

Parameter Identification and Dynamic Matrix Control Design for a Nonlinear Pilot Distillation Column

Manimaran.M^{1*}, Malaisamy.S², Mohamed rafiq.M², Petchithai.V²,
Chitra .V.S², Kalanithi.K², Abirami.H²

^{1,2}Department of Instrumentation and control Engineering Sethu Institute of Technology, Viruthunagar-626115, India.

Abstract: This paper describes the Dynamic Matrix Control design (DMC) for a Pilot distillation column. Essentially in many cases the conventional controllers like PID doesn't provide a sufficient control action for a highly nonlinear system. Here the DMC scheme is designed and it is used to control the composition for a Pilot distillation column it consists a combination of a methanol and water system. Here the Least square technique is used to estimate the parameters and build the exact model of the Process. The MATLAB platform is used and implementation of the DMC and PID.

Keywords: Distillation column, Least square technique (LS), DMC (Dynamic Matrix Control), PID.

I.Introduction:

Distillation column is one of the key elements of the chemical and oil industries, which is having nonlinear, multivariable and nonstationary process. Both modeling and controlling a distillation column is a very difficult task because it's highly nonlinear system^{1,2}. The purpose of the distillation is to separate a liquid mixture into two or more components. Composition control plays the crucial role for a distillation column. Generally modern process control tools have increased the flexibility and performance of the chemical plants³. The conventional controller PID employed to control the distillation columns does not tight control action^{4,5}. To solve critical control issues and to achieve better performance in industrial application, PID controllers are used, but they face difficulties in controlling non-linear process and cannot predict immediate change in an input^{6,7,8}. To overcome these difficulties MPC controller is used and it is mainly used for industries side. Actually the distillation column mathematical model needs to be implemented the predictive controller so that here the real time data will be taken from the distillation column and the model will be developed from with the help of system identification technique^{9,10} Some review articles consider MPC on academic perspective. Some paper deal with (SMPC) simplified model predictive control algorithm¹¹.

Dynamic matrix controller (DMC) is the most popular controller and it is generally used it can be accept the transfer function representation models and reduce the computational time¹².

II. Parameter Identification and Modeling:

Linear model can be obtained by two ways one is system identification and another one is linearization of a nonlinear model. System identification techniques used through experimental study is possible, but the nonlinear model of the process having different open loop and closed loop studies as possible^{12,13}. This paper describes a linear model based Dynamic Matrix Control design using System identification techniques. Linear black box models can be obtained by ARX, ARMAX, ARMA, ARARMAX, ARARX etc., These black box models can be developed by correlating sequence relationship between input and output data, here the input is reboiler temperature (manipulated variable) and the output is overhead product composition (controlled variable). The real time data are taken from by using a reflux rate of the column as keeping constant and to give the sudden step changes of the reboiler temperature. After obtaining the data model has been developed by using a least square algorithm¹⁴ (LS). The main application of least square is model fitting. The least square

technique is mainly used for estimating the system parameter and minimization of error, so that here the system parameter estimation and error minimization developed by least square method it is one of the system identification technique.

$$\begin{aligned}
 y(k) + \alpha_1 y(k-1) + \alpha_2 y(k-2) &= \beta_1 u(k) + \beta_2 u(k-1) \\
 y(0) + \alpha_1 y(-1) + \alpha_2 y(-2) &= \beta_1 + \beta_2 u(-1) \\
 y(1) + \alpha_1 y(0) + \alpha_2 y(-1) &= \beta_1 u(1) + \beta_2 u(0) \\
 y(2) + \alpha_1 y(1) + \alpha_2 y(0) &= \beta_1 u(2) + \beta_2 u(1) \\
 \vdots & \\
 y(n) + \alpha_1 y(n-1) + \alpha_2 y(n-2) &= \beta_1 u(n) + \beta_2 u(n-1)
 \end{aligned} \tag{1}$$

System parameters are given by

$$\theta = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \end{bmatrix} \tag{2}$$

Output values are

$$y = \begin{bmatrix} y(1) \\ \vdots \\ y(n) \end{bmatrix} \tag{3}$$

Recursive vectors are given by

$$\varphi = \begin{bmatrix} \varphi^T(0) \\ \varphi^T(1) \\ \vdots \\ \varphi^T(N-1) \end{bmatrix} = \begin{bmatrix} -Y(0) & -Y(-1) & U(1) & U(0) \\ -Y(1) & -Y(0) & U(2) & U(1) \\ \vdots & \vdots & \vdots & \vdots \\ -Y(N-1) & -Y(N-2) & U(N-1) & U(N-2) \end{bmatrix} \tag{4}$$

$$Y = \varphi \theta \tag{5}$$

E is the N-dimensional error vectors

$$e = y_d - y$$

$$e^T = (e(1), e(2) \dots \dots \dots e(n)) \tag{6}$$

Performance measure of J is given by

$$\begin{aligned}
 J &= e^T e = \sum_{k=1}^n e^2(k) \\
 J &= (y - \varphi \theta)^T (y - \varphi \theta)
 \end{aligned} \tag{7}$$

To optimize the performance measure, parameters are estimated

$$\begin{aligned}
 \frac{\partial J}{\partial \theta} &= -2\varphi^T (y - \varphi \theta) \\
 \theta &= (\varphi^T \varphi)^{-1} \varphi^T y_d
 \end{aligned} \tag{8}$$

III. Dynamic Matrix Control Design (Dmc):

Dynamic Matrix control (DMC) algorithm is designed to predict the future response of the plant^{14,15}. It is mainly used in industries especially in chemical industries. Now days it is mainly used in model identification and global optimization. DMC is the unconstrained multivariable control algorithm. DMC algorithm, key futures are, we are taking the linear step response model of the plant, prediction horizon performance over the quadratic problem and the least square problem is the solution of computed optimal inputs¹⁶. The main objective of DMC is the future response of the plant output behavior trying to follow set point as close as possible to the least square sense with the manipulated variable (MV) moves. The manipulated variable is selected to minimize a quadratic objective it can be considered to minimize the future error. DMC control algorithm started from similar cases of a system without constraints and it extended to multivariable constraint cases.

The step response model employed as

$$y(t) = \sum_{i=1}^{\infty} g_i \Delta u(t - i) \tag{9}$$

Predicted values along the horizon

$$\hat{y}\left(t + \frac{k}{t}\right) = \sum_{i=1}^{\infty} g_i \Delta u(t + k - i) + \hat{n}\left(t + \frac{k}{t}\right) = \sum_{i=1}^k g_i \Delta u(t + k - i) + \sum_{i=k+1}^{\infty} g_i \Delta u(t + k - i) + \hat{n}(t + k/t) \tag{10}$$

Here the disturbance is considered to be constant that is, $\hat{n}(t + k/t) = \hat{n}\left(\frac{t}{t}\right) = y_m(t) - \hat{y}\left(\frac{t}{t}\right)$ it can be written as

$$\begin{aligned} \hat{y}\left(t + \frac{k}{t}\right) &= \sum_{i=1}^k g_i \Delta u(t + k - i) + \sum_{i=k+1}^{\infty} g_i \Delta u(t + k - i) + y_m(t) - \sum_{i=1}^{\infty} g_i \Delta u(t - i) \\ &= \sum_{i=1}^k g_i \Delta u(t + k - i) + f(t + k) \end{aligned}$$

$f(t+k)$ considered as free response of the system and the part of response not depend on the future control action that is given by

$$Xf(t + k) = y_m(t) + \sum_{i=1}^{\infty} (g_{k+i} - g_i) \Delta u(t - i) \tag{11}$$

The system is stable the co-efficient g_i of step response to be constant after the value of N -sampling periods, so it can be considered as

$$X g_{k+i} - g_i \approx 0, i > n \tag{12}$$

That free response $f(t+k)$ computed as

$$f(t + k) = y_m(t) + \sum_{i=1}^N (g_{k+i} - g_i) \Delta u(t - i) \tag{13}$$

The m-control actions the prediction can be computed as the prediction horizon $k=(1, \dots, p)$ it can be derived as

$$\begin{aligned} \hat{y}\left(t + \frac{1}{t}\right) &= g_1 \Delta u(t) + f(t + 1) \\ \hat{y}\left(t + \frac{2}{t}\right) &= g_2 \Delta u(t) + g_1 \Delta u(t + 1) + f(t + 2) \\ &\vdots \\ \hat{y}\left(t + \frac{p}{t}\right) &= \sum_{i=1}^m g_i \Delta u(t + p - i) + f(t + p) \end{aligned}$$

The system dynamic matrix G is given by

$$G = \begin{bmatrix} g_1 & 0 & \dots & 0 \\ g_2 & g_1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_m & g_{m-1} & \dots & g_1 \\ \vdots & \vdots & \ddots & \vdots \\ g_p & g_{p-1} & \dots & g_{p-m+1} \end{bmatrix}$$

Then it can be written by

$$\hat{y} = Gu + f \tag{14}$$

This expression related the future outputs of the control increments, so that it will be use to calculate the necessary action to achieve a system behaviour.

Control algorithm equations derived by

$$J = \sum_{j=i}^p [\hat{y}\left(t + \frac{j}{t}\right) - w(t + j)]^2 \tag{15}$$

The control effort include and it present the generic form

$$J = \sum_{j=1}^p [\hat{y}\left(t + \frac{j}{t}\right) - w(t + j)]^2 + \sum_{j=1}^m \lambda [\Delta u(t + j - 1)]^2 \tag{16}$$

The minimization of cost function $J=ee^T + \lambda uu^T$ and the vector future errors of the prediction horizon and the u vector is composed future control increments and it can be obtained compute the J and it equal to zero and it provides the result as

$$Xu = (G^T G + \lambda I)^{-1} G^T (w - f) \tag{17}$$

IV. Results and Discussion:

The real time data are taken from the experimental Pilot distillation column fig (1) and fig (2) shows that response of input and output of the process. The PID is adjusted by the Ziegler Nichols (Z-N) method. Both the PID controller and DMC controller for the Pilot distillation column validated using MATLAB environment and the result is obtained. The DMC controller tuning strategies are shown in Table (I) and the conventional PID control tuning parameters are shown in Table (II) and then the performance indicates in tabulated in Table (III).The DMC and PID positive disturbance response shown in fig (3) ,fig (4) and the negative disturbance response plotted in the fig (5), fig (6) from the responses we prove that DMC gives fast response and quick setting time of the PID.

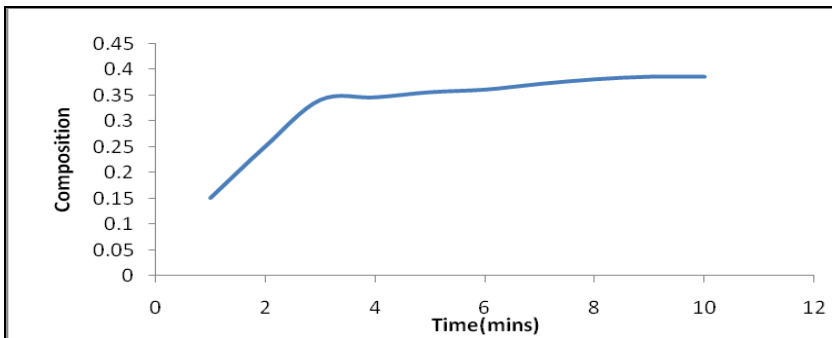


Fig.1.Process reaction curve for composition

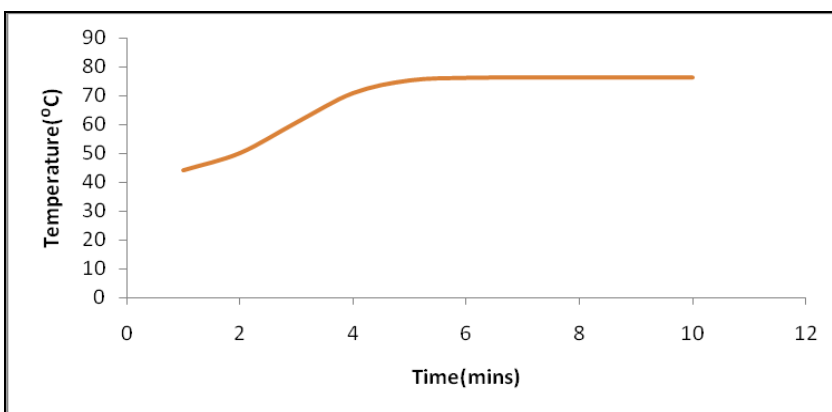


Fig.2.Process reaction curve for Temperature

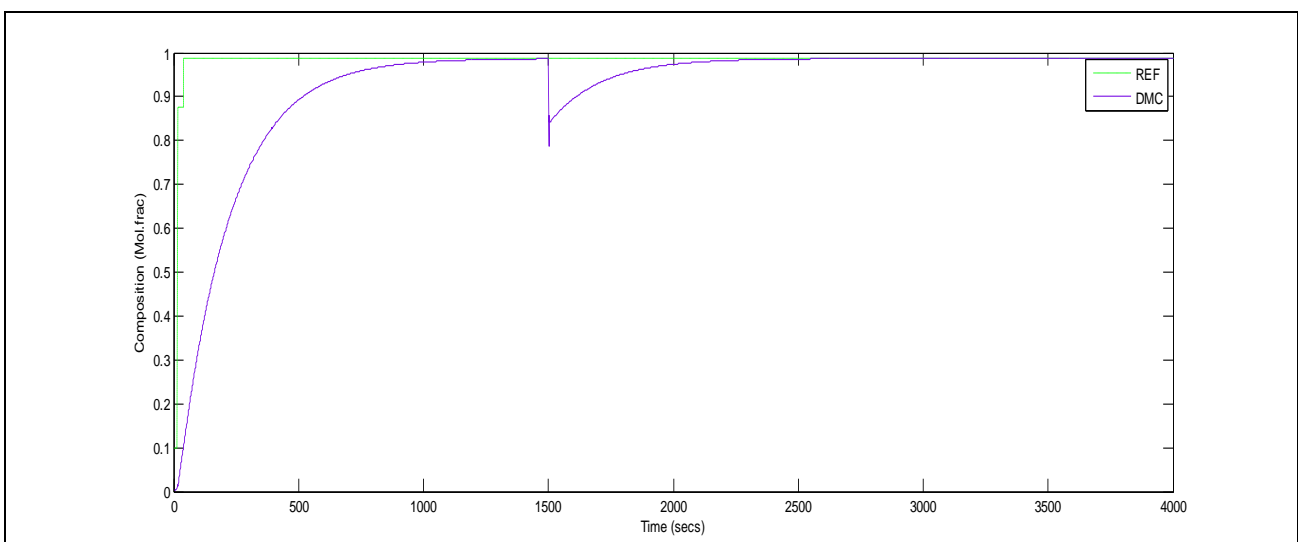


Fig.3. The response of DMC with negative disturbance

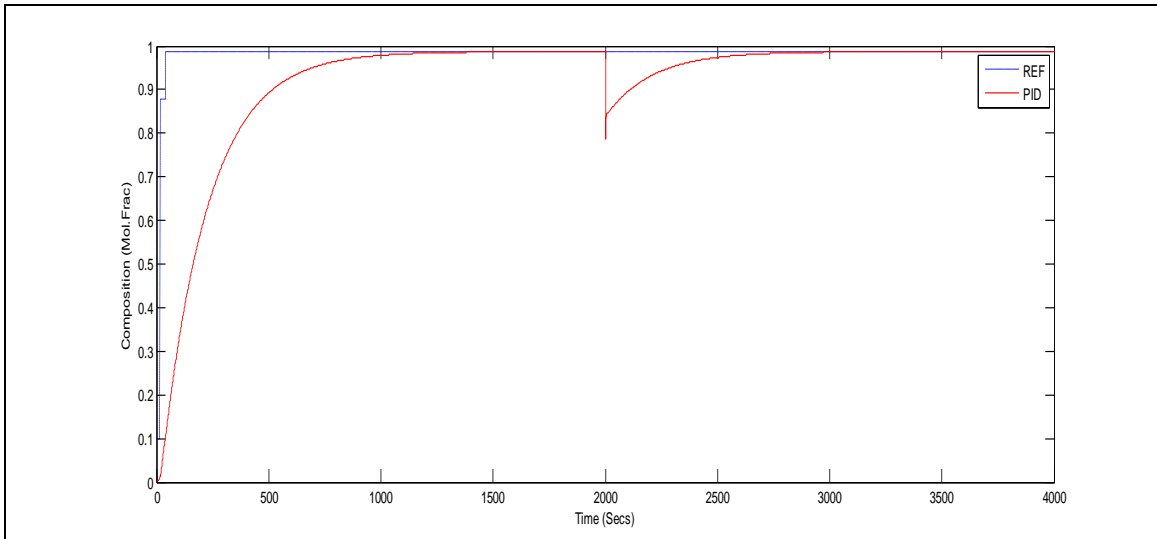


Fig.4. The response of PID with negative disturbance

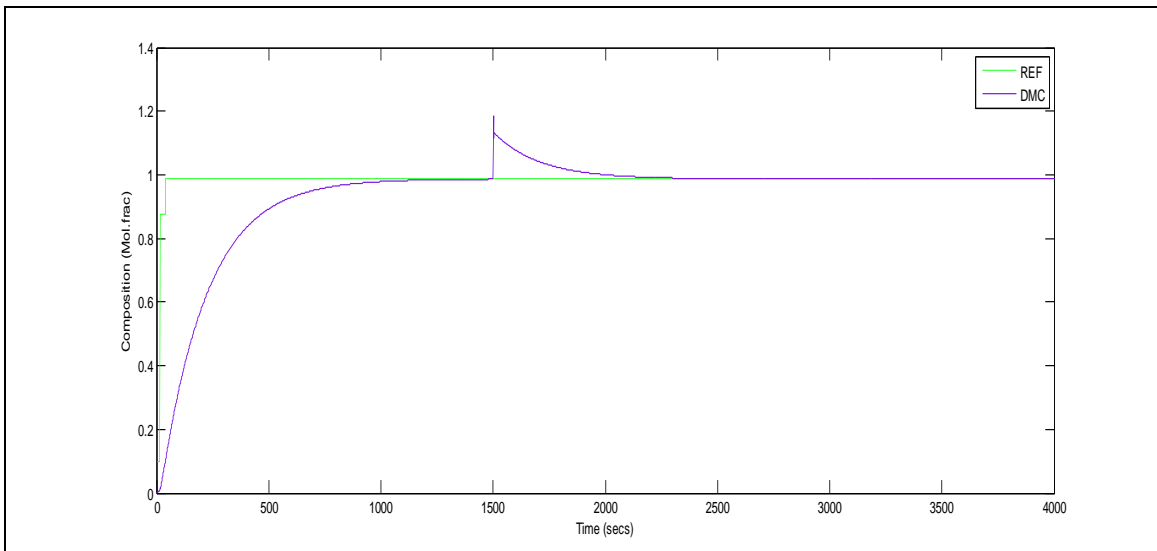


Fig.5. The response of DMC with positive disturbance

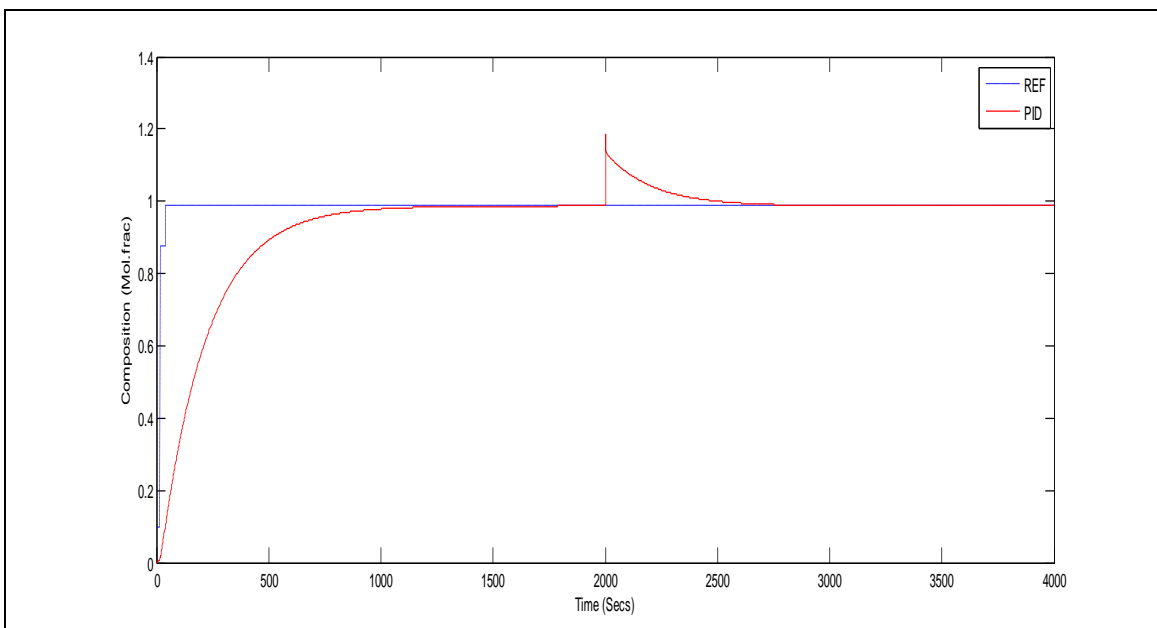


Fig.6. The response of PID with positive disturbance

Table I: Tuning the Parameters of DMC

| Parameter | Value |
|-----------|-------|
| N_p | 10 |
| N_c | 6 |
| T | 2 |

Table II: Tuning the Parameters of PID

| Parameter | Value |
|-----------|-------|
| P | 1 |
| I | 0.8 |
| D | 0.02 |

Table III: Performance Measure Characteristics

| Controller | Ise | Iae | Itae |
|------------|---------|---------|--------|
| PID | 190.970 | 400.750 | 5.1024 |
| DMC | 0.1000 | 0.0100 | 0.1000 |

V. Conclusion

In this work DMC is designed and control a composition of a pilot distillation column and its response compared with a Conventional PID. The comparison has been done between DMC and PID, it shows that DMC provided better performance than PID by observing ITAE (Integral time absolute error), IAE(Integral absolute error) and ISE (Intergral square error).

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