

Adaptive Fuzzy Controller Design for Simulated Moving Bed System

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The simulated moving bed process (SMB), recognized as one of the cleanest options for chromatographic separation, has been widely used in the biopharmaceutical and chemical industries. However, the complex and nonlinear behavior of SMB still poses concerns and challenges in current developments of its precision control. In this study, an adaptive fuzzy controller is designed and presented. Unlike the traditional fuzzy controller, three error terms, the purity error (e), error change (Δe), and the sum of errors (Σe), are used as the influencing parameters of the developed controller. The experimental results demonstrate the potential of adaptive fuzzy controllers in improving system robustness and implementing precision control in SMB.

1. Introduction

Chromatography is a technique used for the separation of a mixture. The simulated moving bed process (SMB) has had increasing application in large-quantity supercritical fluid extraction owing to its advantages such as a low production cost, a low solvent consumption, and its ability to carry out a clean, continuous operation.^(1,2) The basic principle of SMB is to use multiple columns containing the solid adsorbent and move these columns in the opposite direction to the fluid to achieve a countercurrent flow, hence the term “moving bed”.

Among the chromatographic separation technologies, SMB has been recognized as a highly practical and excellent technique that requires little solvent or water while providing a high separation efficiency.^(3,4) SMB is a continuous operation technique that utilizes the adsorption principle to carry out the separation. The material inlet and outlet positions of the fixed bed can be changed at a fixed switching time. Compared with other fixed adsorption systems, SMB exhibits higher production capacity and separation efficiency. An example of the separation process of SMB is shown in Fig. 1.

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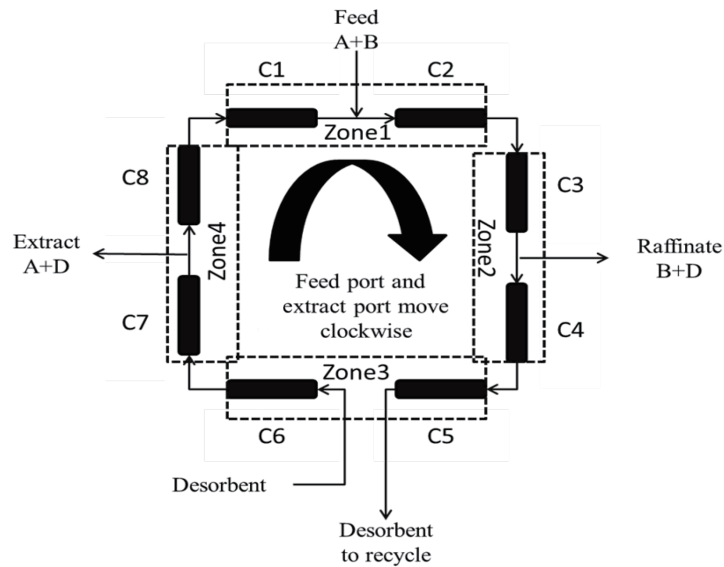


Fig. 1. Separation process of SMB.

However, the complex and nonlinear nature of SMB still poses a challenge in precision control for researchers and developers. An adaptive nonlinear model predictive control method was proposed by Andrade Neto *et al.*⁽⁵⁾ for the separation of enantiomers of praziquantel in a simulated moving bed. The primary focus of this model is to solve the problems of control speed and efficiency in the control framework.

In the classical linear model predictive controller (MPC), an improved prediction mechanism based on the strategy of switching the system was proposed by Nogueira *et al.*⁽⁶⁾ The results showed that this method can control the process in both servo and regulator cases. A method of optimizing separation control to improve the product purity and economic benefit was presented in Ref. 7. Lee and Seidel-Morgenstern proposed a method based on the results of a simulation study, in which the controller can estimate the current process state and find the best operation conditions under the competitive Langmuir isotherm.⁽⁸⁾ Yang *et al.* proposed an optimization strategy based on the improved moving asymptote algorithm, demonstrating that a controller based on the improved moving asymptote method can dynamically control SMB.⁽⁹⁾ A model predictive control method applied to SMB that is based on the established state-space model was presented by Martins *et al.*⁽¹⁰⁾

2. Mathematical Model of SMB

The mathematical model of SMB can be deduced from the true moving bed (TMB) model, which is described as follows.^(11,12) Table 1 gives the meanings of the SMB system's variables in the above equations. In the TMB model, the mass balance of the bulk phase is given by

$$\frac{\partial C_{i,j}}{\partial t} = D_i \frac{\partial^2 C_{i,j}}{\partial x^2} - v_j^* \frac{\partial C_{i,j}}{\partial x} - \frac{1-\varepsilon}{\varepsilon} k_i (q_{ij}^* - q_{ij}), \quad (1)$$

$$\frac{\partial q_{i,j}}{\partial t} = \frac{\partial}{\partial x} u_s q_{ij} + k_i (q_{ij}^* - q_{ij}). \quad (2)$$

For SMB, the mass balance of the bulk phase is given by

$$\frac{\partial C_{i,j}}{\partial t} = D_i \frac{\partial^2 C_{i,j}}{\partial x^2} - v_j^* \frac{\partial C_{i,j}}{\partial x} - \frac{1-\varepsilon}{\varepsilon} k_i (q_{ij}^* - q_{ij}), \quad (3)$$

$$\frac{\partial q_{i,j}}{\partial t} = \frac{\partial}{\partial x} u_s q_{ij} + k_i (q_{ij}^* - q_{ij}). \quad (4)$$

The model can be converted as

$$\frac{\partial C_{i,j}}{\partial t} = D_i \frac{\partial^2 C_{i,j}}{\partial x^2} - v_j^* \frac{\partial C_{i,j}}{\partial x} - \frac{1-\varepsilon}{\varepsilon} k_i (q_{ij}^* - q_{ij}), \quad (5)$$

$$\frac{\partial q_{i,j}}{\partial t} = k_i (q_{ij}^* - q_{ij}). \quad (6)$$

From Eqs. (5) and (6), we obtain

$$\frac{\partial C_{i,j}}{\partial t} = D_i \frac{\partial^2 C_{i,j}}{\partial x^2} - v_j^* \frac{\partial C_{i,j}}{\partial x} - \frac{1-\varepsilon}{\varepsilon} \frac{\partial q_{i,j}}{\partial t}. \quad (7)$$

The adsorption equilibrium of two materials can be expressed by a linear isotherm,

$$q_{i,j} = H_i C_{i,j}, \quad (8)$$

Table 1
Meanings of SMB system's variables.

Parameter	Meaning
x (cm)	Axial distance
k (gL ⁻¹)	Comprehensive mass transfer constant
v^* (cm min ⁻¹)	Effective velocity of body
u_s (cm min ⁻¹)	Solid flow rate
C (gL ⁻¹)	Mobile phase concentration
q (gL ⁻¹)	Solid phase concentration
q^* (gL ⁻¹)	Solid phase concentration at equilibrium between solid and mobile phases
Q (cm ³ min ⁻¹)	Volume flow rate
t (s)	Time
D (cm ² min ⁻¹)	Effective dispersion coefficient
ε	Bulk void fraction
i	Material index: A or B
j	Column number: 1, 2, 3, 4, 5, 6, 7, 8

where H_i is the Henry coefficient, $i = A, B$, and $j = 1, \dots, 8$.

The purity formula can be calculated by

$$c_{E,B} = \frac{C_{E,B}}{C_{E,A} + C_{E,B}}, \quad (9)$$

$$c_{R,A} = \frac{C_{R,A}}{C_{R,A} + C_{R,B}}, \quad (10)$$

where $C_{E,B}$ represents the purity of B from the extract outlet and $C_{R,A}$ represents the purity of A from the raffinate outlet. The relationship between the effective velocity of the body (v_j^*) and the volume flow rate Q_j is described by

$$v_j^* = \frac{Q_j}{\varepsilon \pi d^2}, \quad (11)$$

where d is the radius of the column and ε is the bulk void fraction.

3. SMB Simulation

To observe the system's behavior, a simulation of SMB is performed. The initial values of all the SMB's parameters are shown in Table 2. In this simulation, a 4-area with a 2-2-2-2 model is adopted.

Figures 2(a) and 2(b) display the variations in concentrations versus time. Figure 3 shows the concentration separation results of the two materials at the extract and raffinate outlets with different H_A values.

From the results shown in Figs. 2 and 3, a high similarity can be observed between the simulation model and the real SMB system behavior. The agreement provides a promising condition for the controller we want to develop.

Table 2
Initial parameters for the separation.

Parameter	Value	Parameter	Value
L (cm)	29	$C_{f,i}$ (gL ⁻¹)	6
d (cm)	0.46	θ (min)	3
H_A	0.01	Q_I (cm ³ min ⁻¹)	7.1
H_B	0.45	Q_{II} (cm ³ min ⁻¹)	6.6
D_A (cm ² min ⁻¹)	0.12	Q_{III} (cm ³ min ⁻¹)	9.8
D_B (cm ² min ⁻¹)	1.26	Q_{IV} (cm ³ min ⁻¹)	4.5
$time_step$ (s)	0.1	ε	0.8
$space_step$ (cm)	0.1		

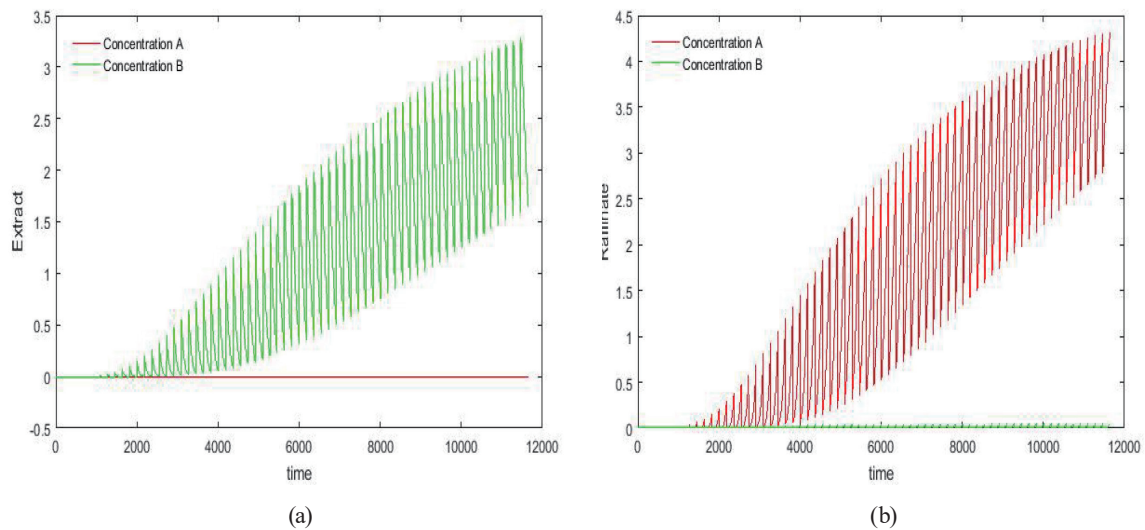


Fig. 2. (Color online) Concentration separation results of extract and raffinate outlets.

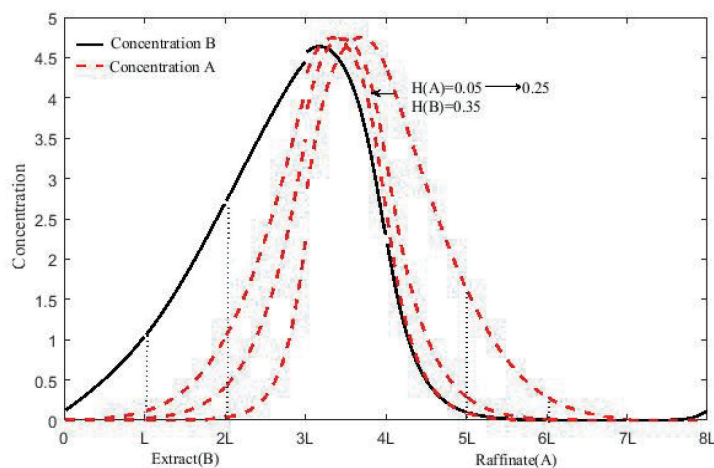


Fig. 3. (Color online) Variations in concentrations versus adsorption rate (H_A).

4. Adaptive Fuzzy Controller

The fuzzy theory was first proposed by Professor Lotfi Zadeh in 1965. It is a knowledge-based or rule-based system containing many fuzzy IF-THEN rules. Usually, a complete fuzzy system is mainly composed of four parts, i.e., a fuzzifier, a fuzzy rule base, a fuzzy inference engine, and a defuzzifier.⁽¹³⁾ Fuzzy controllers have been widely employed in many linear and nonlinear control systems for their simplicity in design, especially for systems whose information is uncertain and unknown.

The control structure of the adaptive fuzzy control mechanism we developed is shown in Fig. 4. The controller is composed of two independent controllers: one is a traditional fuzzy controller and the other is a single-neuron controller. The neuron controller is used to compensate for the lack of precision control of the fuzzy controller.

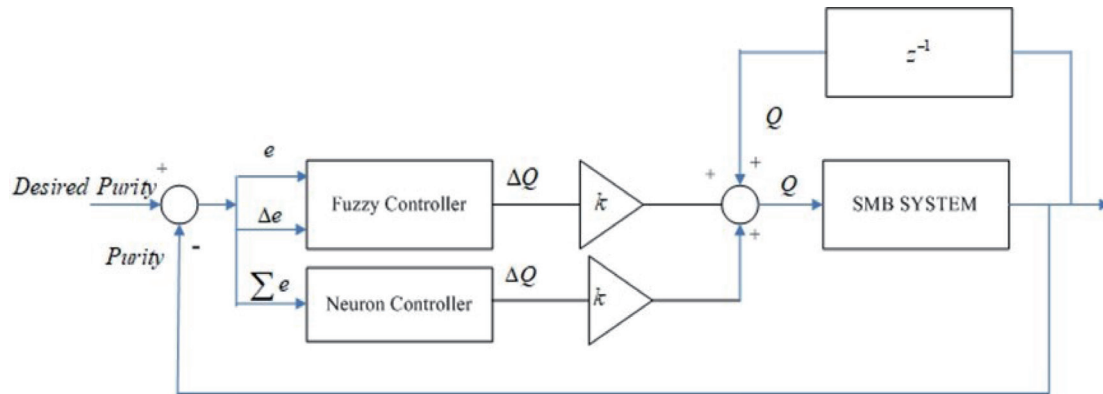


Fig. 4. (Color online) Structure of adaptive fuzzy controller.

In the whole SMB control process, the flow rates of Zones I (Q_1), II (Q_2), and III (Q_3) are controlled by three individual adaptive fuzzy controllers. The variables of purity error (e) and error change (Δe) of materials B and A used as the fuzzy inputs are defined as follows, where $c_{E,B}$ and $c_{R,A}$ are the concentrations of B and A from the extract and raffinate outlets, respectively.

$$e_1 = \text{desired } B - c_{E,B} \quad (12)$$

$$e_2 = \text{desired } A - c_{R,A} \quad (13)$$

$$e_3 = e_1 + e_2 \quad (14)$$

$$\Delta e_1 = e_1(t) - e_1(t-1) \quad (15)$$

$$\Delta e_2 = e_2(t) - e_2(t-1) \quad (16)$$

$$\Delta e_3 = \Delta e_1 + \Delta e_2 \quad (17)$$

Three controllers can generate the increment of their own flow rate (ΔQ_i , $i = 1, 2, 3$). Figure 5 shows the membership functions of all error terms (e_i and Δe_i , $i = 1, 2, 3$), and Fig. 6 presents the singleton membership function of the defuzzifier. Table 3 shows the fuzzy rule table used by the fuzzy controllers. The center values of $\{a_1, a_2, a_3, a_4, a_5\}$ for (ΔQ_i , $i = 1, 2, 3$) are $\{0.15, 0.1, 0, -0.1, -0.15\}$, $\{0.006, 0.004, 0, -0.004, -0.006\}$, and $\{0.08, 0.05, 0, -0.05, -0.08\}$, respectively.

The second controller is the single-neuron controller, which also generates the increment of the flow rate ΔQ . As mentioned above, it is used to improve the drawback of the fuzzy controller to accomplish precision control. The model of the single-neuron controller is expressed as

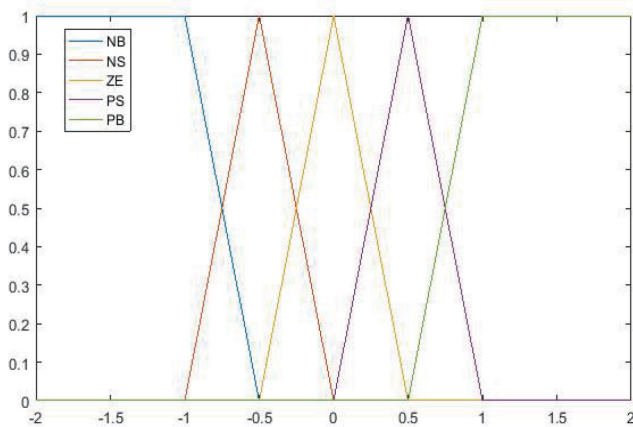


Fig. 5. (Color online) Membership functions of all error variables (e_i and Δe_i).

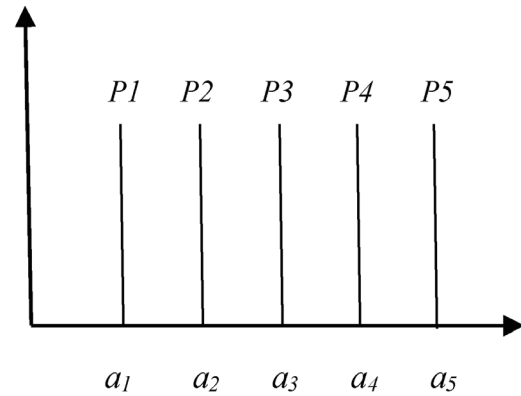


Fig. 6. Membership function of defuzzifier.

Table 3
Rule table of $\Delta Q_i, i = 1, 2, 3$.

		e				
		NB	NS	ZE	PS	PB
Δe	NB	$P1$	$P1$	$P1$	$P2$	$P5$
	NS	$P1$	$P2$	$P2$	$P3$	$P5$
	ZE	$P1$	$P2$	$P3$	$P4$	$P5$
	PS	$P1$	$P3$	$P4$	$P4$	$P5$
	PB	$P1$	$P4$	$P5$	$P5$	$P5$

$$y = c \times \frac{1 - \exp(a \times \sum e)}{1 + \exp(b \times \sum e)}, \tag{18}$$

where y is the output of the neuron and $a, b,$ and c are constants. Here, we set $a = b = -0.1$ and $c = -1$.

5. Experiments

In this study, several purity controls were implemented. Figures 7(a) and 7(b) show the results of control by the adaptive fuzzy controller that we developed in the first experiment. In this experiment, the switching time is 180 s and the desired purities of materials A and B are $A = 0.94$ and $B = 0.96$. The actual purities produced by SMB are $A = 0.94$ and $B = 0.9593$.

Figures 8(a) and 8(b) show the control performance in the second experiment. In this experiment, the switching time is 180 s and the desired purities of materials A and B are $A = 0.90$ and $B = 0.91$. The actual purities produced by SMB are $A = 0.8977$ and $B = 0.9088$.

Figures 9(a) and 9(b) show the control performance in the third experiment. In this experiment, the switching time is 178 s and the desired purities of materials A and B are $A = 0.93$ and $B = 0.95$. The actual purities produced by SMB are $A = 0.9319$ and $B = 0.9519$.

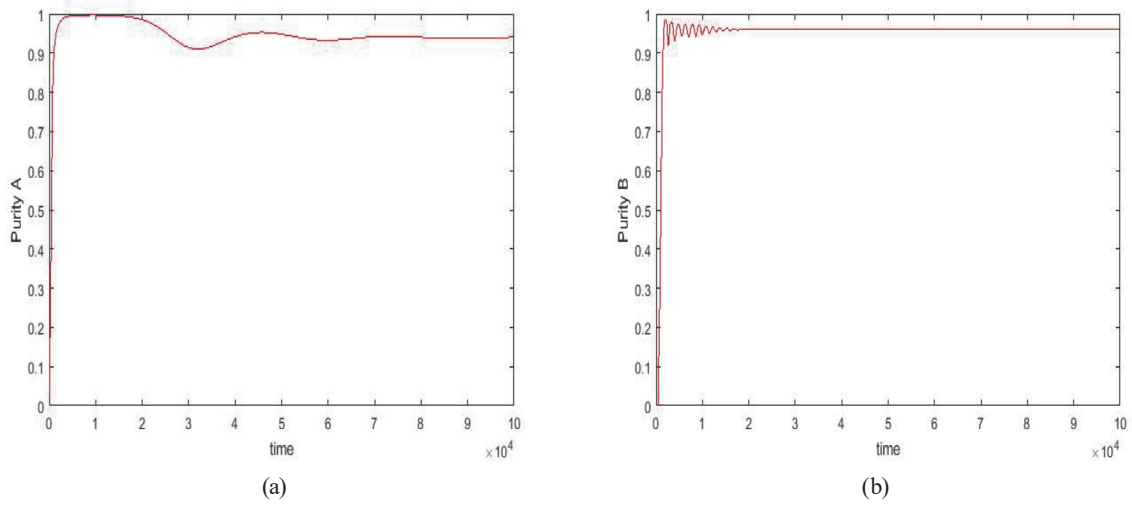


Fig. 7. (Color online) Purities of materials A and B produced by SMB: $A = 0.94$ and $B = 0.9593$.

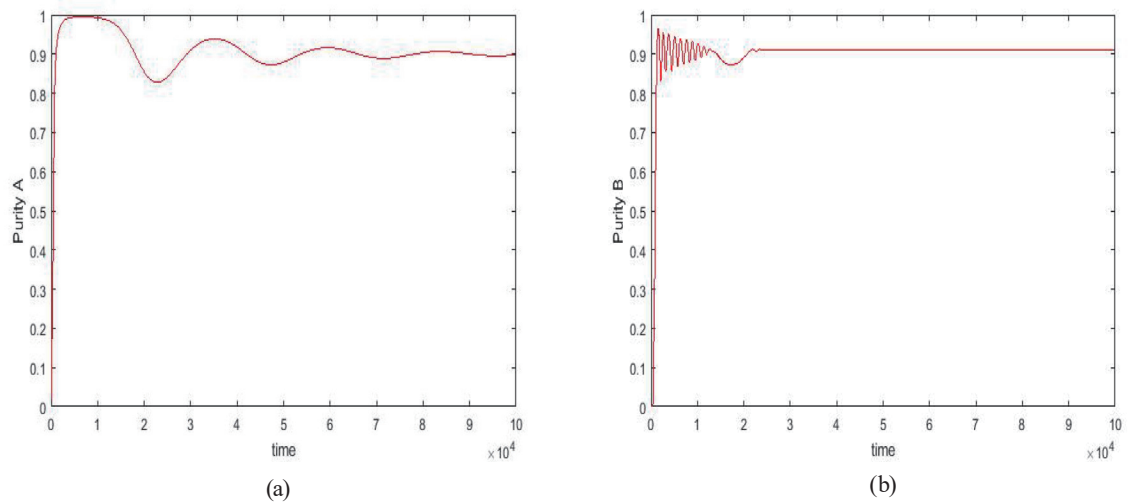


Fig. 8. (Color online) Purities of materials A and B produced by SMB: $A = 0.8977$ and $B = 0.9088$.

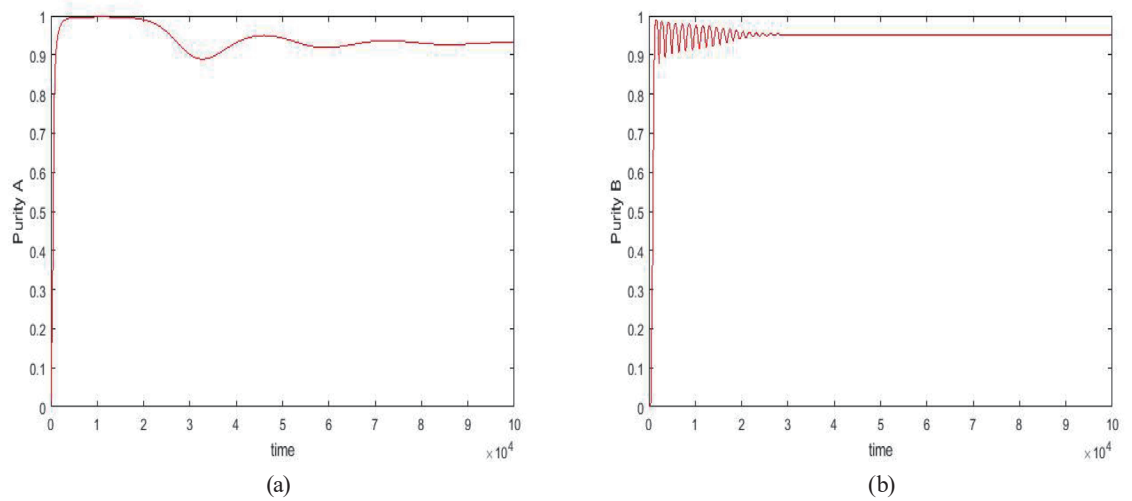


Fig. 9. (Color online) Purities of materials A and B produced by SMB: $A = 0.9319$ and $B = 0.9519$.

6. Conclusions

In this study, an adaptive fuzzy control mechanism with two independent controllers for an SMB chromatographic separation system was designed and presented. In this control mechanism, the fuzzy controller is treated as the master controller, and the neuron controller functions as a slave controller in charge of fine-tuning and improving the drawback of the fuzzy controller to implement precision control. The experimental results show that the chromatographic separation of SMB can indeed be effectively and precisely controlled by using the developed adaptive fuzzy controller. The desired purities can be obtained for the separated substances.

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