Journal of Engineering Science and Technology
Vol. 11, No. 12 (2016) 1784 - 1792

DESIGN AND IMPLEMENTATION OF FUZZY PREDICTIVE CONTROLLER FOR DISTILLATION COLUMN

SIVAKUMAR. R.[1,*], SHENNES MATHEW [1], SURESH MANIC K.[2]

[1]Department of Electronics and Instrumentation, St. Joseph's College of Engineering, Chennai, TN, India
[2]Department of Electrical and Computer Engineering, Caledonian College of Engineering, Muscat, Sultanate Of Oman.
*Corresponding Author: rsivakumar1@gmail.com

Abstract

Most of the real systems exhibit non-linear nature; conventional controllers are not always able to provide good and acceptable results. This paper presents a hybrid control strategy of Model Predictive Control (MPC) and Fuzzy Logic Control (FLC). The Fuzzy Model Predictive Control (FMPC) approach is developed to control various distillation column models. The performance measures like settling time, peak overshoot, Integral Square Error (ISE) and Integral Absolute Error (IAE) of FMPC is validated with MPC, FLC and conventional multi loop PI controller. The simulation results shows that the FMPC has better performance than other controller on various distillation column models.

Keywords: Predictive control, Fuzzy model predictive controller, Distillation column; Control horizon; Model horizon

1. Introduction

Distillation is the separation method in the petroleum and chemical industries for purification of final products. The schematic for the distillation column is based on L-V (Liquid-Vapour) structure or the energy balance method. In this control configuration the vapour flow rate (V) and the liquid flow rate (L) are the control inputs. Here FMPC has been selected for controlling the distillation column [1-3].

This paper presents specific details about the simulated case study of MPC for the Wood and Berry distillation column model, Benzene Toluene Model and Vinante Luyben model. The Wood-Berry is a 2×2 transfer function model of a

Nomenclatures

B	Big
d(s)	Disturbance variable
e	Error
eD	Change in error
F	Feed flow rate
L	Liquid flow rate
M	Control horizon
Mp	Maximum peak overshoot
N	Negative
P	Predictive horizon
Po	Positive
R(s)	Reflux flow rate
S	Small
S(s)	Steam flow rate
t_s	Settling time (sec)
V	Vapour flow rate
xB	Bottom composition
xD	Distillate composition
Z	Zero
zF	Mole percentage

Greek Symbols

Δe	Change in error

Abbreviations

FLC	Fuzzy Logic Control
FMPC	Fuzzy Model Predictive Control
IAE	Integral Absolute Error
ISE	Integral Square Error
L-V	Liquid Vapour
MIMO	Multi Input Multi Output
MPC	Model Predictive Control
PI	Proportional Integral

pilot plant distillation column that separates methanol and water. Then it is extended to Distillation Column model of Benzene Toluene and Vinante – Luyben. The system outputs are distillate xD and bottoms compositions xB, which are controlled by the reflux and steam flow rates R and S [lb/min]. The unmeasured feed flow rate F acts as a process disturbance.

A non-linear 2 input 2 output system Distillation Column (MIMO system) is controlled with FMPC and compared all the performance like settling time, peak overshoot, ISE and IAE with conventional multi-loop PI controller. The MPC simulation was performed using MATLAB and the Model Predictive Control Toolbox. The FLC simulation was also performed using MATLAB and the Fuzzy Toolbox.

2. Distillation Column

Distillation is a process that separates two or more components into an overhead distillate and bottoms (Fig. 1). The bottoms product is most probably a liquid, while the distillate may be liquid or a vapour or both.

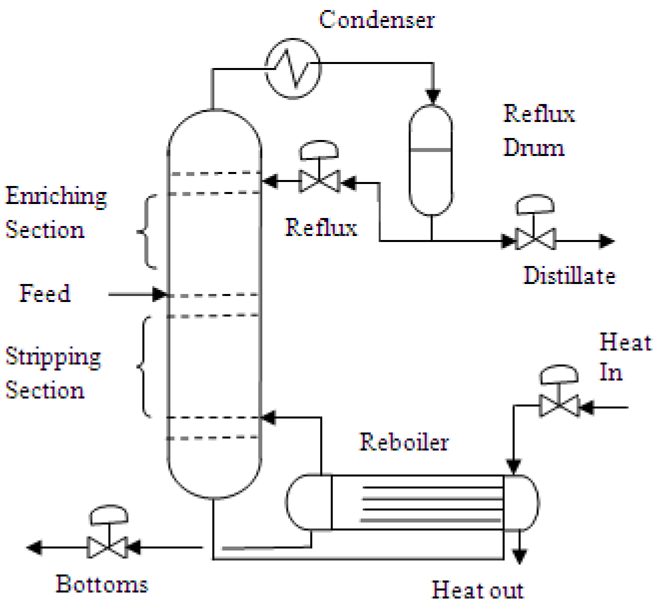


Fig. 1. Schematic diagram of distillation column [3].

The feed contains a mole percentage of the component called zF. The product stream at the top contains a composition of xD. The product stream leaving the bottom has a composition referred as xB of the light component. The important aspects of the steady-state operation, dynamics and control of continuous distillation columns are summarized in [4].

The initial process used in this work is Wood and Berry Distillation Column. Wood and Berry Distillation Column is actually designed and meant for the separation of Methanol and water from the mixture. The top product is Methanol whereas the bottom product is usually water. Methanol has the boiling point of 148 ^{o}F (64.7 ^{o}C) whereas water boils at 212 ^{o}F (100 ^{o}C). Since Methanol having low boiling point, it vaporises and forms the top product of the Distillation Column. It is then allowed to condense and the solidified form is taken. Water being the bottom product is in the liquid state and easily it can be measured out.

3. Fuzzy Model Predictive Controller

Fuzzy Logic Controller (FLC), can control the plant model with no overshoot, lesser error and in faster way. The controller response of MPC also has smoother response for selected processes. Here FMPC is implemented, in such a way that the controlled output of the intelligent FLC controller is given as the input or manipulated variable to the MPC. Thus the combined effect of both the controllers makes the FMPC to outperform the individual effect of controllers [5-7].

MPC uses a dynamic plant model to predict the effect of future reactions of the manipulated variables on the output and control signal is obtained by minimizing the cost function. An optimal input sequence is calculated. The measurements are then sent back to the controller, and a new optimizing problem is solved [8-10].

Fuzzy reasoning is capable of handling uncertain and imprecise information. Fuzzy logic is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values), Fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. A fuzzy logic based scheme or Fuzzy Inference System is a computer paradigm based on fuzzy set theory, fuzzy if then- rules and fuzzy reasoning.

In this work, a fuzzy predictive controller based on Takagi and Sugeno fuzzy models is considered where a linear predictive controller is derived for each rule of the fuzzy model. Therefore, the fuzzy controller includes the same premises as the fuzzy process model and the consequences are given by the resulting control action.

3.1. Parameters

FMPC includes both MPC and FLC. The control horizon and prediction horizon are tuned and accordingly select the control interval value. The prediction horizon (P) tells the controller how many sample steps ahead should be used when minimizing the object function. The control horizon (M) tells the controller how many control steps should be used when minimizing. The larger M is compared to P, the bigger the chance is that the controller will find an input sequence to minimize the function.

In Fuzzy side, the rules are framed first and the FIS file should import into the controller. Now the output of the Fuzzy Controller is given as the input of the MPC. Again this MPC controls the whole system and thus the final output.

3.2. Prediction

FMPC networks combine the advantages of both intelligent techniques and predictive techniques. The effective modelling and identification techniques, based on fuzzy structures, combined with MPC strategy result in effective control for nonlinear MIMO plants. MPC contributions like explicit handling of constraints, shorter development time, special ability to anticipate future events and can take control action, along with FLC's robustness, better stability, small overshoot, and fast response makes FMPC to take a step further than others.

3.3. FMPC tuning parameters

The closed-loop MPC and FLC simulations are performed using MATLAB Model Predictive Control Toolbox and Fuzzy Control Toolbox. The MPC controller is tuned based on trial and error method and General Predictive control method (GPC). This approach shows that the tuning values of Control Horizon (M) = 4, Prediction Horizon (P) = N = 96 produce considerably fair response. Takagi and Sugeno based FIS has been taken for fuzzy part.

Each element of this rule table represents 'IF'-'THEN' rule. For example: 'IF' error is Z and Rate of change of error is N 'THEN' output is S. Manipulated variables for top composition loop are the error (eD(k)) and the rate of change of error (ΔeD(k)). The output variable for the top composition controller is the variation in reflux flow rate (Δr(k)).

These variables are defined as:

$$eD(k) = xDr(k) - xD(k) \tag{1}$$

$$\Delta\, eD(k) = eD(k) - eD(k-1) \tag{2}$$

where xD is composition of top product, xDr is setpoint for xD and ΔR(k) is variation in reflux rate.

Manipulated variables for bottom composition are the error (eB(k)) and the rate of change of error (ΔeB(k)). The output variable for bottom composition controller is the variation in steam flow rate (Δs(k)).

These variables are defined as:

$$eB(k) = xBr(k) - xB(k) \tag{3}$$

$$\Delta\, eB(k) = eB(k) - eB(k-1) \tag{4}$$

where xB is composition of bottom product, xBr(k) is setpoint for xB and Δs(k) is variation in steam flow rate.

Three values have been taken in associated with each crisp variables eB(k), eD(k), ΔeB(k) and Δ eD(k) variables. The fuzzy set associated with all these variables are taken as [N , Z, P] where N- Negative, Z- Zero, Po-Positive.

In FMPC, model rules are tuned by a reinforcement learning method which has been applied for SOC (Self-organising fuzzy Controller) successfully. The difference between them is the evaluation target as the FMPC evaluates the model prediction performance whereas SOC learns control rules by evaluating the control performance. The fuzzy model proposed by Takagi and Sugeno the input variables of the premises of each rule are combined by "and" operators and the output variables represent linear models. Thus, the fuzzy model rules are the following:

R_1 : If (eB(k) = N and ΔeB(k) = N then Y = B

R_2: If (eB(k) = Z and ΔeB(k) = Z then Y = B

R_3: If (eB(k) = P and ΔeB(k) = P then Y = S

The entire rules are given in table form as shown in Table 1.

Table 1. Rule table for bottom and top composition control.

Δe \ **e**	N	Z	Po
N	B	S	S
Z	B	B	S
Po	B	B	S

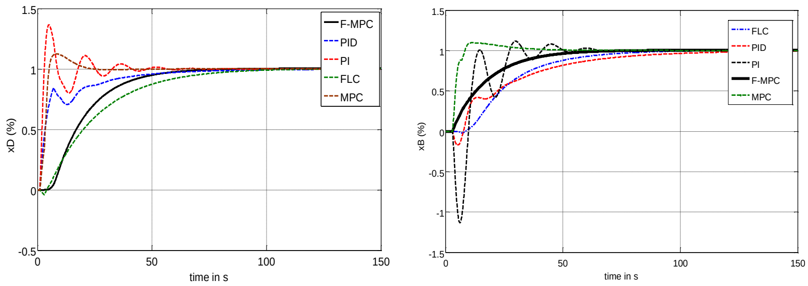
The defuzzification approach which has been used here is Centre of Gravity method. After completion of firing of each rule, fuzzy form output is converted to crisp form by centre of gravity method.

4. Simulation Results

4.1. Wood and Berry Model

The Wood and Berry distillation column model (Fig. 2) is taken as primary model, which is a 2×2 transfer function model of that separates methanol and water.

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.9e^{-3s}}{21s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{5}$$



(a) Top product **(b) Bottom product**

Fig. 2. Performance of Wood and Berry column.

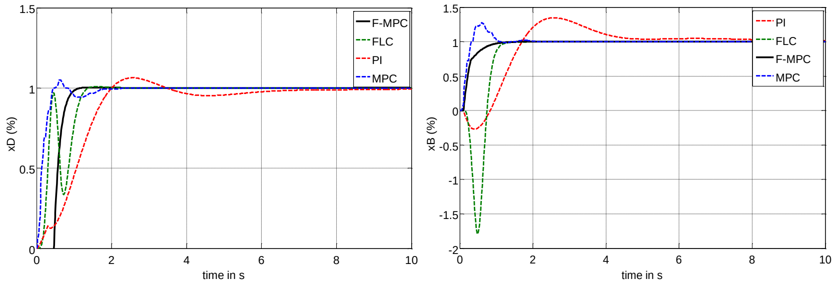
Table 2. Controller response of Wood and Berry column.

	Top product				Bottom product			
	$t_s(s)$	M_p	ISE	IAE	$t_s(s)$	M_p	ISE	IAE
PID	78	0.365	33.46	46.13	102	-0.13	61.28	57.92
MPC	35	0.15	31.77	41.36	65	0.15	60.36	54.63
FLC	70	0	30.06	40.13	60	-0	58.76	52.79
FMPC	64	0	29.14	38.04	55	0	57.31	51.24

4.2. Benzene Toluene model

As the name suggests, Benzene-Toluene distillation column model (Fig. 3) is to separate out benzene and Toluene from the mixture. Benzene having the boiling point of 80^0C vaporises fast and forms the top product of the Distillation Column whereas Toluene boils only at 110^0C so it forms as the bottom product. It is then allowed to condense and the solidified form is taken. Toluene being the bottom product is in the liquid state and easily it can be measured out.

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \dfrac{0.1687e^{-0.02s}}{4.219s+1} & \dfrac{-0.1236e^{-0.3s}}{5.618s+1} \\ \dfrac{-2.75e^{-1.8s}}{8.2s+1} & \dfrac{-4.28e^{-0.35s}}{9s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{6}$$



(a) Top product **(b) Bottom product**

Fig. 3. Performance of Benzene Toluene model.

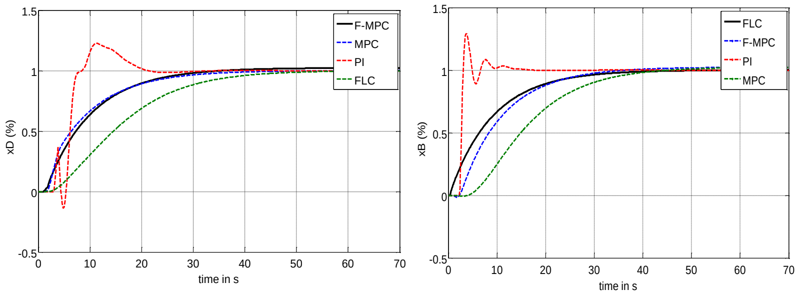
Table 3. Controller response of Benzene Toluene model.

	Top product				**Bottom product**			
	t_s(s)	**M_p**	**ISE**	**IAE**	**t_s(s)**	**M_p**	**ISE**	**IAE**
PID	6	1.07	2.68	6.12	5	1.35	1.67	5.63
MPC	3	1.05	2.46	5.67	3.5	1.27	1.21	4.98
FLC	2	-1.85	2.03	4.92	1.5	-1.750	1.01	4.12
FMPC	2	0	1.89	4.32	1.5	0	0.98	3.89

4.3. Vinante Luyben model

Vinante and Luyben in 1972 developed this model and thus the name Vinante Luyben Distillation Column model (Fig. 4).

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \dfrac{-2.2e^{-s}}{7s+1} & \dfrac{1.3e^{-0.3s}}{7s+1} \\ \dfrac{-2.8e^{-1.8s}}{9.5s+1} & \dfrac{4.3e^{-0.35s}}{9.2s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{7}$$



(a) top product **(b) bottom product**

Fig. 4. Performance of Vinante Luyben model.

Table 4. Controller response of Vinante Luyben model.

	Top product				Bottom product			
	t_s(s)	M_p	ISE	IAE	t_s(s)	M_p	ISE	IAE
PID	30	1.2	10.74	18.63	25	1.8	8.4	14.72
MPC	27	0	9.63	17.47	23	0	8.1	13.92
FLC	27	0	9.12	15.98	27	0	7.8	12.62
FMPC	23	0	8.16	15.06	23	0	7.6	12.12

5. Conclusion

In this work, an attempt is made to control various 2x2 distillation column models. A hybrid controlling method (MPC + Fuzzy) is proposed and its performance is validated with traditional MPC, FLC and conventional PI controller. Performance indices like settling time, maximum peak overshoot, ISE and IAE is compared with different controllers. The simulated result depicts the FMPC Controller performances are better than other controllers.

References

1. Seborge, D.E.; Edgar, T.F.; and Mellichamp, D.A. (2004). *Process dynamics and control*. Singapore, John Wiley &Sons.
2. Bequette, B.W. (2003). *Process control: modelling design and simulation*. Prentice-Hall international series in the physical and chemical engineering sciences.
3. Skogestad, S. (1997). Dynamics and control of distillation columns - A tutorial introduction. *Chemical Engineering Research and Design*, 75(6), 539-562
4. Wood, R.K.; and Berry, M.W. (1973). Terminal composition control of a binary distillation column. *Chemical Engineering Science*, 28(9), 1707-1717.
5. Sivakumar, R.; Suresh Manic, K.; Nertiga,V.; Akila, R.; and Balu, K. (2010). Application of fuzzy model predictive control in multivariable control of

distillation column. *International Journal of Chemical Engineering and Applications*, 1(1), 39-42.

6. Sivakumar, R.; and Shennes Mathew (2013). Design and development of model predictive controller for binary distillation column, *International Journal of Science and Research*, 2(12), 445-451
7. Prakash, J.; and Srinivasan, K (2009). Design of nonlinear PID controller and nonlinear model predictive controller for a continuous stirred tank reactor, *ISA Transactions*, 48, 273-282
8. Allgöwer, F.; Findeisen, and Nagy, Z.K. (2004). Nonlinear model predictive control: from theory to application. *Journal of the Chinese Institute of Chemical Engineers*, 35(3), 299-315.
9. Gaurav; and Kaur, A. (2012). Comparison between conventional PID and fuzzy logic controller for liquid flow control: Performance evaluation of fuzzy logic and PID controller by using MATLAB/Simulink. *International Journal of Innovative Technology and Exploring Engineering*, 1(1), 84-88.
10. Gupta, H.; and Verma, O.P. (2012). Intelligent controller for coupled tank system. *International Journal of Advanced Research in Computer Science and Software Engineering*, 2(4), 154-157
11. Morari, M.; and Ricker, N.L. (1995). *Model predictive control toolbox: for use with MATLAB*. The MathWorks, Inc. Mail 3 Apple Hill Drive Natick,1995
12. Manikandan, P.; Geetha, M.; Jovitha, J.; and Jubi, K. (2013). Design and critical evaluation of an intelligent fuzzy logic controller for nonlinear CSTR process. *International Journal of Information Technology and Electrical Engineering*; 2(5), 14-18
13. Raduca, M.; Raduca, E.; Hatiegan, C.; and Ungureanu, D. (2011). Fuzzy controller for adjustment of liquid level in the tank. *Annals of the University of Craiova, Mathematics and Computer Science Series*, 38(4), 33-44
14. Malhotra, R.; and Sodhi, R. (2011). Boiler flow control using PID and fuzzy logic controller. *International Journal of Computer Science Engineering & Technology*, 1(6), 315-319
15. Shridhar, R.; and Cooper, D.J. (1997). A tuning strategy for unconstrained SISO model predictive control. *Industrial & Engineering Chemistry Research*, 36(3), 729-746
16. Luan Vu, T.N.; Lee, J.; and Lee, M. (2007). Design of multi-loop PID controllers based on the generalized IMC-PID method with Mp criterion, *International Journal of Control, Automation, and Systems*, 5(2), 212-217.