ISSN 2321 – 2004

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

MIMO Identification and Controller design for Distillation Column

S.Meenakshi[1], A.Almusthaliba[2], V.Vijayageetha[3]

Assistant Professor, EIE Dept, Sethu Institute of Technology, Tamilnadu, India [1]

PG Student, EIE Dept, KalasalingamUniversity, Tamilnadu, India [2]

Assistant Professor, EIE Dept, Sethu Institute of Technology, Tamilnadu, India [3]

Abstract: This paper discusses the system identification of Multi-input Multi-output (MIMO) system and design of Model Predictive Controller (MPC) for identified model. Distillation column process is taken for studies. It is an important processing unit in petroleum refining and chemical industries, and needs to be controlled close to the optimum operating conditions because of economic incentives. Subspace identification method is used to identify the MIMO model and Model Predictive Controller is designed for identified model. MPC is widely adopted in the process industry as an effective means to deal with large multivariable constrained control problems.

Keywords: Distillation column, Subspace identification, Model Predictive Controller.

I. INTRODUCTION

In the System Control Design the most important consideration is a well defined model for the plant that we want to control. One way to obtain this model is by using a numerical process known as system identification. Most of the industrial distillation columns are currently controlled by multiloop controllers based on linear models which are penalized by several shortcomings. It is obvious that the use of PID control has a long history in control engineering and is acceptable for most of real applications because of its simplicity in architecture, even though a great number of advanced control techniques have been exhibited successively [10]. But some of the processes are difficult to control with standard PID algorithm (e.g., large time constants, substantial time delays, inverse response, etc.) hence we go for better controller design like Model predictive controller.

MPC has been used in industry for more than 30 years, and has become an industry standard (mainly in the petrochemical industry) due to its intrinsic capability of dealing with constraints and multivariable systems [2]. Most commercially available MPC technologies are based on a linear model of the process. MPC controller considers process input, state and output constraints directly in the control calculation. This means that constraint violations are far less likely, resulting in tighter control at the optimal constrained steady-state for the process. It is the inclusion of constraints that most clearly distinguish MPC from other process control techniques.

In section 2, distillation column is discussed and in section 3 subspace identification methods and formation of MIMO model from MISO models are given and Model predictive controller is designed for identified model in section 5.

II. DISTILLATION COLUMN

Distillation is one of the most important operation units in chemical engineering. The aim of a distillation column is used to separate a mixture of components into two or more products of different compositions [9]. The physical principle of separation in distillation is the difference in the volatility of the components. Distillation control is a challenging endeavour due to

- Nonlinearity
- Multivariable interaction
- The non-stationary behaviour
- The severity of disturbances.

Effective control of distillation columns leads to better product quality and production flexibility, lower energy consumption and lower pollution. [2]. A typical two-product distillation column is taken as study model indicating the most important loops of a binary distillation is shown in Fig. 2.1 [4]. Binary distillation column normally requires the following control objects:

- Distillate composition control
- Bottom product composition control
- Reflux drum level control
- Liquid level control at the base of the column

The first two control objectives characterize the two product streams, where the other two objects are required for operational feasibility (i.e. to prevent flooding and drying up of the reflux drum and the base of the column). The dynamic responses of control loop 3 and 4 are usually much faster than the dynamic responses of other control loops**.**

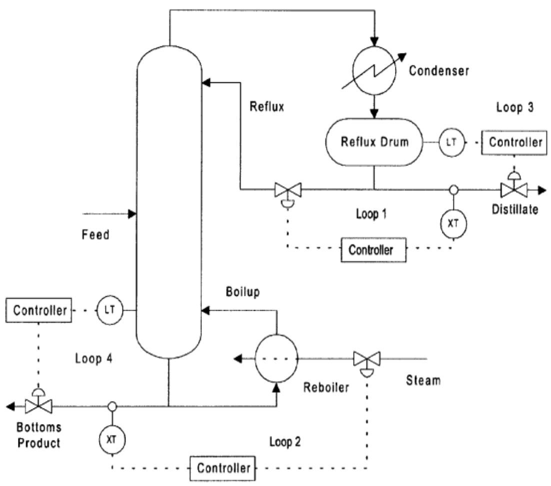

Fig.2.1 Control of binary distillation column

III. SUBSPACE SYSTEM IDENTIFICATION METHOD

System identification is a process that includes acquiring, formatting, processing, and identifying mathematical models based on raw data from a real-world system. We then validate that the resulting model fits the observed system behavior. If the results are unsatisfactory, we revise the parameters and iterate through the process. There are many methods available for Multi-input Multi-output system identification. Here, subspace identification method is done by using N4SID algorithm. Subspace methods estimate a state space model of a multivariable process directly from input/output data. MIMO identification is performed as two separate MISO identifications as MISO1 and MISO2. The two MISO models are then combined into a single MIMO statespace model. Two approaches are used for estimating the order of state-space model, i.e., by examining the singular value decompositions of N4SID algorithm and by looking at the simulation errors [1]. N4SID (Numerical methods for Subspace Identification), PEM (Prediction Error Minimized method), MOESP (Multivariable Output Error Subspace), CVA (Canonical Variate Analysis) are some of the algorithms used for subspace identification.

A. Order Estimation

The order of state-space model is estimated by examining the singular value decompositions and also by comparing the loss function and final prediction error (FPE) estimated by N4SID algorithm for various model orders. In which order gives the minimum loss function and FPE that will be chosen as a model order for statespace estimation.

B. Formulation of MIMO Model

The method to combine the two MISO models into a single MIMO model is formulated by the following three steps (Tri Chandra et al).

Step 1: Constructing the new state (u), input (x) and output (y) vectors.

$$x=\begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix};\quad u=\begin{bmatrix} RRF \\ RXF \\ RDF \\ XE \\ PT \end{bmatrix};\quad Y=\begin{bmatrix} XD \\ XB \end{bmatrix}$$

Step 2: Estimating the coefficient matrices A, B, C & D for two MISO models

Step 3: Constructing the new coefficient matrices by combining the estimated coefficient matrices of MISO models.

$$A=\begin{bmatrix} A1 & 0 \\ 0 & A2 \end{bmatrix};\ B=\begin{bmatrix} B1 \\ B2 \end{bmatrix};\ C=\begin{bmatrix} C1 & 0 \\ 0 & C2 \end{bmatrix};\quad D=\begin{bmatrix} D1 \\ D2 \end{bmatrix}$$

IV. OVERVIEW OF MODEL PREDICTIVE CONTROL

Mainly MPC is used for the processes which are associated with the following problems:

- Large number of manipulated and controlled variables
- Constraints imposed on both the manipulated and controlled variables
- Changing control objectives
- Time delays

A. Principle of MPC

The MPC follows the principle of Receding horizon control as shown in fig.4.1 [4]. Here, the control moves are calculated by following steps.

ISSN 2321 – 2004
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

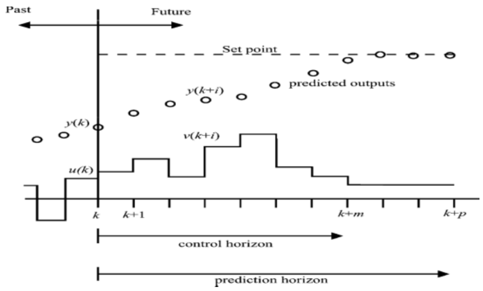

Fig.4.1 Receding Horizon Control

1. At the k-th sampling instant, the values of the manipulated variables, u, at the next M sampling instants, {u (k), u (k+1), u (k+M -1)} are calculated.
This set of M "control moves" is calculated so as to minimize the predicted deviations from the reference trajectory over the next P sampling instants while satisfying the constraints. M = control horizon, P = prediction horizon
2. Then the first "control move", u (k), is implemented.
3. At the next sampling instant, k+1, the M-step control policy is re-calculated for the next M sampling instants, k+1 to k+M, and implement the first control move, u(k+1).
4. Then Steps 1 and 2 are repeated for subsequent sampling instants.

The output weights are used for setpoint tracking of MPC. Specifically, the controller predicts deviations for each output over the prediction horizon. It multiplies each deviation by the output's weight value, and then computes the weighted sum of squared deviations, $S_y(k)$, as 4.11

$$S_y(k) = \sum_{i=1}^{P} \sum_{j=1}^{n_y} \{w_j^y [r_j(k+i) - y_j(k+i)]\}^2 \qquad 4.11$$

One of the controller objectives of MPC is to minimize the weighted sum of controller adjustments, calculated according to 4.12

$$S_{\Delta u}(k) = \sum_{i=1}^{M} \sum_{j=1}^{n_{mv}} \{w_j^{\Delta u} \Delta u_j(k+i-1)\} \qquad 4.12$$

Where, M is control horizon, n_{mv} is the number of manipulated variables, $\Delta_{uj}\ (k+i-1)$is the predicted adjustment in manipulated variable j at future (or current) sampling interval k+i–1, and $w_j^{\Delta u}$ is the weight on this adjustment, called the rate weight because it penalizes the incremental change rather than the cumulative value. By increasing this weight forces the controller to make smaller, more cautious adjustments. For each sampling instant in the prediction horizon, the controller multiplies predicted deviations for each output by the output's weight, squares the result, and sums over all sampling instants and all outputs. One of the controller's objectives is to minimize this sum, that is, to provide good setpoint tracking. The weights specify trade-offs in the controller design.

V. RESULTS AND DISCUSSION

For MIMO system identification, 90 samples of ethane-ethylene distillation column with sampling interval 15min and with 10% additive white noise are collected from DAISY system identification lab which is having five inputs and two outputs as followings and Input-output datas are shown in figure.5.1
Inputs:
RRF- ratio between the reboiler duty and the feed flow
RXF- ratio between the reflux rate and the feed flow RDF- ratio between the distillate and the feed flow XE- input ethane composition
PT- top pressure
Outputs:
XD- top ethane composition
XB- bottom ethylene composition

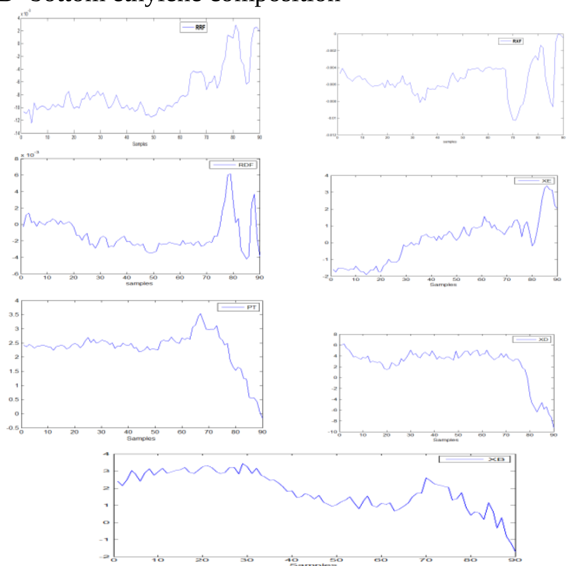

Fig.5.1 Input-Output data set

MIMO identification is carried out by subspace identification method. MIMO model is formulated by combining two MISO models as MISO1 and MISO2. The input variables of the first MISO model are RRF, RXF, RDF, XE & PT and its output variable is XD. For the second MISO model, the input variables are RRF, RXF, RDF, XE & PT and its output variable is XB.
For model order selection, N4SID algorithm is used which suggests order of the model according to Singular value decomposition. Considering the loss function and final prediction error(FPE), model order '3' gives less loss function and FPE which is given in table.5.1. So, the model order is chosen as '3' for both MISO models. After the

ISSN 2321 – 2004

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

selection of model order, N4SID, MOESP, CVA algorithms are used to estimate the parameters of the model. From 90 samples 69 are taken for estimation and remaining samples are taken for validation. During validation MOESP gives better fitness value for both MISO models which is shown in fig.5.2 and fig.5.3.

Model order	MISO1		MISO2	
	Loss function	Final prediction error	Loss function	Final prediction error
1	0.234832	0.289286	0.0438408	0.0540068
2	0.245053	0.358701	0.0413254	0.0604909
3	0.165676	0.280929	0.0222913	0.0377984
4	0.158068	0.3048982	9.96708	19.2119
5	0.184763	0.398982	0.0330724	0.0714173

Table.5.1 Model order selection using N4SID algorithm

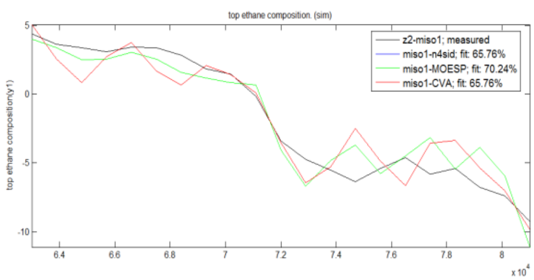

Fig.5.2 Validation of MISO1

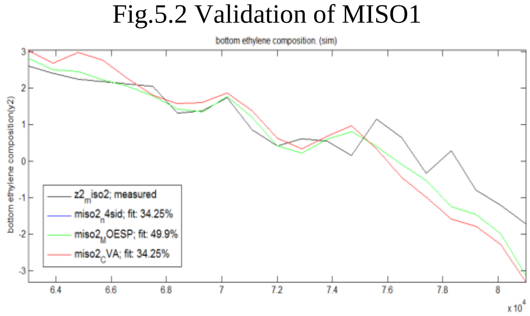

Fig.5.3 Validation of MISO2

The identified State-space model of discrete -time LTI system is as the following:

$$x(k+1) = A\,x(k) + B\,u(k) \qquad 5.1$$

$$y(k) = C\,x(k) + D\,u(k) \qquad 5.2$$

$$A=\begin{bmatrix} 0.9607 & 0.5216 & -0.1667 & 0 & 0 & 0 \\ 0.000641 & -0.0723 & 0.9488 & 0 & 0 & 0 \\ 0.1856 & -0.5248 & -0.4089 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.8102 & 0.5213 & -0.2534 \\ 0 & 0 & 0 & -0.1308 & -0.2129 & -0.9478 \\ 0 & 0 & 0 & -0.1409 & 0.5728 & 0.09643 \end{bmatrix}$$

$$B=\begin{bmatrix} -4.93 & -161.9 & 299.3 & 0.09287 & -0.06773 \\ -78.82 & 104.4 & 567.7 & 1.18 & -0.9773 \\ -214.2 & 42.44 & -234 & -0.3599 & 1.992 \\ -12.06 & 2.8 & 8.037 & 0.3244 & -0.3144 \\ -83.9 & 48.92 & 114 & 0.6266 & -0.09466 \\ 24.89 & 101 & -130.2 & 0.2287 & -0.07217 \end{bmatrix}$$

$$C=\begin{bmatrix} -0.56 & 0.671 & -0.1144 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.6668 & 0.6017 & -0.23 \end{bmatrix}$$

$$D=\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Model predictive controller was designed for the identified model of ethane-ethylene distillation column. The servo response of controller is as shown in fig.5.4. MPC designed for identified model with the following parameters Prediction horizon=150; Control horizon = 50; Output Weights = [0.05 0.01]; Manipulated Variables Rate Weights = [5 5 5 0.5 1].

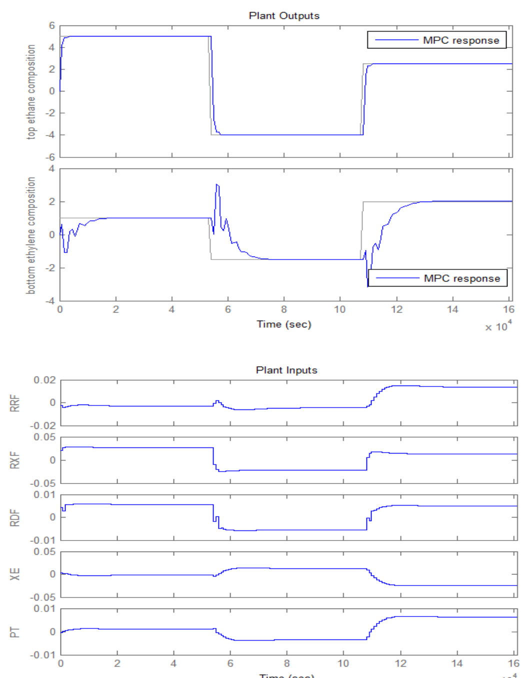

Fig.5.4 Closed loop servo response of MPC

VI. CONCLUSION

The MIMO system identification has done for ethane-ethylene distillation column successfully by using Subspace identification method. MOESP algorithm gives better results during estimation as well as validation of MISO1 and MISO2 than the other algorithms. The identified model replicates the behaviour of original system while designing the MPC. So the identified model is well suited for control applications.

REFERENCES

[1] Tri Chandra S. Wibowo, Nordin Saad, "*MIMO model of an interacting series process for Robust MPC via System Identification*", ISA Transactions 49 (2010) 335_347[J].

[2]Zhu.Y ,"*Distillation Column Identification for Control using Wiener Model*". (1999). Proceedings of the American Control Conference (pp. 3462-3466).

[3] Mahfouf.M & Abbod. M, "*Online elicitation of Mamdani-type fuzzy rules via TSK-based generalized predictive control*", IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, VOL. 33, NO. 3, JUNE 2003

[4] Kanthasamy. R,"*Nonlinear Model Predictive Control Of A Distillation Column Using Hammerstein Model And Nonlinear Autoregressive Model With Exogenous Input*", (2009),Phd thesis.

[5] Mollov, S., Babu, R., Abonyi, J., & Verbruggen, H. B Effective "*Optimization for Fuzzy Model Predictive Control*", (2004). IEEE TRANSACTIONS ON FUZZY SYSTEMS, VOL. 12, NO. 5. October, 661-675.

[6]Turner.D. G. A. M, "*Application Of A Model Based Predictive Control Scheme To A Distillation Column Using Neural Networks*",(1896). American Control Conference.

[7] Zhong zhou Chen, Michael A. Henson, *Senior Member, IEEE*, Paul Belanger, and Lawrence Megan," *Nonlinear Model Predictive Control of High Purity Distillation Columns for Cryogenic Air Separation*", IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, VOL. 18, NO. 4, JULY 2010.

[8] George Stephanopoulus, "*Chemical Process Control: An Introduction to Theory and Practice*", Published by Pearson education, ISBN 978-81-7758-403-5

[9] José de O. B. Neto*, Guilherme Medeiros Barçante, "*Multivariable Control Applied to Temperature and Humidity Neonate Incubators*", 2010 9th IEEE/IAS International Conference on Industry Applications.