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RESEARCH ARTICLE

INVERSE NEURO-FUZZY MODEL BASED CONTROLLER DESIGN FOR A PH NEUTRALIZATION PROCESS

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ABSTRACT

Since pH neutralization processes have extremely nonlinear characteristics, controlling it might be difficult. Therefore, a special controller design is needed to handle the high nonlinearities of the process. In this study, an inverse neuro-fuzzy model-based controller (NFMBC) design is presented for control of a pH neutralization process (NP). Input-output (IO) data set of the process is collected by applying a proper excitation signal. Then, forward and inverse neuro-fuzzy models of the process are constructed by using this data set after a training process. In terms of design simplicity, a two-input-one-output model structure is chosen for both neuro-fuzzy models. These forward and inverse neuro-fuzzy models are used in a nonlinear internal model control (NIMC) structure in order to provide robustness against disturbances and model mismatches. To examine the proposed controller's performance, simulation studies are carried out under setpoint variation and disturbance conditions. Additionally, the performance of the inverse NFMBC is compared to that of a fuzzy proportional integral derivative (FPID) controller with a 7x7 rule base. The results demonstrate that the designed controller provides more effective control performance for setpoint variations and also exhibits higher robustness against disturbances in the acid flow rate than the FPID controller.

Keywords: *Fuzzy Model, Inverse Controller, Adaptive Network Based Fuzzy Inference System, pH Neutralization Process, Internal Model Control,*

1. INTRODUCTION

The problem of pH control is a widespread issue in sectors such as chemical processes, sewage treatment and wastewater management [1]. The safety and stability of the system operation directly depend on the performance of pH control. The aim of pH control in neutralization systems is to keep the pH value at a certain setpoint by regulating the neutralizing agent flow rate. However, the control of pH NPs is a challenging task due to their extremely nonlinear characteristics [2]. The titration curve of a neutralization process, in general, is an S-shaped curve depending on both process and neutralization stream compositions. In some cases, process stream composition may change during the operation, making the control issue much more challenging [3]. Therefore, deriving an analytical model and also designing an effective controller are difficult tasks for pH processes.

In the literature, several linear and non-linear control approaches are proposed to solve the pH control problem. Classical linear PID controllers can hardly ever provide an efficient control performance for pH control applications [4]. Therefore, one way of applying the linear PID control approach to the pH control problem is to use a multi-model approach by linearizing the process model at a few operating points [5]. For instance, Nyström has successfully implemented the multi-model control technique to a pH NP [6]. There are some studies successfully applying linear model predictive control approach to pH neutralization processes [2], [7]. Despite the fact that linear controllers are simple to design, adaptive control or nonlinear control methods provide better control performance than the classical linear control methods [5], [8]. In [2], [9], nonlinear model predictive and adaptive control structures are proposed for the control of pH processes. Although all of these techniques are successful, it is still hard to obtain an adequate model representing the pH NP in any operating condition for practical applications [5].

Highly nonlinear systems can be modeled and controlled using fuzzy logic since fuzzy models are universal approximators and fuzzy controllers have a nonlinear structure [10]. Therefore, fuzzy models and controllers can effectively be used for pH neutralization processes. For example, a fuzzy PI controller design is presented by considering the titration curve in [5]. In [11], an adaptive fuzzy PI control structure with an online tuning mechanism is proposed for pH control. Similarly, there are some fuzzy model (FM) based control approaches proposed in literature such as fuzzy model predictive control [12].

One easy and effective way of controller design is to use an inverse model of a process as the main controller. But it is not an easy task to derive inverse definitions of analytical models of processes. However, there are various exact and approximate inversion methods for fuzzy models [13]–[16]. Therefore, inverse fuzzy model-based control approaches are effective alternatives to conventional control approaches since forward and inverse fuzzy models of nonlinear systems can be derived without the need for any mathematical model. Several inverse fuzzy model based control approaches are proposed and effectively applied to the control problem of pH processes [1], [13], [16].

The adaptive network-based fuzzy inference system (ANFIS) technique described by Jang makes it simple to construct forward and inverse fuzzy models of nonlinear systems [17]. ANFIS approach is widely used in various modeling and control applications [18]. Some studies about ANFIS-based modeling and also control of pH processes are presented in the literature [19-21]. In this study, an inverse NFMBC design for a pH NP is presented. Although the inverse controllers are able to provide perfect control in an open loop (OL) manner, they can show poor control performance or become unstable in case of sudden disturbances and in the presence of noises. Therefore, an internal model control (IMC) structure, which is a closed loop structure, is used in this study. A proper excitation signal is applied to the system for modeling purposes and the input and output data are collected.

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Then, forward and inverse ANFIS models of the process are trained by using the collected IO data set. These forward and inverse models are used in the IMC structure to advance the robustness of the control system against disturbances and model mismatches. The effectiveness of the designed inverse model-based controller is demonstrated through simulations under setpoint variation and disturbance conditions and the performance of this controller is compared to that of an FPID controller. The main advantage of the designed inverse NFMBC compared to the existing approaches is that it provides an effective performance although it uses only simple forward and inverse fuzzy models with 2 inputs and 1 output.

This article is arranged as follows: the pH process model is presented in Section 2, the fuzzy model design is presented in Section 3. The inverse controller design technique is demonstrated in Section 4. Section 5 presents simulation studies to show the effectiveness of the constructed inverse controller. Finally, the conclusions are presented in Section 6.

2. pH PROCESS MODEL

pH neutralization is a process involving reactions between acids and bases. In this study, the neutralization reaction among strong acid and weak acid mixture and strong base is considered as a process model due to its non-linear characteristic. Figure 1 shows the NP in a continuous stirred tank reactor (CSTR). It is assumed that there is perfect mixing within the CSTR. Since the base concentration is relatively high compared to the acid concentrations, a constant liquid level is assumed in the CSTR. Accordingly, the model can be written as:

$$V\frac{dx_i}{dt} = F(c_i - x_i) + u(b_i - x_i) \quad \text{for } i = 1,\dots n \tag{1}$$

where c_i, b_i, and x_i represent the total ion concentration of the species in the corresponding streams in Figure 1. Because of the assumption of a constant liquid level, here the constant for the volume of liquid inside CSTR is symbolized by V. The simulation parameters of the model given in Eqn. 1 are listed in Table 1.

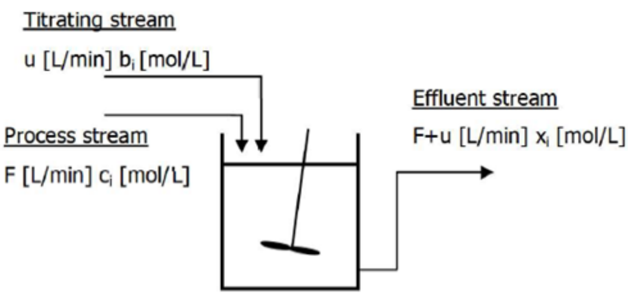

Figure 1. pH neutralization system.

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Table 1. pH NP parameters.

Symbol	Process Parameters	Value
V	Volume or the reactor [L]	1
F	Flow rate of process stream [L/min]	1
u	Flow rate of titrating stream [L/min]	0-0.27
c_i	Total ion concentration vector of process stream [C_{a1} C_{a2} C_b] [mol/L]	[0.001 0.001 0]
b_i	Total ion concentration vector of titrating stream [C_{a1} C_{a2} C_b] [mol/L]	[0 0 0.1]

3. FUZZY MODELING of the pH PROCESS

An appropriate excitation signal is used to stimulate the system at each set-point to construct the forward FM of the NP. The uniform random signals plus constant values are used as the excitation signal and the corresponding output is obtained. Then, by using this input-output data set, the neuro-fuzzy based forward model of the system is obtained. In the data collection process, the sampling time is determined as 1 s, and the data is collected for 30000 seconds. The excitation signal and the corresponding output signal are demonstrated in Figure 2a and Figure 2b, respectively.

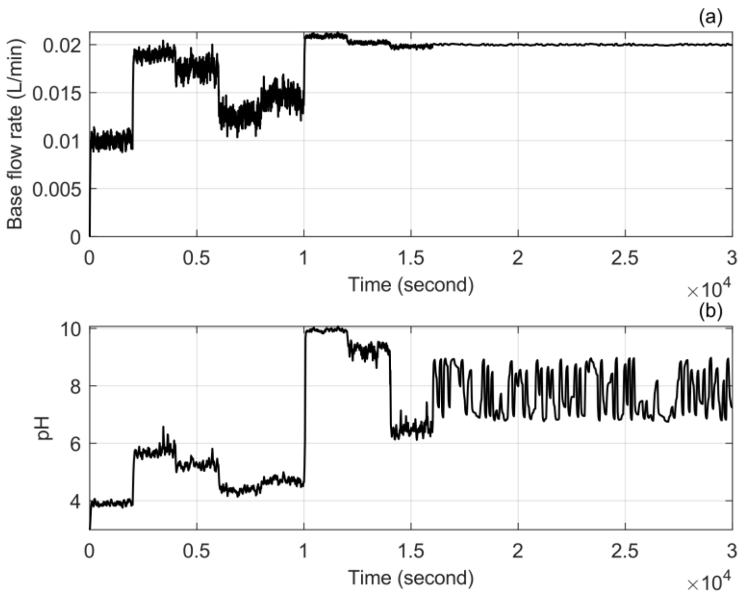

Figure 2. (a) Input signal (b) system output signal.

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A two-input one-output Takagi-Sugeno (TS) FM structure is constructed as illustrated in Figure 3 since it provides an acceptable model approximation. The inputs of the FM are y(k-1) and u(k), and the output of the FM is y(k). The input of y(k-1) is expressed by 11 triangular membership functions (MFs), and the input of u(k) is constructed by 3 triangular MFs. Here y denotes pH value and u denotes titrating stream flow rate. 33 singleton MFs are used to define the output y(k). The training process uses the first 75% of the data and the validation process uses the remaining 25%. The rule base and MFs of the FM after training are represented in Table 2 and Figure 4, respectively.

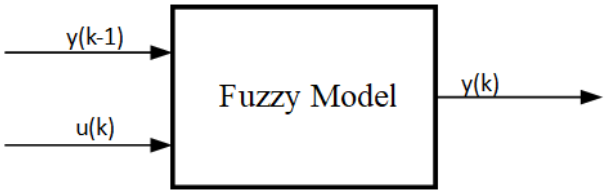

Figure 3. Input-output configuration of the fuzzy model.

Table 2. Rule base of the forward FM.

		u(k)		
		A1	A2	A3
y(k-1)	A1	2.989	3.032	0
	A2	3.163	3.718	3.837
	A3	4.244	4.387	4.493
	A4	0	5.044	5.169
	A5	0	5.582	5.886
	A6	0	5.084	6.772
	A7	0	-0.892	8.413
	A8	0	-6.014	9.889
	A9	0	4.698	9.182
	A10	0	8.399	9.467
	A11	0	9.785	10.07

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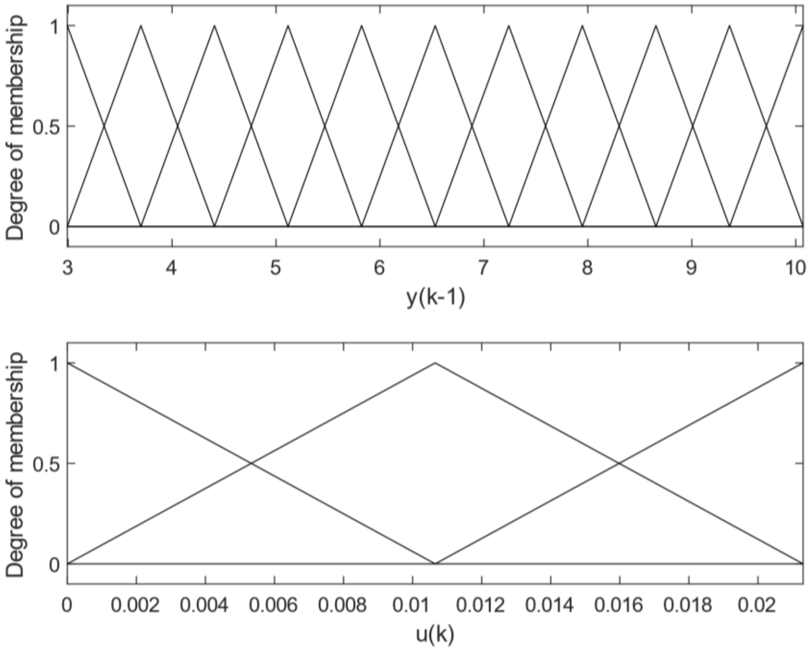

Figure 4. Antecedent membership functions of the trained FM.

The derived FM is compared with the neutralization system output for different setpoints. The forward FM response and the error between the system and the FM outputs are represented in Figure 5a and Figure 5b, respectively. The modeling performance of the derived fuzzy model is acceptable since it provides the root mean square error (RMSE) value of $4.8\ x\ 10^{-3}$.

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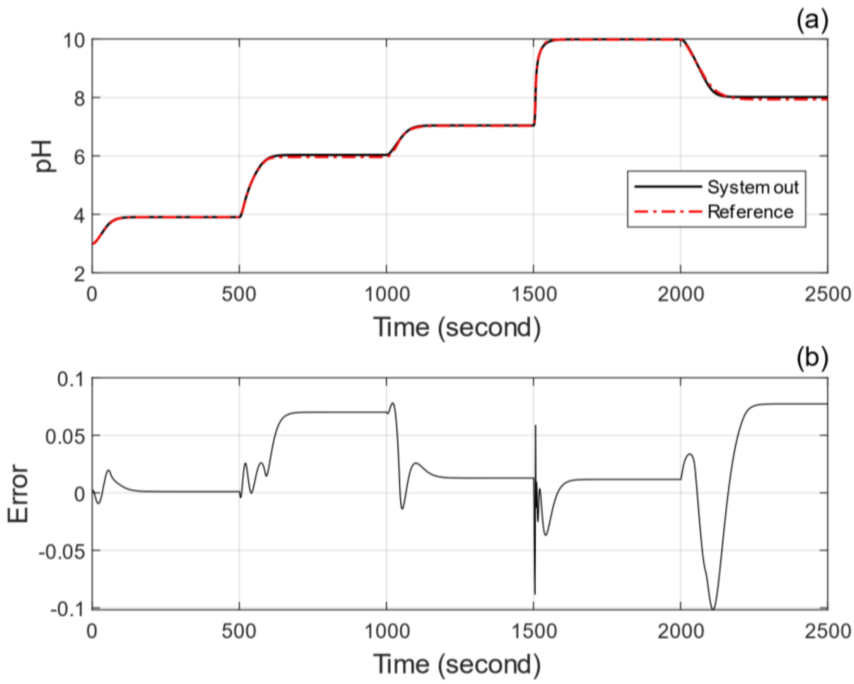

Figure 5. (a) Comparison of the system and the FM outputs (b) modeling error.

4. INVERSE NFMBC DESIGN

The inverse FM of the pH NP is designed by using ANFIS approach. Although the inverse controllers are able to provide perfect control in an OL manner, they can show poor control performance or become unstable in case of sudden disturbances and in the presence of noises. Therefore, the inverse FM of the pH NP is directly used as the main controller in the IMC structure shown in Figure 9 to increase robustness against disturbances and model mismatches.

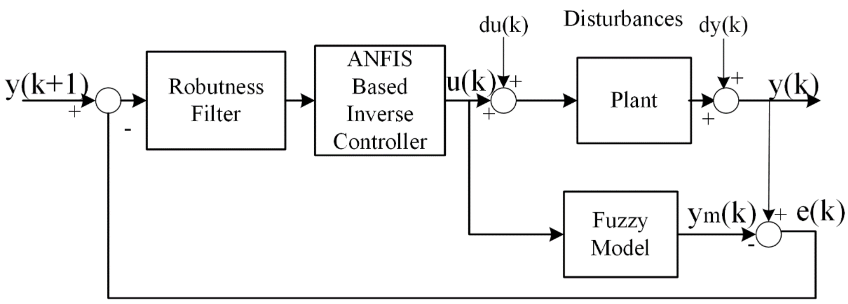

Figure 6. Proposed IMC structure.

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y(k) and y(k-1) are used as inputs and u(k) is used as the output by exchanging the IO data of the collected data set to derive the inverse FM of the pH NP. The IO configuration of the neuro-fuzzy based inverse controller is represented in Figure 6.

Figure 7. Input-output configuration of the neuro-fuzzy based inverse controller.

For inputs y(k) and y(k-1), 11 and 3 triangular MFs are used, respectively. 33 rule consequents are determined by using linear functions as shown in Table 3. The training process uses the first 75% of the data, while the validation process uses the remaining 25% of the data. The rule base and MFs of the trained inverse FM are represented in Table 3 and Figure 7, respectively.

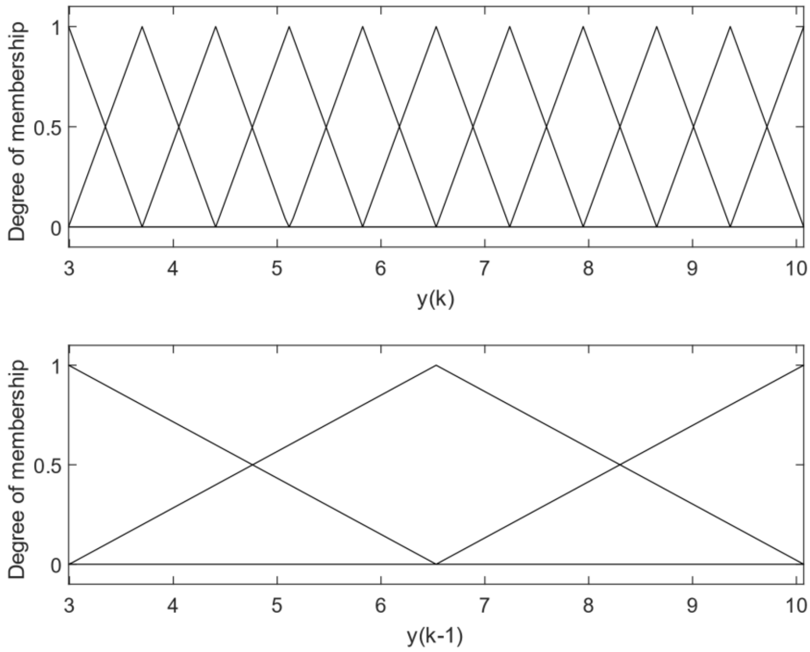

Figure 8. Antecedent MFs of the trained inverse FM.

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Table 3. Rule base of the inverse FM.

		y(k-1)		
		A1	A2	A3
y(k)	A1	[0.34 -0.31 -0.11]	[-0.006 0.026 -0.17]	[0 0 0]
	A2	[0.11 -0.1 0.004]	[0.03 -0.02 -0.02]	[0 0 0]
	A3	[0.05 -0.04 0.004]	[0.14 -0.14 -0.03]	[0 0 0]
	A4	[0.14 -0.14 0.006	[0.03 -0.03 -0.03]	[0 0 0]
	A5	[0.07 -0.07 0.02]	[0.02 -0.01 -0.02]	[-0.008 -0.009 -0.001]
	A6	[-0.001 0.002 0.03]	[0.009 -0.002 -0.02]	[-0.01 0.02 -0.02]
	A7	[0.02 0.01 0.002]	[0.005 -0.001 -0.009]	[-0.002 0.003 0.007]
	A8	[0 0 0]	[0.004 -0.0002 -0.01]	[0.0004 0.001 0.006]
	A9	[0 0 0]	[0.003 0.0008 -0.01]	[0.004 -0.002 0.006]
	A10	[0 0 0]	[-0.009 0.01 -0.009]	[0.01 -0.01 0.006]
	A11	[0 0 0]	[-0.08 0.08 0.004]	[0.04 -0.04 0.002]

In order to show the inverse FM validation, the output of the inverse controller is compared to the excitation signal in Figure 8a. The associated error signal is demonstrated in Figure 8b and the obtained RMSE value is $7.11\ x\ 10^{-5}$. As it is seen from Figure 8, the performance of the derived inverse FM is acceptable.

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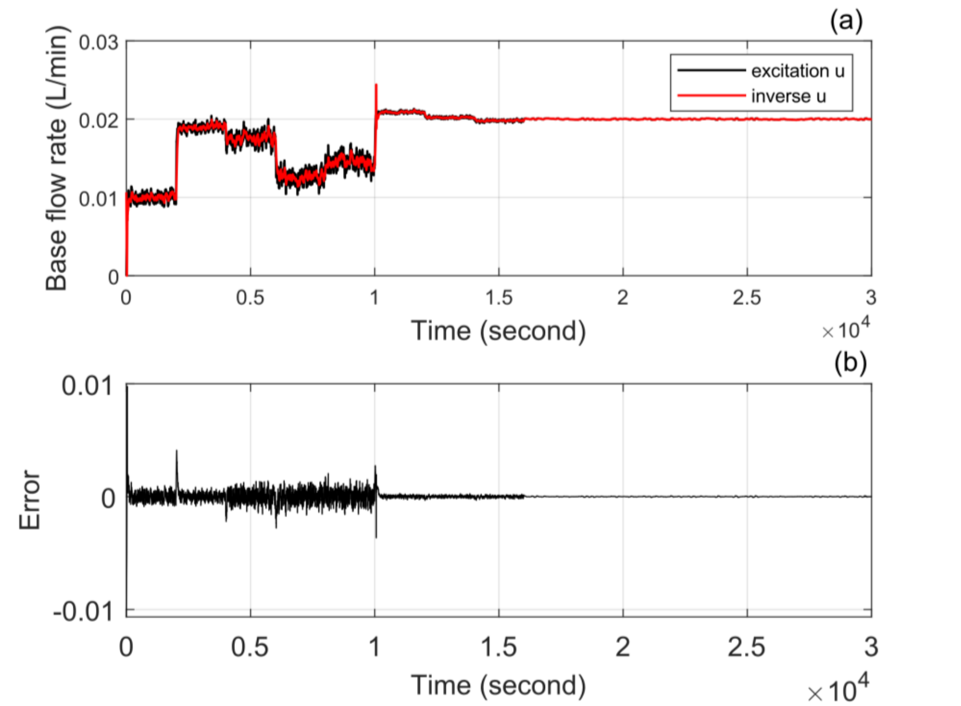

Figure 9. (a) Comparison of the excitation signal and the output of the inverse FM (b) the inversion error.

5. SIMULATION STUDIES

To demonstrate the performance of the proposed controller, simulation studies are performed under different setpoint and disturbance conditions. In the simulations, a FPID controller is also used for performance comparison. The block diagram of the FPID controller is demonstrated in Figure 10.

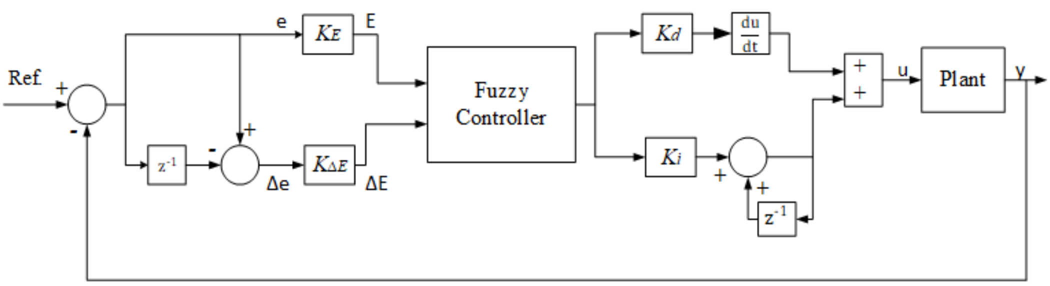

Figure 10. Block diagram of the FPID controller.

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In order to design the FPID controller, TS fuzzy inference structure is chosen and a 7x7 symmetrical rule base is used. Triangular MFs are chosen for the definition of input variables E and ΔE as shown in Figure 11. Singleton MFs are defined for the control variable *U*. The parameters of the FPID controller are determined as $K_E=0.015$, $K_{\Delta E}=0.001$, $K_i=0.003$ and $K_d=0.95$.

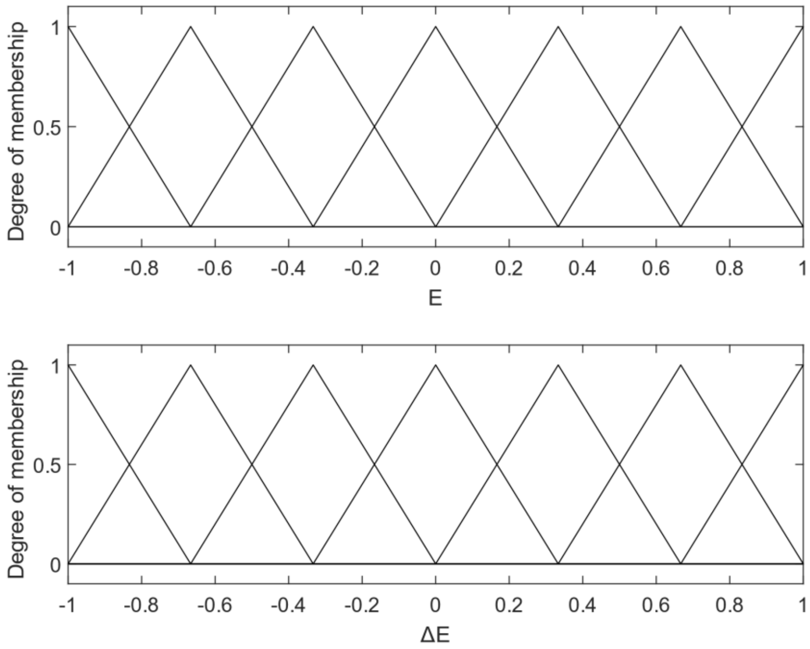

Figure 11. Antecedent MFs of the FPID controller.

The robustness filter in IMC structure is chosen as follows to provide a suitable control performance.

$$G_f(z) = \frac{0.09516}{z-0.9048} \tag{2}$$

In comparisons, the following integral square error (ISE) and integral absolute error (IAE) performance criteria are used.

$$\text{ISE: } \int e^2(t)dt \tag{3}$$

$$\text{IAE: } \int |e(t)|dt \tag{4}$$

The controller performances under setpoint variation are demonstrated in Figure 12 and performance results are compared in Table 4.

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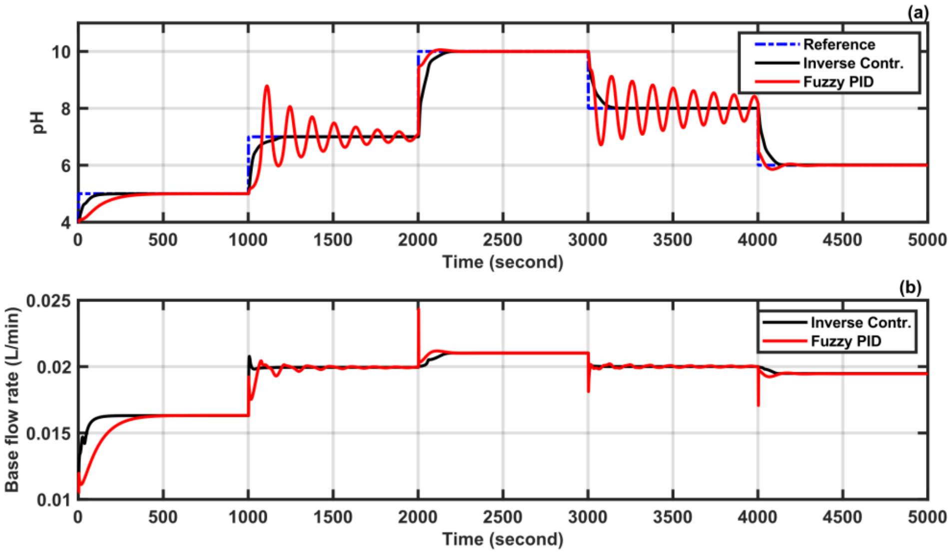

Figure 12. a) Comparison of the system responses under the setpoint variation b) control signals.

Table 4. Performance comparison under the setpoint variation.

Controller	IAE	ISE
FPID	1.392	1.072
Inverse Controller	0.4303	0.3601

As seen in Figure 12 and Table 4, the proposed inverse controller is able to provide significant control performance at all setpoint changes. On the other side, the FPID controller is able to provide satisfactory control performance only at certain pH values where the system gain is relatively low. For setpoint values where the system gain is high, the FPID controller gives oscillating system responses.

In order to evaluate the control performances under disturbance conditions, change in acid flow rate is considered. The reference signal, applied disturbances, corresponding system responses, and control signals are represented in Figure 13. The performance criteria values are given in Table 5. As it is seen from Figure 13 and Table 5, the proposed controller exhibits superior robustness performance under disturbance conditions compared to the FPID controller.

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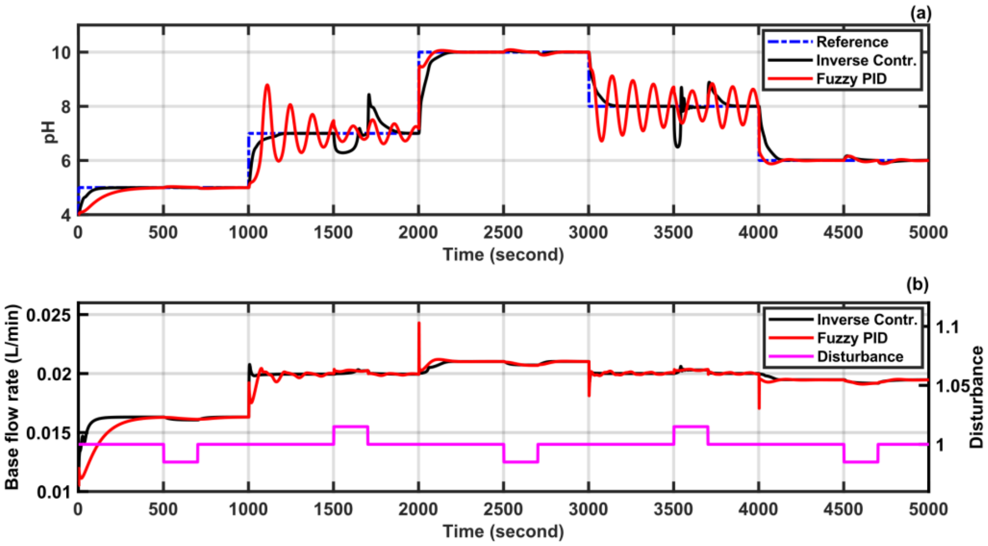

Figure 13. a) Comparison of the system responses under the input disturbance condition b) control signals.

Table 5. Performance comparison under the disturbance condition.

Controller	IAE	ISE
FPID	1.472	1.105
Inverse Controller	0.7168	0.5339

The pH NP is a highly nonlinear system depending on the nonlinear characteristic of its titration curve. The process has different process gains at different pH interval values. The process has lower gains for the pH intervals of [3-6] and [9-12] whereas it has higher gains for the pH intervals of [6-9]. Since the inverse controller is the inverse definition of the fuzzy model of the pH NP, it inherently possesses the process gain information and exhibits significant control performance for different pH levels. However, the conventional FPID controller with the symmetrical rule base is not able to handle these system gain variations as much as the inverse controller. Additionally, since the inverse controller is used in the IMC structure, it has the capability of handling disturbances. On the other hand, the conventional FPID controller has no special configuration to handle disturbances. Therefore, the inverse NFMBC provides superior robustness performance against disturbances compared to the conventional FPID controller. Consequently, the superior pH control performance is obtained by using the inverse NFMBC having only simple forward and inverse fuzzy models with 2 inputs and 1 output as compared to the conventional FPID controller.

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6. CONCLUSION

In this study, an inverse NFMBC design is presented for a pH NP. An NIMC structure is used to provide robustness against disturbances and model mismatches. The forward and inverse fuzzy models of the pH NP are represented by simple fuzzy models with two inputs and one output. The training procedures of the fuzzy models are performed by using an input-output data set collected from the pH NP. The effectiveness of the designed inverse NFMBC is demonstrated through simulations under setpoint variation and disturbance conditions. The simulation results illustrate that the inverse NFMBC exhibits superior control performance compared to the FPID controller with a 7x7 rule base.

The forward and inverse fuzzy models of the pH NP used in the design procedure are in a basic structure with 2 inputs and 1 output, which makes the approach very suitable for real-time control applications. Additionally, these fuzzy models are obtained automatically based on the ANFIS approach without the need for any expert knowledge or tuning. Thanks to these properties, simple but effective controllers can be designed for highly nonlinear systems by using the proposed approach.

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