Optimization and composition control of Distillation column using MPC

M.Manimaran[1],A.Arumugam[2],G.Balasubramanian[3],K.Ramkumar[4]
[1,3,4]School of Electrical and Electronics Engineering, SASTRA University,
Thanjavur, India 613401.
[2]School of Chemical and Biotechnology, SASTRA University,
Thanjavur, India 613401.
[1]maran.11188@gmail.com

***ABSTRACT*: This paper proposes the Model Predictive Control (MPC) scheme in a bubble cap distillation column . Even though PID controllers are widely used for the control of nonlinear system, there is a need for optimizing and conservation of energy. Here, MPC scheme is designed and it is used for controlling the composition in distillation columns.The tuning of PID controller is done using Sundaresan-Krishnaswamy method. The MATLAB platform is used for the implementation of MPC and the conventional PID controller.**

Keywords: Distillation column, Model predictive control, PID

I. INTRODUCTION

The Distillation is a nonlinear, multivariable and non-stationary process, which is used in chemical and petroleum industries etc.,purpose of the distillation system is to separate a liquid mixture into two or more components [1]. The conventional controller like PID provides appropriate results for linear systems, but they cannot provide tight control action for the non-linear systems as its response rate is slow [2, 3,4]. Advanced control approaches like minimum variance controllers cannot work effectively on nonlinear systems due to its difficulty and tough control actions. Fuzzy logic based model and control approach applied [5] and neural network employed to both the model and identification for distillation column [6] and it has been used to fuzzy-neural based inferential control [7] but all the scenarios did not provide any scope of optimization technique.

The MPC algorithms are widely used for many industrial applications [8] as it considers the constraints applied to the input and output variables compared to other control techniques. This paper ordered as follows:The model development and process description are clarified in section (II) , section (III) deals with controller synthesis and finally the section (IV) deals with results and discussion.

II. EXPERIMENTAL SETUP AND MODELLING

Distillation process extensively used in the chemical industry. The purpose of the system is to separate the two or more components depend on the boiling point. The separation wants relatively huge amount of energy .The structure of distillation column shown in Fig 1. Basically the column has been divided into three section bottom section is called a stripping section and the top of the column is called rectification section then the intermit section is called flash zone.This column had 10 theoritecal trays and one reboiler and one condenser.

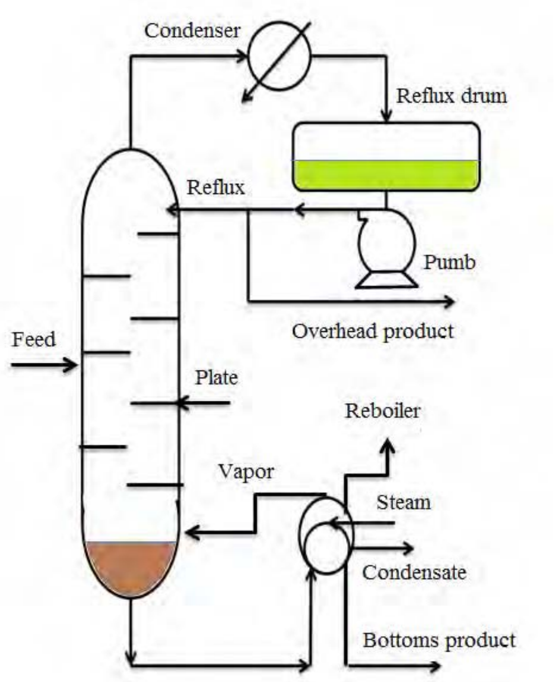

Fig. 1. Structure of distillation column

The reboiler provides necessary heat to the column and the condenser delivers the essential cooling to condense the overhead product. In many cases composition control and composition monitoring play the vital role in a distillation column [9].In this work composition is controlled by varying the reboiler temperature while reflux rate is kept constant. In order to obtain a real time data , the open loop test is conducted and the steady state curves are plotted as shown in Fig 2 and Fig 3. From the structure, the model is identified as First order plus time delay (FOPDT) model and the process parameters are obtained by Sundaresan-Krishnaswamy method [10]

$$G(S) = \frac{Ke^{-\theta s}}{\tau s + 1}$$

The validation curve for the system is shown in Fig 4.

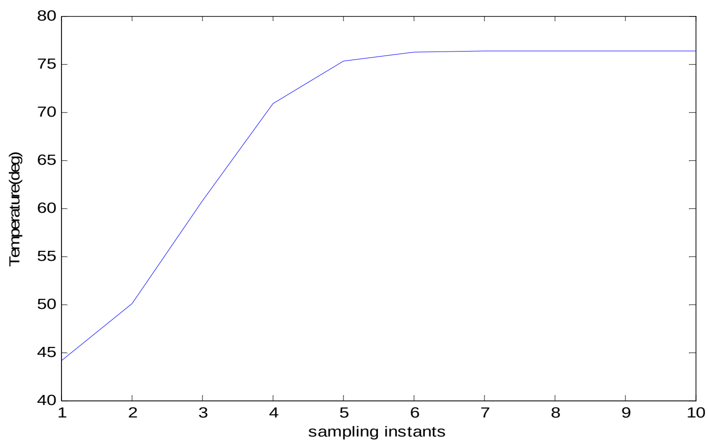

Fig.2.Process reaction curve of temperature

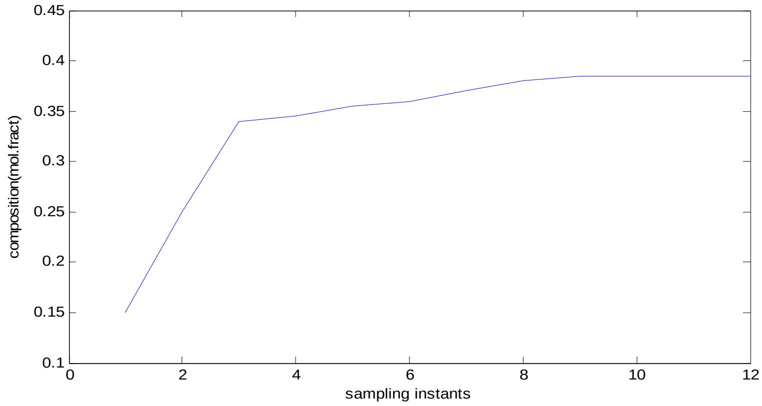

Fig.3.Process reaction curve for a composition

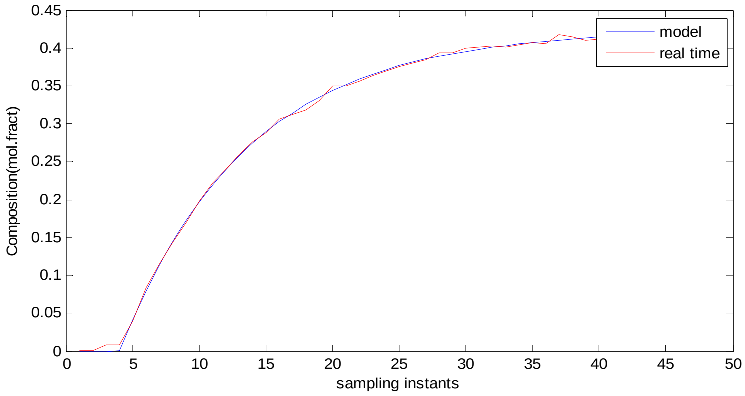

Fig.4. Model validation curve

III. DESIGN OF MODEL PREDICTIVE CONTROLLER

MPC is one of the advanced control strategies, which can forecast the future response of the plant and optimize the control input with the help of a model of the plant . The calculation of future response of the plant is made for a one Time duration(T) called as Prediction Horizon (Np) and right control action is taken for certain time limits created as control horizon (N_C).The prediction model will be augmented by the model of state space matrices. The structure of MPC is shown in Fig 5.

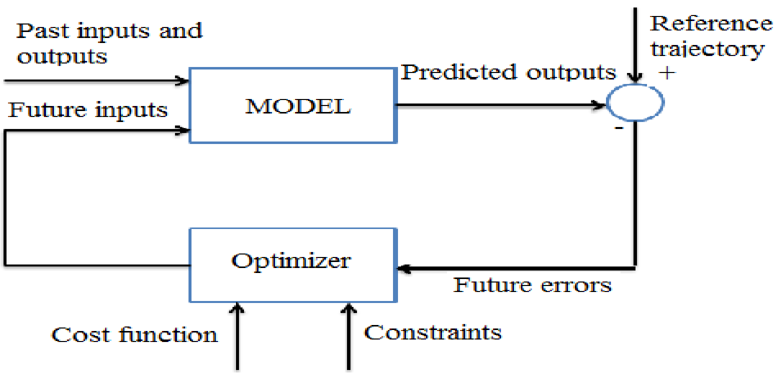

Fig.5. Structure of MPC

The augmented state-space model is given as

$$\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \overbrace{\begin{bmatrix} \beta_m \\ \gamma_m \beta_m \end{bmatrix}}^{\beta} \Delta u(k) \quad (1)$$

$$y(k) = \overbrace{\begin{bmatrix} 0_m & 1 \end{bmatrix}}^{\gamma} \begin{bmatrix} x_m(k) \\ y(k) \end{bmatrix} \quad (2)$$

Where $\quad 0_m = \underbrace{[0_m \quad 1]}_{n_1}$

$\alpha_{m,}\beta_m$ *and* γ_m are represented by the plant parameters. $\Delta u(k1) + \cdots + \Delta u(k_i + N_c - 1)$ are represented by the future control signals .Here the N_C represents the control horizon and N_P represents the prediction horizon. The future state variables are estimated as

$$x(k_i + 1|k_i) = \alpha x(k_i) + \beta \Delta u(k_i)$$

$$x(k_i + 2|k_i) = \alpha^2 x(k_i) + \alpha\beta\Delta u(k_i) + \beta\Delta u(k_i + 1)$$

$$x\left(k_i + N_p\middle|k_i\right) = \alpha^{N_p} x(k_i) + \alpha^{N_p - 1}\beta\Delta u(k_i) + \ \dots\ + \alpha^{N_p - N_c}\beta\Delta u(k_i + N_c - 1) \tag{3}$$

The future output is,

$$y(k_i + 1|k_i) = \gamma\alpha x(k_i) + \gamma\beta\Delta u(k_i)$$

$$y(k_i + 2|k_i) = \gamma\alpha^2 x(k_i) + \gamma\alpha\beta\Delta u(k_i) + \gamma\beta\Delta u(k_i + 1)$$

$$y\left(k_i + N_p\middle|k_i\right) = \gamma\alpha^{N_p} x(k_i) + \gamma\alpha^{N_p - 1}\beta\Delta u(k_i) + \ \dots + \gamma\alpha^{N_p - N_c}\beta\Delta u(k_i + N_c - 1) \tag{4}$$

From the eqn (4), output generalized use

$$Y = Fx(k_i) + \emptyset u \tag{5}$$

$$\text{Where } F = \begin{bmatrix} \gamma\alpha \\ \gamma\alpha^2 \\ \vdots \\ \gamma\alpha^{N_p} \end{bmatrix}_{(N_p X 1)} \tag{6}$$

$$\text{And } \emptyset = \begin{bmatrix} \gamma\beta & 0 & 0 & \dots & 0 \\ \gamma\alpha\beta & \gamma\beta & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \gamma\alpha^{N_p - 1}\beta & \gamma\alpha^{N_p - 2}\beta & \gamma\alpha^{N_p - 3}\beta & \dots & \gamma\alpha^{N_p - N_c}\beta \end{bmatrix}_{(N_p X N_c)} \tag{7}$$

Eqn (6) and Eqn (7) further used to minimize the cost function.

$$R_s^T = \overbrace{[1 \quad 1 \quad \dots \quad 1]}^{N_p} r(kk) \tag{8}$$

Now, assume the set point is constant and the cost function J is defined by

$$J = (R_s - Y)^T (R_s - Y) + U^T \bar{R} \mathrm{U} \tag{9}$$

$R = r_{W_{N_c X N_c}}$ Where the r_w is tuning parameter,

Substituting the output (Y) equation and we get

$$J = (R_s - Fx(k_i))^T (R_s - Fx(k_i)) - 2\Delta U^T \Phi^T (R_s - Fx(k_i)) + \Delta U^T (\Phi^T \Phi + R)\Delta U \tag{10}$$

Here our objective cost function is minimized and we get J is respect to ΔU

$$\Delta U = \left(\Phi^T \Phi + R\right)^{-1} \Phi^T (R_s r(k_i) - Fx(k_i) \tag{11}$$

The MPC controller tunning strategies are derived based on Sridhar and cooper tuning method [11] and the values are shown in Table I

IV. RESULTS AND DISCUSSION

The Ziegler- Nichols (Z-N) method is used to tune the PID controller and parameter values are tabulated in Table II. Both the controllers are compared using MATLAB environment and the result is shown in Fig 6. It is also analysed for different step changes and the corresponding responses are shown in the Fig 7 and Fig 8.The disturbance rejection of the controller for both the cases are plotted in Fig 9 and Fig 10. From the responses it is found that the MPC gives fast response and quick setting time compared to PID controller. The effectiveness of the controller is also verified based on the performance indices and it is tabulated in Table III.

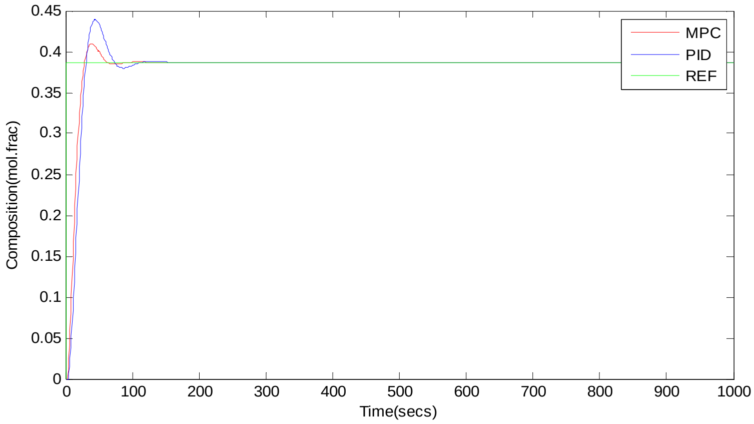

Fig.6. Comparison of the response of PID and MPC

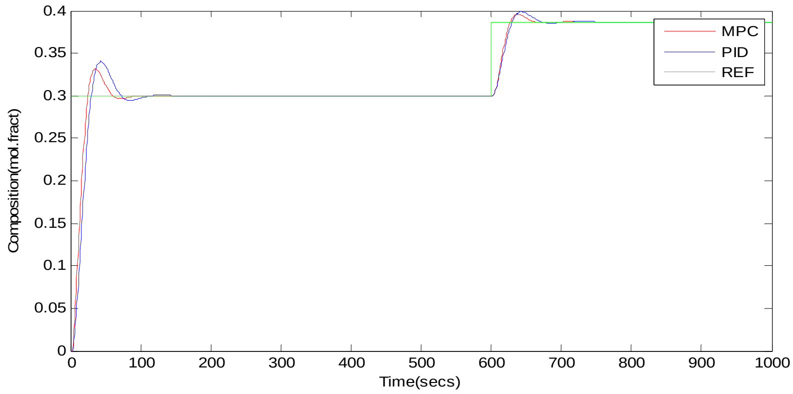

Fig.7. Positive set point changes response of PID and MPC

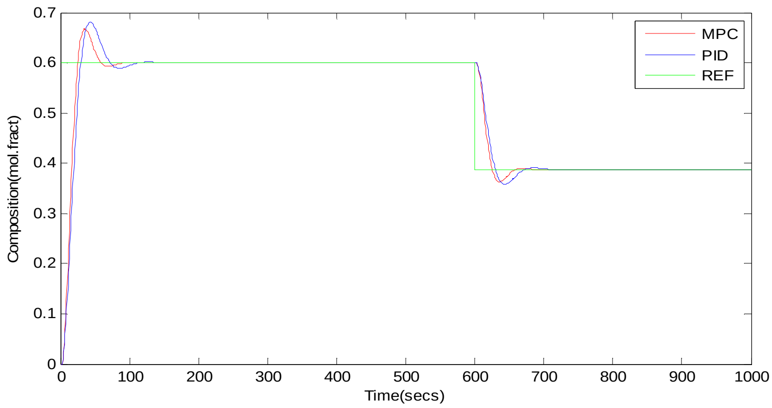

Fig.8. Negative set changes response comparison of PID and MPC

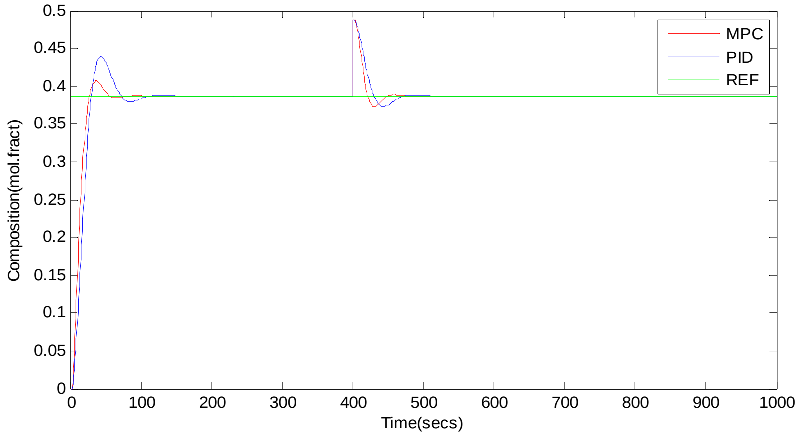

Fig.9.comparison the response of positive disturbance in PID and MPC

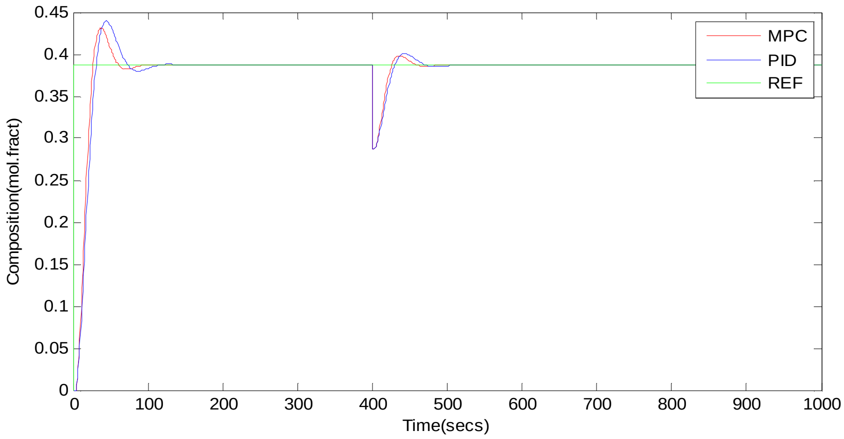

Fig.10.comparison the response of negative disturbance in PID and MPC

TABLE I: TUNING PARAMETERS OF MPC

PARAMETER	VALUE
N_P	20
N_C	10
T	1

TABLE II: TUNING PARAMETERS OF PID

PARAMETER	VALUE
K_p	0.11
K_i	0.6
τ_d	0.1

TABLE III: PERFORMANCE CHARACTERISTICS

CONTROLLER	ISE	IAE	ITAE
PID	2.8025	10.116	197.94
MPC	2.14	8.420	174.05

V. CONCLUSION:

In this work, MPC controller is proposed for composition control in a Bubble cap distillation column and it played a vital role for optimization of energy used by the process. The comparison has been done between MPC and PID and it shows that MPC provides better performance than PID by observing ISE, ITAE and IAE.

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