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Improvement of Linear Distillation Column Control Performance Using Fuzzy Self-Tuning PI Controller

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Abstract. PI and PID controllers are usually found to provide poor performance for high-order, nonlinear processes, and multiple-input and multiple-output (MIMO) systems with strong loop interactions. One of the most common multivariable system found is the distillation column. In this study, a new structure of fuzzy self-tuning PI (fuzzy-PI) controller for distillation column is proposed. The values of *Kp* and *Ki* are initially tuned with Ziegler-Nichols closed loop method and are always updated based on the system's condition. With the self-tuning structure, the fuzzy-PI controller improves the conventional PI controller in terms of the linear distillation column control performance. The controllers' performance are tested by X_D and X_B set point change and X_F disturbance change.

INTRODUCTION

Multivariable systems are generally encountered in real industrial processes due to the complexity, resulting in an increased number of loop controls to maintain the quantity and quality of industrial productions. The industrial processes include petrochemical industry, oil and gas industry, refinery industry, cement industry, power plants, and etc. Recently, the development of science and technology generate many types of controllers, but the PI and PID controllers still have an important role in industrial processes due to the simple design and tuning methods [1-3]. However, these controllers provide poor performance for high-order, nonlinear processes [1-3], and multiple-input and multiple-output (MIMO) systems with strong loop interactions [4]. To overcome these problems, various tuning methods have been developed. The fuzzy logic control has proved its broad potential in industrial applications because of its good performance for controlling systems that could not be controlled satisfactorily by using PI and PID controllers [4]. With the addition of self-tuning to the fuzzy logic control, it advances the controller to overcome the aforementioned problems [4].

One of the most common multivariable system found in industrial processes is the distillation column. There are a lot of researches regarding the distillation column, including the areas of process synthesis, process dynamics, and process control. Various process control methods have been studied and applied to various distillation column systems. Mishra et al. [3] and Almeida and Coelho [4] then developed different structures of fuzzy self-tuning PID controllers. Mishra et al. [3] uses a Takagi-Sugeno (TSK) type inference engine to calculate the output signal of a fuzzy controller (formula based) for the PI/PD controller. The distillation column model used is a mathematical model of a binary distillation column that separates 1-propanol and ethanol. The initial parameters of the controller are tuned using genetic algorithm (GA). Meanwhile, Almeida and Coelho [4] uses a fuzzy gain scheduling method to calculate the output signal of fuzzy controller (rule based) for the PID controller. The distillation column model used is a 2×2 linearized Wood and Berry model that separates methanol and water. The initial parameters of the controller are tuned using Ziegler-Nichols method.

This paper proposes a new structure of fuzzy self-tuning PI (fuzzy-PI) controller for distillation column. The controller design is adapted from Si and Wang [5], where the fuzzy rules used are based on a medical robot that can approach the target quickly and stable. Based on the error (*e*) and error changing rate (*ec* or *de/dt*) input, the fuzzy controller calculates the values of ΔKp and ΔKi, so that the values of *Kp* and *Ki* in the PI controller are

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always updated. Hence, the controller is adaptive towards various situations, including set point and disturbance changes. Meanwhile, the program routine structure is adapted from Yusivar and Wakao [6], where instead of using a default fuzzy logic and PI controller from MATLAB/Simulink, two C-MEX S-function blocks are used separately to input the program routine for the fuzzy and PI controller. The distillation column model used is a 2 × 2 linearized McAvoy and Weischedel model as shown in Marlin [7]. The initial parameters of the controller are tuned using Ziegler-Nichols closed loop method [8]. The simulation is done in MATLAB/Simulink software. The performance of both conventional PI and fuzzy-PI controller are evaluated and compared to see whether there is an improvement. The controllers' performance are evaluated qualitatively based on overshoot and settling time and quantitatively based on integral absolute error (IAE) and integral square error (ISE). The fuzzy-PI controller is considered to have improved the linear distillation column control performance when it produces smaller overshoot, settling time, IAE, and ISE values than the conventional PI controller.

METHODOLOGY

1. Distillation Column Model

The distillation column model used in this simulation is a 2 × 2 linearized McAvoy and Weischedel model as shown in Marlin [7]. The scheme of the distillation column and the initial parameters used are described in detail in Marlin [7]. The model is based on a two-product distillation column with high purity separating a binary feed. The transfer function model is given by Eq. 1.

$$\begin{bmatrix} X_D \\ X_B \end{bmatrix} = \begin{bmatrix} \frac{0.0747e^{-3s}}{12s+1} & \frac{-0.0667e^{-2s}}{15s+1} \\ \frac{0.1173e^{-3.3s}}{11.75s+1} & \frac{-0.1253e^{-2s}}{10.2s+1} \end{bmatrix} \begin{bmatrix} F_R \\ F_V \end{bmatrix} + \begin{bmatrix} \frac{0.7e^{-5s}}{14.4s+1} \\ \frac{1.3e^{-3s}}{12s+1} \end{bmatrix} [X_F] \quad (1)$$

According to Marlin [7], the controlled variables are distillate and bottom compositions (X_D and X_B), while the manipulated variables are reflux and reboiler flow rates (F_R and F_V). It is assumed that other variables such as pressure and level are controlled tightly. The disturbance is the feed composition (X_F) because it depends on upstream operations and is assumed not free to be adjusted. The distillate light key (X_D) is maintained at 0.98 mole fraction and the bottom light key (X_B) is maintained at 0.02 mole fraction.

2. Conventional and Fuzzy Self-Tuning PI Controller

The general expression of a conventional PI controller is given by Eq. 2.

$$MV(t) = K_p e(t) + K_i \int_0^\infty e(t)dt \quad (2)$$

where *MV(t)* is the PI controller output, *Kp* is the proportional constant, *Ki* is the integral constant, and *e(t)* is the error. The values of *Kp* and *Ki* used in the PI controller are tuned using the Ziegler-Nichols closed loop method [8].

The fuzzy self-tuning PI controller (fuzzy-PI) is a controller that takes the conventional PI controller structure as its base, where the parameters of the PI controller are first tuned with any conventional tuning methods, e.g. Ziegler-Nichols closed loop method [8], and then are automatically regulated by the fuzzy controller. The fuzzy controller structure used in the fuzzy-PI controller is the same as a fuzzy logic controller, which consists of a fuzzification interface, a knowledge base, an inference, and a defuzzification interface. Each component's functions are described in detail in Zhang et al. [9] and Lee [10].

The block diagram of the proposed fuzzy-PI controller is shown in Fig. 1, which is adapted from Si and Wang [5]. Fig. 1 shows the input and output variables of each controller. For the fuzzy controller, the input variables are error (*e*) and error changing rate (*ec* or *de/dt*), while the output variables are *ΔKp* and *ΔKi*. For the PI controller, the input variables are error (*e*), *ΔKp*, and *ΔKi*, while the output variable is the actual output signal value (a manipulated variable value, as stated in Eq. 2) that will affect the process or system. The controller design is adapted from Si and Wang [5], which includes the fuzzy set, linguistic values, fuzzy rules, and the equations to calculate the new values of *Kp* and *Ki* in the PI controller.

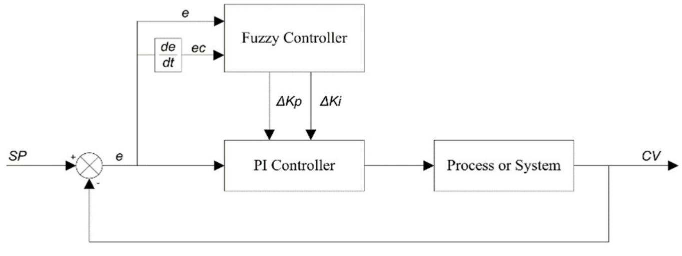


FIGURE 1. Block diagram of the proposed fuzzy-PI controller.

The fuzzy set used in the fuzzy controller is a series of linguistic values, which are { NB, NM, NS, ZO, PS, PM, PB }. Each abbreviation represents "negative big", "negative medium", "negative small", "zero", "positive small", "positive medium", and "positive big" respectively. The input and output value ranges for each linguistic value are defined by Eq. 3-4. However, there is a modification from Si and Wang's [5] design on the value ranges, where instead of using fixed value ranges, the value ranges can change based on the set point (SP) of the controlled variable. Selection of the appropriate error tolerance (ET) 1, 2, and 3 values are based on the system's response and are done by trial and error. In this case, the error tolerance 1, 2, and 3 values used are 0.5, 0.3, and 0.05 respectively.

$$PB = ET\ 1*SP;\ PM = ET\ 2*SP;\ PS = ET\ 3*SP \tag{3}$$

$$ZO = 0;\ NS = -PS;\ NM = -PM;\ NB = -PB \tag{4}$$

After classifying the input values of *e* and *ec* into one of the linguistic values, the linguistic values for calculating the output values of ΔKp and ΔKi can be determined by a fuzzy rule that is defined based on a simple fuzzy logic, which is "if *e* is A and *ec* is B, then ΔKp is C and ΔKi is D". Table 1(a) and 2(b) show the summarized fuzzy rules for ΔKp and ΔKi respectively.

TABLE 1. Fuzzy rules for (a) ΔKp and (b) ΔKi.

(a)

ec	***e***						
	NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

(b)

ec	***e***						
	NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	NM	NS	NS	ZO	PS	PS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

After determining the linguistic values for ΔKp and ΔKi, the output values of ΔKp and ΔKi can be calculated by Eq. 5 and 6. This is another modification of Si and Wang's [5] design on the output values of ΔKp and ΔKi, where instead of directly using the linguistic values, the linguistic values must be divided by a re-scaling factor. The aim of using a re-scaling factor is avoid very rapid changes in the values of *Kp* and *Ki* used in the PI controller, which causes the system's response to be unstable. Selection of the appropriate re-scaling factor is based on the system's response and is done by trial and error. In this case, the re-scaling factor used is 5,500.

$$\Delta Kp = \Delta Kp' \ /\ \text{re-scaling factor} \tag{5}$$

$$\Delta Ki = \Delta Ki' \ /\ \text{re-scaling factor} \tag{6}$$

After obtaining the scaled values of ΔKp and ΔKi from the fuzzy controller, the new values of *Kp* and *Ki* used in the PI controller can be calculated by Eq. 15 and 16.

$$Kp = Kp' + \Delta Kp \tag{7}$$

$$Ki = Ki' + \Delta Ki \tag{8}$$

Eq. 7 and 8 show that the values of *Kp* and *Ki* used in the PI controller are continuously changing based on the output values of the fuzzy controller (ΔKp and ΔKi), while the output values of the fuzzy controller (ΔKp and ΔKi) are continuously changing based on the system's condition (*e* and *ec*). Meanwhile, in a conventional PI controller, the values of *Kp* and *Ki* are constant and unaffected by the system's condition. Hence, the fuzzy-PI controller is adaptive towards various situations, including set point and disturbance changes and gives it an advantage than the conventional PI controller.

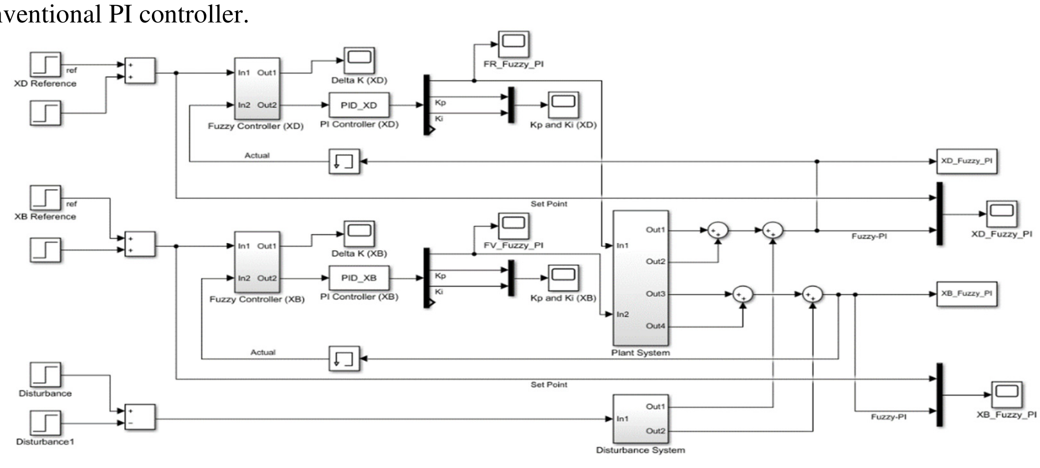


FIGURE 2. Simulink model of the linear distillation column with fuzzy-PI controller.

The Simulink model of the linear distillation column with fuzzy-PI controller is shown at Fig. 2. There are two separate fuzzy-PI controllers for controlling X_D and X_B. Both X_D and X_B controllers have the same fuzzy-PI controller structure as mentioned previously.

3. Simulation Testing and Evaluation

Simulation testing is carried out by set point change test and disturbance rejection test.

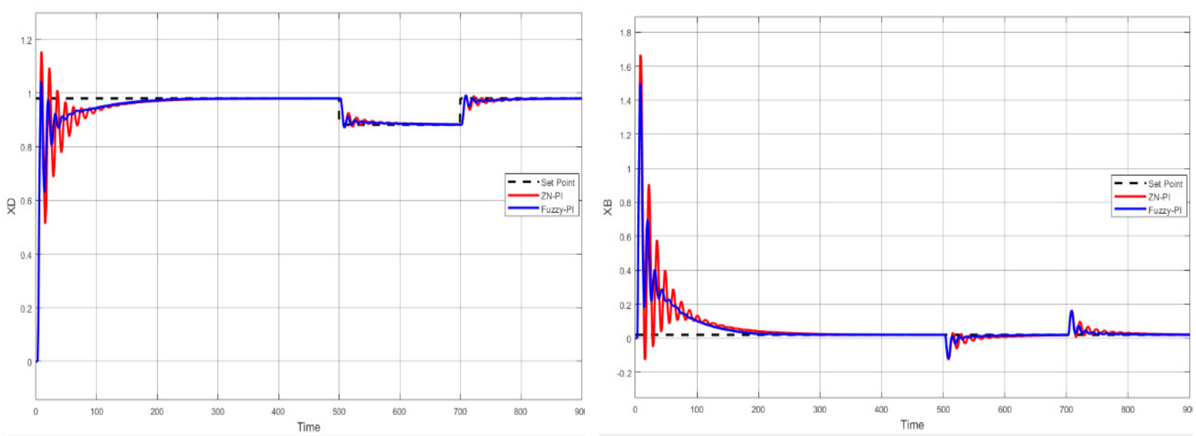
1. Set point change test is done by two methods: (1) changing ±10% of the X_D set point to see the changes in both X_D and X_B and (2) changing ±10% of the X_B set point to see the changes in both X_D and X_B.
2. Disturbance rejection test is done by changing ±20% of the X_F value to see the changes in both X_D and X_B.

The controllers' performance will be evaluated qualitatively based on overshoot and settling time and quantitatively based on integral absolute error (IAE) and integral square error (ISE). The fuzzy-PI controller is considered to have improved the linear distillation column control performance when it produces smaller overshoot, settling time, IAE, and ISE values than the conventional PI controller.

RESULTS AND DISCUSSION

1. Set Point Change Test

Fig. 3 shows the comparison of the system's response between conventional PI and fuzzy-PI controller due to ±10% X_D set point change towards X_D and X_B. Table 2 shows the comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to due to ±10% X_D set point change. Fig. 4 shows the comparison of the system's response between conventional PI and fuzzy-PI controller due to ±10% X_B set point change towards X_D and X_B. Table 3 shows the comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to due to ±10% X_B set point change. Overall, for both set point change cases, the fuzzy-PI controller outperforms the conventional PI controller with smaller overshoot, settling time, IAE, and ISE values. Smaller IAE and ISE values in the fuzzy-PI controller means that the error that happens in the controller can be overcame quickly, shown by how the controller is able to reduce the overshoot and to damp the oscillations quickly.

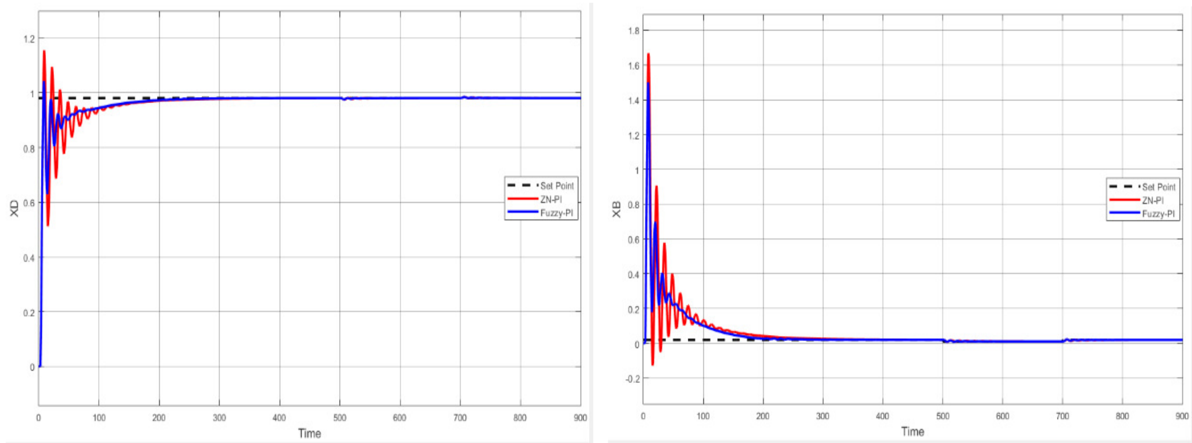


(a) (b)

FIGURE 3. Comparison of the system's response between conventional PI and fuzzy-PI controller due to ±10% X_D set point change towards (a) X_D, (b) X_B

TABLE 2. Comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to ±10% X_D set point change.

Controller	IAE		% IAE Reduction		ISE		% ISE Reduction	
	X_D	X_B	X_D	X_B	X_D	X_B	X_D	X_B
ZN-PI	20.4820	41.1116	17.12%	14.64%	6.2372	20.4129	15.68%	23.51%
Fuzzy-PI	16.9763	35.0946			5.2590	15.6131		



(a) (b)

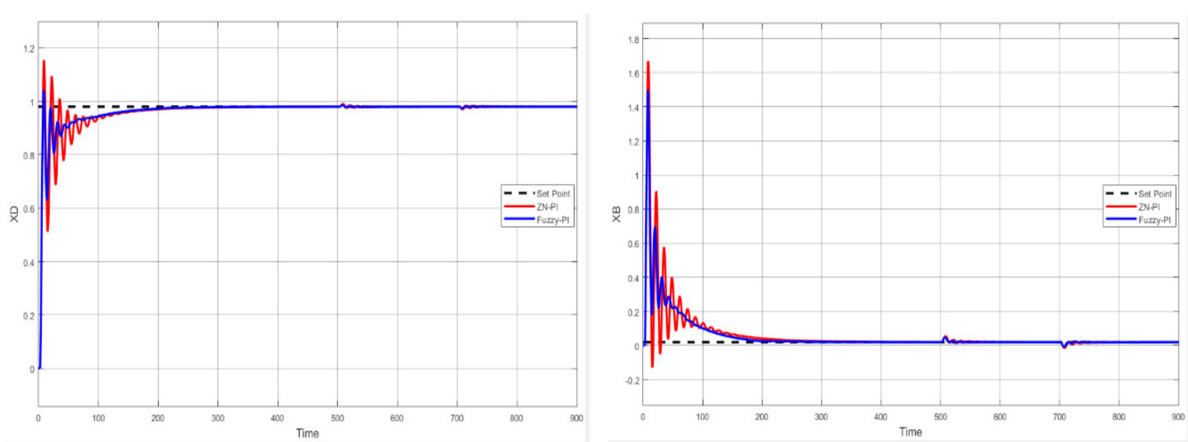
FIGURE 4. Comparison of the system's response between PI and fuzzy-PI controller due to ±10% X_B set point change for (a) X_D, (b) X_B

TABLE 3. Comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to ±10% X_B set point change.

Controller	IAE		% IAE Reduction		ISE		% ISE Reduction	
	X_D	X_B	X_D	X_B	X_D	X_B	X_D	X_B
ZN-PI	17.4540	35.3364	17.71%	11.07%	6.1193	20.0899	15.70%	23.40%
Fuzzy-PI	14.4410	31.4242			5.1587	15.3881		

2. Disturbance Rejection Test

Fig. 5 shows the comparison of the system's response between conventional PI and fuzzy-PI controller due to ±20% X_F (disturbance) change towards X_D and X_B. Table 4 shows the comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to due to ±20% X_F (disturbance) change. The results are similar to the set point change test, where the fuzzy-PI controller outperforms the conventional PI controller with smaller overshoot, settling time, IAE, and ISE values.



(a) (b)

FIGURE 5. Comparison of the system's response between conventional PI and fuzzy-PI controller due to ±20% X_F (disturbance) change for (a) X_D, (b) X_B

TABLE 4. Comparison of IAE and ISE values between conventional PI and fuzzy-PI controller due to ±20% X_F (disturbance) change.

Controller	IAE		% IAE Reduction		ISE		% ISE Reduction	
	X_D	X_B	X_D	X_B	X_D	X_B	X_D	X_B
ZN-PI	17.5860	35.8540	17.73%	11.51%	6.1202	20.1039	15.71%	23.42%
Fuzzy-PI	14.4673	31.7264			5.1589	15.3957		

CONCLUSION

A new structure of fuzzy self-tuning PI (fuzzy-PI) controller for distillation column has been proposed. The values of *Kp* and *Ki* used in the PI controller are continuously changing based on the output values of the fuzzy controller (*ΔKp* and *ΔKi*), while the output values of the fuzzy controller (*ΔKp* and *ΔKi*) are continuously changing based on the system's condition (*e* and *ec*). Simulation testing is done by X_D and X_B set point change test and X_F disturbance rejection test. Results show that for all simulation tests, the fuzzy-PI controller outperforms the conventional PI controller with smaller overshoot, settling time, IAE, and ISE values.

In the present study, the error tolerance values and re-scaling factor used in the fuzzy controller are tuned by trial and error. Further works may be done to find the more appropriate values. Implementing the fuzzy-PI controller to a nonlinear or mathematical distillation column model can also be done to see whether the fuzzy-PI controller is able to handle nonlinear and MIMO system with strong loop interactions.

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