and $v_i(k)$ is a compensated setpoint. Combining the input-output linearizing controller with the empirical model in eq (8), the control action can be formulated as follows

$$u_i(k+1)=\frac{(v_i(k)-y_i(k))\frac{\Delta t}{\beta_i}-\tilde{\phi}_i(k+1))}{j_{y,i}(k)}+u_i(k) \quad (10)$$

By substituting variables of the studied bench-scale pH process, Therefore, the flow rate of sodium hydroxide ($u_1=F_B$) and the feed flow ($u_2=F_W$) are showed by

$$u_1(k+1)=\frac{(v_1(k)-y_1(k))\frac{\Delta t}{\beta_1}-\tilde{\phi}_1(k+1))}{j_{y,1}(k)}+u_1(k)$$
$$u_2(k+1)=\frac{(v_2(k)-y_2(k))\frac{\Delta t}{\beta_2}-\tilde{\phi}_2(k+1))}{j_{y,2}(k)}+u_2(k) \quad (11)$$
$$v_1(k)=y_{1,sp}(k)-(y_1(k)-\tilde{y}_1(k))$$
$$v_2(k)=y_{2,sp}(k)-(y_2(k)-\tilde{y}_2(k))$$

Since the data-driven model is sensitive to noises of the process, a moving average filter in eq (12) is used to reduce the chattering effect in the process

$$u_i(k+1)=\alpha(u_i(k))+(1-\alpha)u_i(k+1) \quad (12)$$

where α is a weighting factor of the weighted moving average.
A schematic diagram of the proposed control system is illustrated in Fig. 2

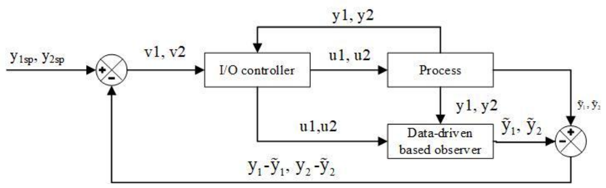

Fig. 2 *Schematic of the Proposed Control System*

5 RESULT AND DISCUSSION

5.1 Model Validation

The empirical model of the bench-scale pH reactor in eq (8) is used to predict the controlled output. Fig. 3 shows a comparison between the output predicted by the physical model and the output predicted by the empirical model in eq (8) under the variation in the flow rates of sodium hydroxide and the feed streams. The lag parameters (n_y , n_u , and n_ϕ) are set to be equal to ten. The predicted data by the empirical model provides a good agreement to the physical model for both the liquid level and pH. The integral square error (ISE) of liquid level and pH are 3.18e-06 and 0.0197 respectively. Mismatches between the empirical model and the physical model of the process are relatively small.

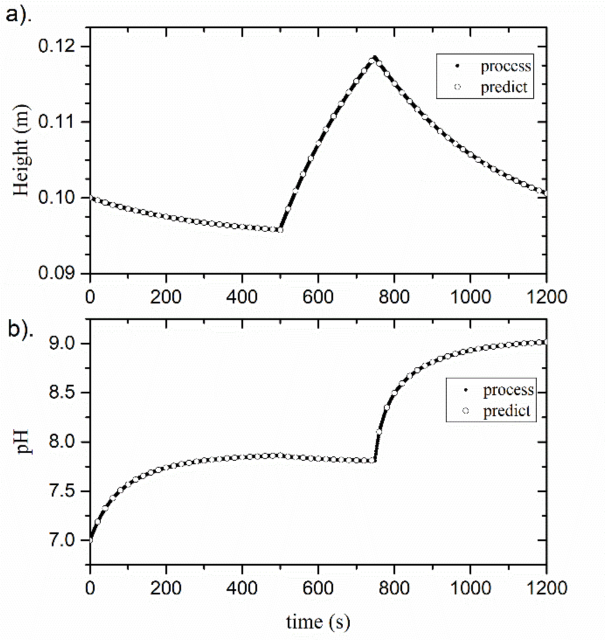

***Fig. 3** The Controlled Output From the Data-driven Model and the Physical Model of the Process*

5.2 Setpoint Tracking Performance

The proposed control method is embedded in the myRIO, and its performance is evaluated and compared with the PI controller through the servo test in the bench-scale pH reactor. An initial condition and tuning parameters of the PI controller input-output linearizing controller are shown in Table 1. Tuning parameters of the I/O linearizing controller (β) and the PI controller (K_c and τ_i) are obtained from trial-and-error and the internal model tuning rule [14], respectively. The servo test is implemented by tracking two desired setpoints: setpoint 1 ($y_{1,sp}$ = 9.7, $y_{2,sp}$ = 14 cm) at the start, setpoint 2 ($y_{1,sp}$ = 10, $y_{2,sp}$ = 18 cm) at 700 seconds. The results are illustrated in Fig. 4. Both the proposed control method and the PI controller can force the liquid level and pH to track desired setpoints. Tables 2 and 3 show the performance of the proposed control method and the PI controller for various indexes. The results show that the proposed method has lower rise time, lower settling time, and lower percentage of overshoot value of the pH and liquid level compared with the PI controller except for the rise time of second step change in height, the rise time of PI controller is lower than the proposed method. Also, the integral square error (ISE) of the whole considered time of the proposed method is lower than the PI controller for pH tracking. The ISE of the proposed method is higher than the PI controller for height tracking, since the initial height of the PI controller is closer to the second setpoint than the proposed method. However, the ISE of the proposed method and the PI controller, for the time after settling time are 0.0012 and 0.0081 respectively. Both pH and liquid level responses under both controllers slightly oscillate around the setpoint because both control methods are sensitive to noise of the process. Thus, the results show that the proposed method has better control performance than the PI controller for the servo test.

***Table 1** An Initial Condition and Tuning Parameters*

	Initial condition	Tuning parameter of PI controller	Tuning parameter of I/O controller
pH	7	Kc=1.0357e-4 and τ_i = 10	β_1 = 0.2
Liquid level	5 cm.	Kc=0.0357e-4 and τ_i = 20	β_2 = 0.6

***Table 2** Summary of Performance Results Under pH Tracking*

Performance Index	1st pH setpoint		2nd pH setpoint	
	Proposed	PI controller	Proposed	PI controller
Rise time (min)	1.67	2.5	1.67	1.67
Settling time (min)	3.33	6.67	3.33	6.67
Overshoot (%)	1.03	1.80	0.01	1.25
ISE	Proposed		PI controller	
	56.17		112.48	

***Table 3** Summary of Performance Results Under Liquid Level Tracking*

Performance Index	1st level setpoint		2nd level setpoint	
	Proposed	PI controller	Proposed	PI controller
Rise time (min)	0.66	0.66	1.67	1.50
Settling time (min)	3.33	5.00	2.50	2.83
Overshoot (%)	1.43	7.14	1.67	5.56
ISE	Proposed		PI controller	
	0.16		0.15	

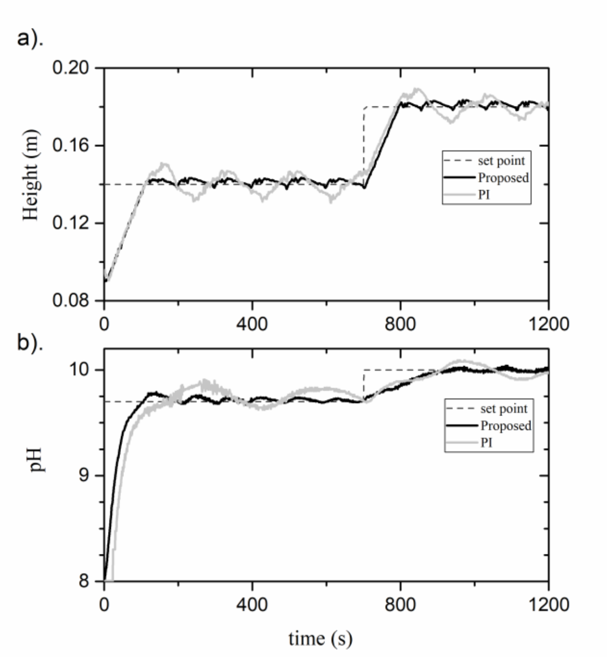

Fig. 4 *The Process Responses of Setpoint Tracking Test a)the Liquid Level Response and b)the pH Response*

6 CONCLUSION

This work developed the controller that the data-driven based model and the discrete-time, I/O linearizing controller are integrated into the pH process control system. The proposed control system is evaluated and compared the PI controller through the servo test with a bench-scale pH reactor in real-time. The results show that the proposed control method provides effective performance to force the liquid level and pH of the process to the desired setpoints. The proposed control method can force the controlled output to the desired setpoint faster than that of the PI controller. In addition, the proposed control method provides a lower overshoot than PI controller for liquid level and pH control.

7 ACKNOWLEDGMENT

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C. Panjapornpon, photograph and biography not available at the time of publication.